Societal Level Impacts of Connected and Automated Vehicles

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ABSTRACT

There have been high expectations about introducing connected and automated vehicles in the transport systems, in terms of their impacts on safety, mobility, environment, and prosperity. A large body of previous research has focused on the technology and functionality of CAVs while there still exists a gap in knowledge of the likely wider impacts of these vehicles particularly during the transition phase. In this context, this study seeks to contribute to the societal level impact assessment of connected and automated vehicles. For this purpose, a variety impacts along direct (vehicle operating costs, access to travel), systemic (congestion, amount of travel, modal split changes), and wider (road safety, energy efficiency, accessibility in transport, parking demand, and public health) categories have been identified while various appropriate methodologies have been used for the assessment of these impacts including microscopic simulation, surrogate safety assessment, system dynamics modelling, and Delphi panel study. The analysis results on various direct, systemic, and wider impact analysis of connected and automated vehicles indicate a mixture of positive and negative impacts. The results also show the need for full impact assessment in order to identify improved opportunities to achieve city policy goals or set measures to mitigate negative impacts.

Keywords: Connected and Automated Vehicles, Societal Impacts, Traffic Microsimulation, System Dynamics, Delphi, Impacts Assessment

INTRODUCTION

Increasing deployments of connected mobility technologies and the prospect of highly automated vehicles in use has raised the public expectations of major benefits to society. Safety, mobility, transport efficiency and wider societal benefits are all expected once connected and automated vehicles (CAVs) become widespread.

A large body of previous research has focused on the safe operation of automated vehicles and the development of effective mobility services, however there is very little knowledge about the wider impacts on society and on cities in particular. The need to measure the impacts of existing systems as well as forecasting the impacts of future systems represent a major challenge since CAVs are not present in traffic in any large numbers and the operational performance is unknown. Additionally, the dimensions of potential impacts are wide with many sub-divisions adding to the complexity of future mobility forecasts. In this regard, the recently completed European Commission supported Horizon 2020 project LEVITATE (*1*) has developed a new body of evidence to enable cities to identify opportunities where CAVs can support policy goals and also to identify potential negative impacts that cities may need to address through new interventions.

In this regard, this paper seeks to contribute to literature on various societal level impacts of connected and automated vehicles as well as potential policy implications, by presenting some selected findings of the LEVITATE project.

LITERATURE REVIEW

Previous literature has provided forecasts on the potential impacts of introducing automated transport services (at different levels of technological development) along various impact dimensions including safety, mobility, environment, and economy. Some of the findings on these impact categories are presented as follows.

Impacts on Safety

Literature indicates reductions in crashes as one of the most promising benefits of introducing automated vehicles in the traffic mix. Road safety was investigated as part of the wider impacts in the DriveC2X project at several test sites across Europe (*2*). Field demonstrations were conducted and provided some estimates of accidents reduction due to Cooperative Intelligent Transport System (C-ITS) services usage, followed by safety and efficiency assessment of C-ITS services. These services comprised of: In-vehicle Signage (IVS), Speed Limits and other signs, Obstacle Warning, Road Works Warning, Car Breakdown Warning, Traffic Jam Ahead Warning, Green Light Optimal Speed Advisory (GLOSA), Weather Warning, Rain and Slippery Road/Ice & Snow, Approaching Emergency Vehicle and Emergency Electronic Brake Light. The safety impact of these C-ITS applications was assessed for both fatal accidents and injuries for the years 2020 and 2030 (*3*). The most effective service for crash reduction was speed limit warning through IVS, which averted 16% fatalities and 8.9% injuries. The other C-ITS services were predicted to prevent 0.1-3.4% fatalities and 0.2-3.3% injuries at 75% fleet penetration.

Increase in the automation levels (e.g. levels 3, 4 and 5) is expected to yield significant safety benefits. The US Federal Highway Administration (FHWA) predicted that 50-80% of highway crashes could be eliminated with the adoption of Automated Highway Systems (*4*). Similarly, Autonomous Emergency Braking (AEB) has been found to reduce rear-end crashes by 35% to 41%. As a more general consideration, (*5*) suggested that since CAVs are not affected by alcohol, distraction, medication and/or fatigue (cause of 40% of fatal accidents in the US), it could have the potential of at least 40% reduction in fatalities. It is estimated that wide adoption of automated vehicles in Australia would reduce the likelihood of injuries by 80% for drivers and passengers, 70% for cyclists, 40% for motorcyclists and 45% for pedestrians (*6*).

Impacts on the Environment

Using the automation technologies of levels 2-5 (eco-driving – for example, speed control, smooth and gradual acceleration and deceleration) are expected to further improve fuel economy. Eco-driving can improve fuel economy by 4-10% (*7*). In addition, since connected systems can optimize traffic flow and reduce the distance required for safety between vehicles, there may be an increase in the capacity of travel lanes and a reduction in congestion fuel consumption. Folson, 2012 (*8*) estimated that a fleet of automated vehicles could lead to fuel economy of up to 0.47 to 0.235l/100km. As part of the drive to reduce vehicle emissions the EU has recently adopted a 100% reduction target by 2035 (*9*) while the UK (*10*) has announced that Sale of new petrol and diesel cars and vans will be phased out by 2030.

Impacts on Society

The broader implementation of CAVs is expected to have numerous societal impacts including. lower travel costs, higher user comfort and increased accessibility to different user groups, resulting in higher vehicle kilometres travelled (VKT) per day. According to (*11*) the increased accessibility due to the wider adoption of automated vehicles could lead to an increase of the average kilometres covered per day by more than 50%, especially given the fact that CAVs could allow disabled people to travel the same distance and do the same number of car journeys. Similarly, (*12*) estimated an increase in travel for young people, the elderly and the disabled using data from NHTS 2009 (National Household Travel Survey) conducted by FHWA and the 2003 Freedom to Travel project. An overall increment due to automated driving in the VKT per vehicle was estimated to be 40%. (*13*) reported a potential increase of VKT of 3-27% for various automated vehicle deployment scenarios in the Netherlands.

With regard to changes in land use due to adoption of automated vehicles, literature has presented two theories on potential impacts; one predicts more dispersed and low-density land-use due to increased accessibility and reduction in travel times, while the other indicates rise in urban growth in central districts due to lesser demand for parking spaces (*14*). Additionally, the potential increase in congestion in major cities can lead to increased energy consumption. In this context, policies on road use and parking pricing can potentially help promoting more efficient land use and use of resources.

Previous studies forecast increase in travel demand by 3-27% with a connected and automated transport system, primarily due to changes in destination choices, shift from public transport, and the increase in new users. Shared automated vehicles could be a promising solution for reducing the number of private vehicles. For example, (*15, 16*), based on simulation studies, reported replacement of 10-14 conventional vehicles due to one shared automated vehicle. In this regard, The International Transport Forum Report-2015 (*17*), based on analysis of different scenarios of automated transport systems, penetration levels, and availability of high-capacity public transport, has indicated that shared automated vehicles can offer significant benefits in terms of replacing conventional vehicles (with up to 89.6% (65% during rush hour) fewer vehicles on roads).

As indicated by (*13*), the social equality in transport can be negatively affected for low-income populations in short and medium term futures due to those owning high cost private automated vehicles. In this context, Mobility as a Service could improve social equity and accessibility for all income groups.

Public health is another important factor taken into account when designing the future for CAVs. (*18*) emphasized the likelihood of abandonment of active modes of travel such as walking and cycling due to comfortable door-to-door travel via CAVs, leading to decreased public health due to a sedentary lifestyle. To address this challenge, a medium- or long-term policy, when the penetration rates of CAVs will be higher, could be to limit access of CAVs to certain zones, promoting other healthier modes of transport.

Impacts on Economy

Concerning the impact on the economy of the deployment of CAVs, the estimated overall economic benefits due to reduction in accidents and in travel time, fuel savings and parking facility, could amount from 2000-4000$ per vehicle per year (*5*). According to U.S. Department of Transportation (*19*), the wide adoption of CAVs can lead to a reduction in fuel consumption up to 50%, emissions from 12-50%, travel time from 12-48%, journey delays up to 85%, and also save significant number of lives every year.

STUDY METHODOLOGY

Impact Identification

It is expected that connected and automated vehicles will have substantial impacts on road transport. A taxonomy of potential impacts was developed in the LEVITATE project (*20*), which makes a distinction between direct, systemic and wider impacts. Direct impacts are changes that are experienced by each road user on each trip. Systemic impacts are system-wide impacts within the transport system and wider impacts are changes that occur outside the transport system, such as changes in land use and employment. Moreover, a distinction is made between primary impacts and secondary impacts. Primary impacts are intended impacts that directly result from the automation technology, whereas secondary impacts are generated by a primary impact. **Figure 1** presents the various impacts of the taxonomy and their expected interrelations (based on scientific literature and expert consultation). In the figure, impacts are ordered from those that are direct, shown at the top, to those that are more indirect or wider, shown further down in the diagram. Therefore, direct impacts generally correspond to the short term, Systemic impacts to medium term and Wider impacts to the long-term. The diagram is inspired by the detailed model of Hibberd et al. (*21*).

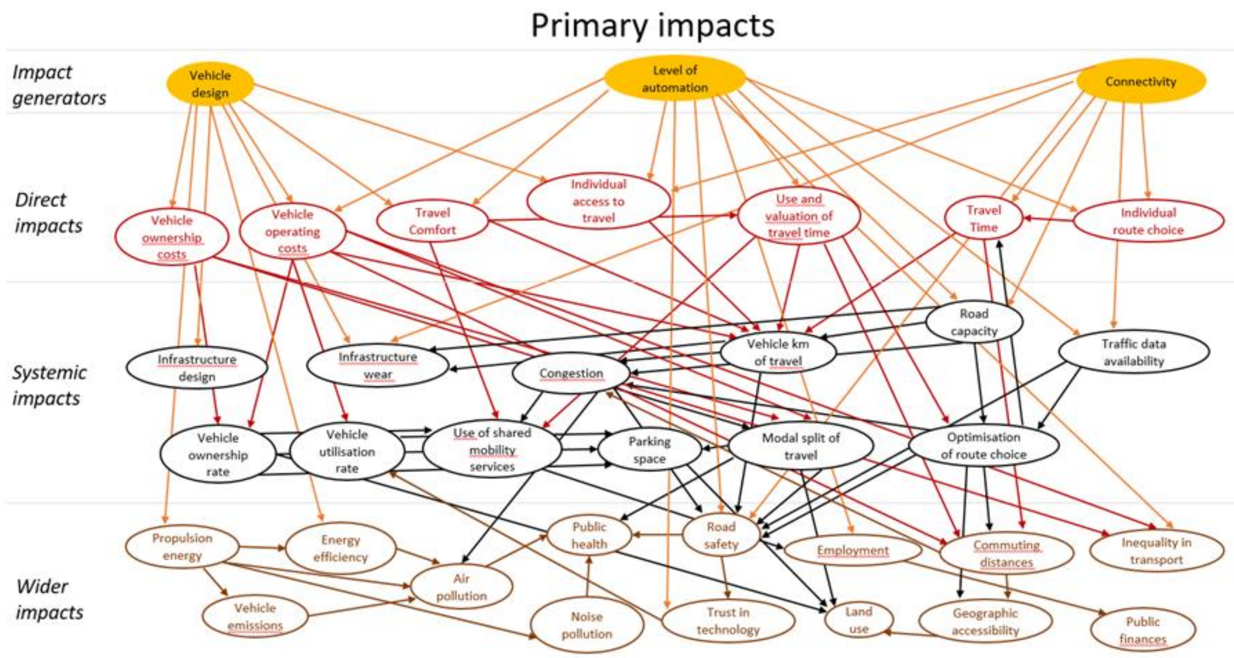


Figure 1 Taxonomy of impacts generated by transition to connected and automated vehicles (*20*)

There is considerable overlap among the lists of impacts presented by the studies, suggesting a high level of scientific consensus about the potential impacts of CAVs. Among a wide range of impact dimensions, some selected impacts pertaining to direct, systemic, and wider category are analysed and discussed in this paper as follows.

- **Direct Impacts:** vehicle operating costs and access to travel
- **Systemic Impacts:** congestion, amount of travel, and modal split changes
- **Wider Impacts:** road safety, demand for parking space, accessibility in transport, energy efficiency, and public health

Methodological Framework

It was envisaged that a broad range of methods must be used in order to adequately quantify as many of the potential impacts as possible. A taxonomy of potential impacts of connected and automated vehicles at different levels of implementation (*2*) were estimated and forecast using appropriate assessment methods including:

- Microscopic Simulation
- Surrogate Safety Assessment Method
- System Dynamics Model
- Delphi Panel Study

Microscopic Simulation

Traffic simulation has been widely applied to estimate the potential impacts of connected and automated vehicles. As identified in (*22*), many studies have used microsimulation technique to estimate the potential impacts of CAVs on traffic performance indicators. It is envisaged that the microsimulation approach can be used to calculate the direct impacts of CAVs. In most cases, a commercially available traffic microsimulation tool is used along with an external component. The microsimulation tool is applied to represent the infrastructure and creates the traffic in the predefined road system, while the external component aims to simulate the CAV functionalities.

AIMSUN Next Microsimulation tool was used in this study, utilising calibrated and validated city networks, including Manchester and Leicester in the UK, Santander in Spain, and Athens in Greece. CAV functionalities/behaviours were modelled by adjusting a wide spectrum of parameters in the simulation framework.

Test Networks

The impact assessment of CAVs was performed on four different calibrated and validated network models of areas within different European cities. The cities include:

- Manchester (United Kingdom)
- Leicester (United Kingdom)
- Athens (Greece)
- Santander (Spain)

Table 1 summarises key network characteristics and traffic composition of microsimulation networks.

TABLE 1 Network Characteristics

Network Attributes	Manchester Network	Leicester Network	Athens Network	Santander Network
Area	13 km²	10.2 km²		
Centroids		209×208	290×292	28
Nodes	308	788	1137	108
Sections	732	1988	2580	382
Traffic Characteristics	Car: 23226 trips (89.83%)	Car: 23391 trips (87.39%)	Car: 82,270 trips (96.36%)	Cars: 42,337 trips
	LGV: 1867 trips (7.22%)	LGV: 3141 trips (11.73%)	Truck:3,110 trips (3.64%)	
	HGV: 763 trips (2.95%)	HGV: 16 trips (0.06%)		
		Bus: 219 trips (0.81%)		

In general, the model development and calibration involved details of road network in the study area, peak hour traffic demand, vehicle types, signal timing data, vehicular behaviour and lane usage, journey times, bus routes, stations, and timetable information. A comprehensive set of traffic counts was used to compare and validate the modelled flows with observed traffic counts. Modelled journey times were also compared and validated against observed journey times during the peak hours.

Modelling CAV Behaviour

Two types of CAVs were considered in this study:1st Generation CAVs and 2nd Generation CAVs. Both types are assumed to be fully automated vehicles with level 5 automation. The main idea behind modelling these two types is based on the assumption that technology will advance with time. Therefore, 2nd Gen CAVs will have improvements in sensing and cognitive capabilities, decision making, driver characteristics, and anticipation of incidents etc. In general, the main assumptions made on CAVs characteristics are as follows:

- 1st Generation: limited sensing and cognitive ability, long gaps, early anticipation of lane changes than human-driven vehicles and longer time in give way situations.
- 2nd Generation: advanced sensing and cognitive ability, data fusion usage, confidence in taking decisions, small gaps, early anticipation of lane changes than human-driven vehicles and less time in give way situations.

These characteristics were defined through various model parameters in AIMSUN Next including reaction time, time gap, acceleration and deceleration characteristics, parameters related to lane changing and over taking behaviour and several others. The default car-following model in AIMSUN is based on Gipps model (*23, 24*). Various parameters of the car-following model were adjusted to implement HDV and CAV behaviours. The assumptions on CAV parameters and their values were based on a comprehensive literature review and can be found in LEVITATE CAV parameters working paper (*25*). The traffic impact of CAVs were assessed in mixed traffic conditions that contain, in addition to passenger cars, freight and public transport (PT) vehicles. The deployment of CAVs was tested from 0 to 100% MPR with 20% increments as shown in **Table 2**.

TABLE 2 CAV Deployment Scenarios

Type of Vehicle	A	B	C	D	E	F	G	H
Human-Driven Vehicle - passenger vehicle	100%	80%	60%	40%	20%	0%	0%	0%
1st Generation (Cautious) CAV - passenger vehicle	0%	20%	40%	40%	40%	40%	20%	0%
2nd Generation (aggressive) CAV - passenger vehicle	0%	0%	0%	20%	40%	60%	80%	100%
Human-Driven LGV	100%	80%	40%	0%	0%	0%	0%	0%
LGV-AV	0%	20%	60%	100%	100%	100%	100%	100%
Human-Driven HGV	1	0.8	0.4	0	0	0	0	0
HGV-AV	0	0.2	0.6	1	1	1	1	1

Surrogate Safety Assessment

Traffic simulation also provides further input to assess other types of impacts by processing those results appropriately to infer such impacts, such as safety impacts through identification of traffic conflicts which involves processing of vehicular trajectories through a surrogate safety assessment model. The road safety impacts were analysed through a surrogate safety assessment by processing vehicular trajectories, obtained through microsimulation output, in the Federal Highway Administration's (FHWA) surrogate safety assessment model (SSAM) (*26*).

The details on TTC threshold values assumed for different vehicle types and other background information can be found in (*27*). The estimated conflicts were also translated to potential crashes by using a probabilistic method proposed by Tarko, 2018 (*28*).

System Dynamics Models

System Dynamics (SD) modeling in LEVITATE is used as a supplementary approach, in order to investigate several longer-term impacts which cannot be covered by other methods: the modal split (for use of public transport as well as active modes), the demand for public parking space and the (average) commuting distance.

The basic system dynamics model used within LEVITATE project can be considered as three sub-models which are interacting with each other.

- At the core, the Transport Model modelled the travel demand and trips (based on segmentation of the target area into geographical zones and the mode of transport). Both the change of total travel demand and the shift between several modes are influenced by the generalized costs that depend on the mode and are impacted by the use of CAV technologies and services. Total modal split is the most important impact variable calculated in this sub-model.
- In order to generate and drive the travel demand, a precise population model has been implemented (segmentation into age groups, zones and income groups). Further, this sub-model is used to calculate the average commuting distance impact variable.
- Finally, the use of public (street) space is modelled on a zone level, distinguishing between parking space, driving lanes and other purposes (multi-functional areas). The relative demand for parking space is calculated in this sub-model.

The generalized costs for travelling are composed by four influencing variables in the following way (**Equation 1**):

$$\textit{Generalized Costs} = \textit{Travel Costs} + (\textit{Travel Time}) * (\textit{Value of Travel Time}) - \textit{Attractiveness} \quad (1)$$

Obviously, lower generalized costs might result from changes in any of these four variables, and lead to an increase in corresponding trips. Such changes are caused by increasing CAV penetration rate, and by the various interventions that have been tested.

For calibration of the model, City of Vienna data (*29*) have been used providing the correct population structure, number of trips and modal split.. The parameters of the SD model were tuned in such a way, that the baseline results for modal split agreed with those of a much more detailed agent-based simulation model for Vienna. Finally, for several specific sub-use cases (interventions), the results of microscopic simulation method have been used in the SD model for quantifying certain relationships (e.g. calculating the impact on average travel time).

Further details pertaining to the SD model description, model data and calibration, can be found in LEVITATE Deliverable 6.3 (*30*).

Delphi Panel Study

Within LEVITATE, the Delphi method is used to determine all impacts that cannot be defined by the other aforementioned quantitative methods (traffic simulation and system dynamics). Initially, a long list of experts was identified and contacted via an introductory mail asking them to express the willingness of participation. Those who responded positively participated in the main Delphi process, amounting to 70 experts in total (5 experts accepted to answer to 2 questionnaires). The characteristics of the experts are shown through Figure 2.

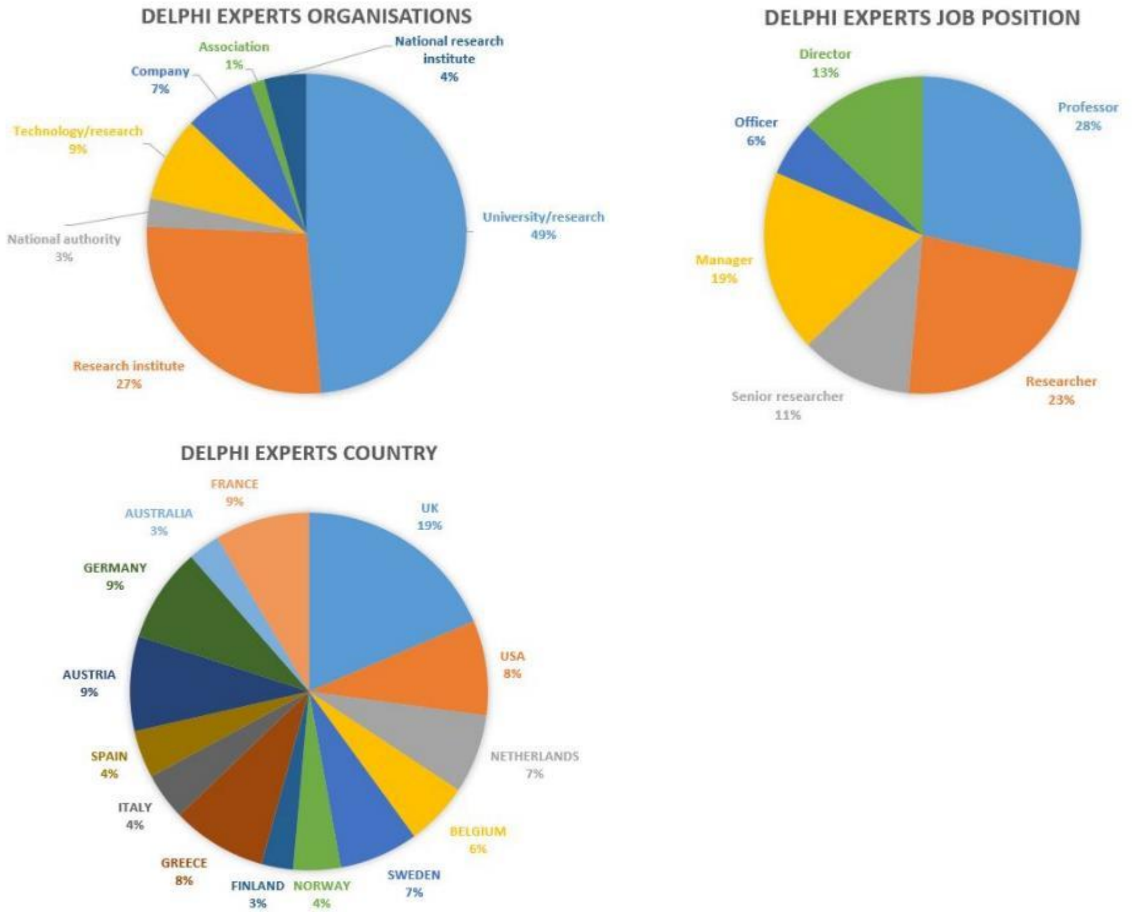
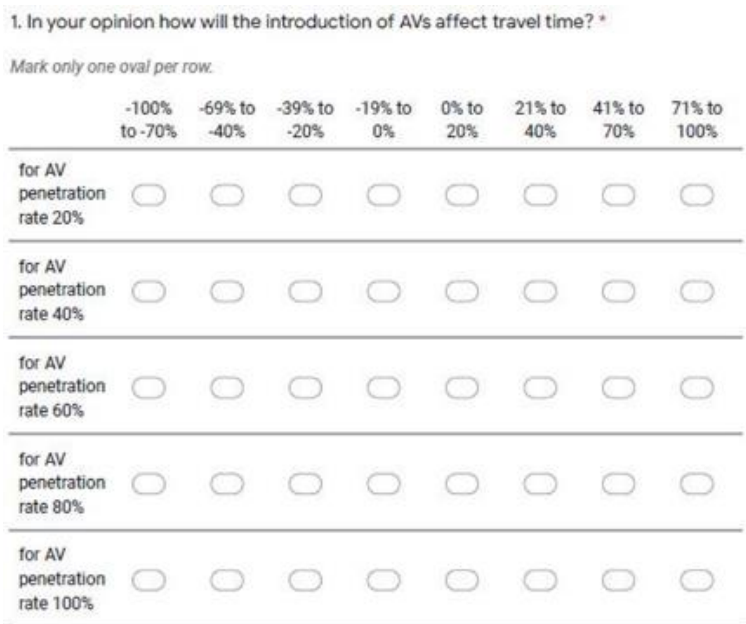


Figure 2 Delphi experts' characteristics

For each impact and each automation related scenario the participants were asked to indicate the percentage of change for the mentioned CAV market penetration rates (**Figure 3**). The percentages varied from -100% to +100% where the negative (minus sign) was either an improvement or a deterioration depending on the type of impact. Further details on the Delphi panel panel study and the questionnaire can be found in LEVITATE Deliverable 5.2 (*31*).



1. In your opinion how will the introduction of AVs affect travel time? *

Mark only one oval per row.

	-100% to -70%	-69% to -40%	-39% to -20%	-19% to 0%	0% to 20%	21% to 40%	41% to 70%	71% to 100%
for AV penetration rate 20%								
for AV penetration rate 40%								
for AV penetration rate 60%								
for AV penetration rate 80%								
for AV penetration rate 100%								

Figure 3 Example Delphi question

ANALYSIS AND RESULTS

Direct Impacts

Vehicle Operating Cost

Vehicle operating cost is considered as the direct outlay for operating a vehicle per kilometer of travel (€/km). The impact on vehicle operating cost of the introduction of automation in urban transport is estimated by the Delphi method. According to experts, the introduction of CAVs will lead to a slight increase for MPR up to 40% and then a small reduction of vehicle operating cost for CAV MPR up to 100%. This fluctuation is explained by the fact that during the early transition period, it will be more expensive to own an AV than a conventional vehicle. The majority of the 2nd round participants stated that they agree definitely (26%) or moderately (59%). Some experts (10%) slightly agreed with the resulted trends and proposed higher reduction of vehicle operation cost for a CAV market penetration rate of 100% reaching -50%.

Access to Travel

Access to travel is defined as the opportunity of taking a trip whenever and wherever wanted (10 points Likert scale which is a qualitative scale used to assess the level of agreement or disagreement with various statements). The general experts' opinion was that the introduction of automation in urban transport will increase access to travel. More precisely, the introduction of CAVs will not influence access to travel for CAVs penetration rate up to 40%, then with the increase of CAV market penetration rate access to travel increases up to 27% for 100% AVs MPR. This can be explained by the fact that in the early transition period, from conventional to automated vehicles, people will not trust CAVs, as it was also suggested by several user acceptance studies, that showed a general relactancy to the overall adoption of CAVs (*32*). The majority of the 2nd round participants stated that they agree definitely (41%) or moderately (36%) with the first Delphi round trend.

Systemic Impacts

Congestion

Congestion in the network was determined through the delays using microscopic simulation results from four different study networks including Manchester, Leicester, Santander, and Athens. **Figure 4** presents the curves on delays vs MPR of CAVs from four different networks. There are some irregularities in the trends with increasing MPR of CAVs which is more prominent in Manchester and Santander networks. Overall, it can be observed that with the inclusion of first generation CAVs in mixed traffic with human-driven vehicles (HDVs) only and also with HDVs and second-generation CAVs, some variation in delays can be expected based on the network characteristics. Manchester and Santander show irregular pattern under these traffic mix scenarios, while there is slight variation found in case of Leicester network and slight decrease to almost no change in case of Athens network. The reasons for irregularities when human-driven and either first- or both first- and second-generation CAVs are in the demand composition could be due to the complexities of interactions between these vehicle types.

When the Human Driven Vehicles (HDVs) are no longer part of the demand and larger proportion of vehicle fleet is replaced by the second-generation vehicles, the delays are found to decrease relatively consistently, which is potentially due to the reason that complexity of interactions primarily due to HDVs are eliminated and also due to shorter headways maintained by the second generation (aggressive) which can result in improved traffic flow.

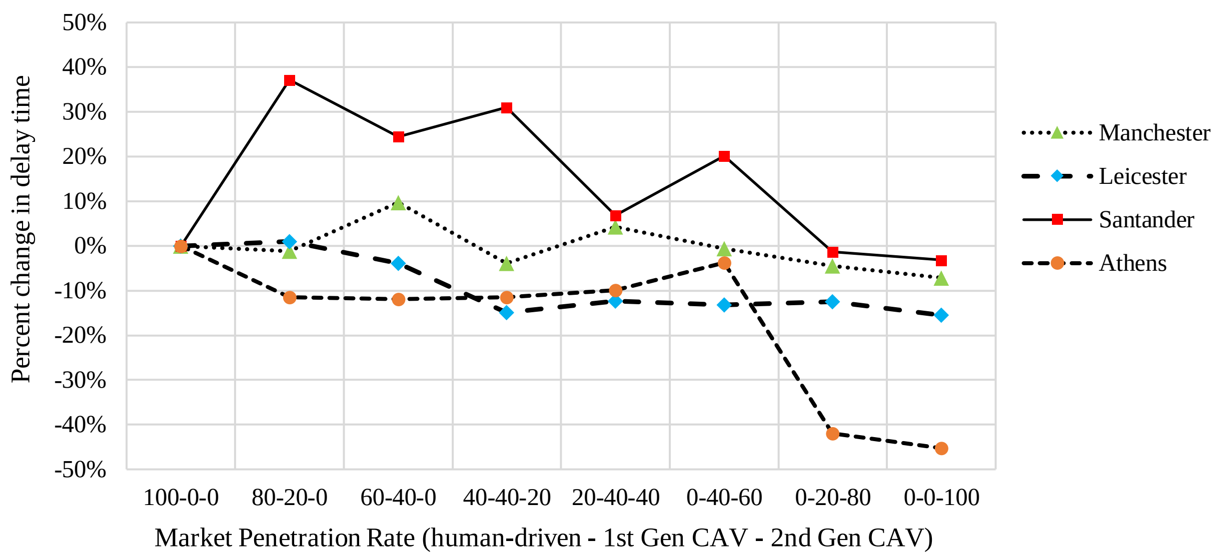


Figure 4 Impact on delay time based on test networks

The above results also show that the degree of impacts on congestion can vary between different networks depending on the network characteristics, however, with absence of HDVs in traffic and when more than 60% of automated vehicular fleet consists of second generation CAVs, delays can be expected to decrease consistently.

Amount of Travel

The impact of amount of travel was measured through microsimulation output in terms of distance travelled within the analysis period. The impact on amount of travel can be related to congestion impacts presented under the previous heading. The network with higher congestion levels will have lesser distance travelled as compared to those having lower congestion. With respect to increasing MPR of CAVs, as explained earlier, as the congestion decreases at higher MPR levels of second-generation vehicles, the amount of travel in terms of distance travelled is increased (**Figures 4** and **5**).

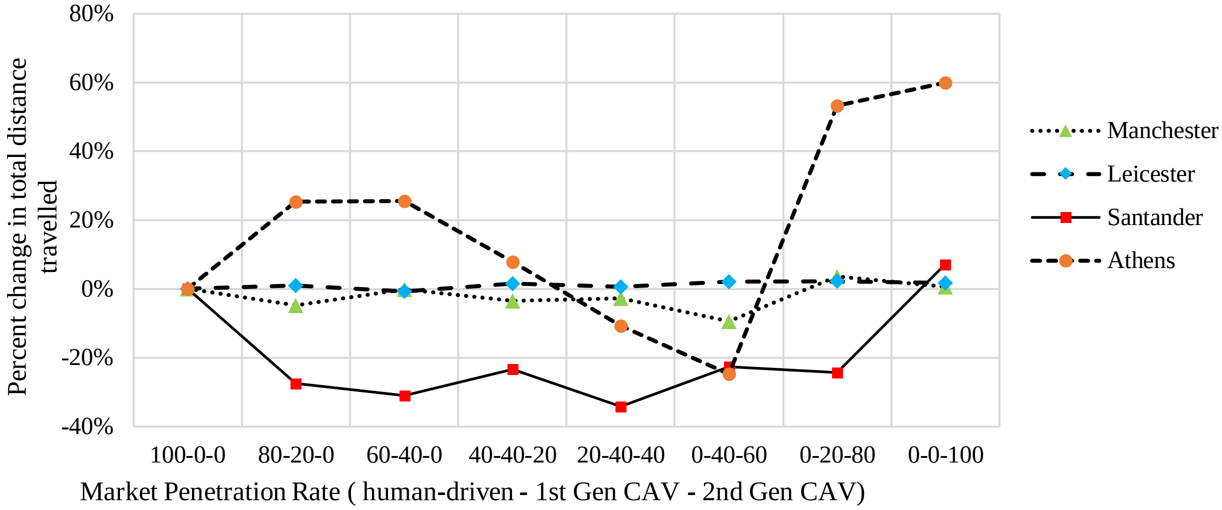


Figure 5 Impact on total distance travelled based on test networks

Changes in Modal Split

The modal split is determined as share by distance of trips carried out using that transport mode, shown as a fraction of the total distance travelled in any available mode, thiswas predicted using the system dynamics model.

The percentage of public transport usage (taking the current value of 0.48 for Vienna as initial value) is estimated to slowly decrease with increasing MPR of AVs with maximum decrease at full fleet penetration (**Figure 6(a)**). This can be foreseen as a consequence that increase in access, convenience, and affordability of private automated cars with time and increasing automated fleet.

With respect to the no-automation case, modal split of active travel (taking the current value of 0.16 for Vienna as initial value) is predicted to decrease even more with increasing MPR of AVs in the transport system (**Figure 6(b)**).

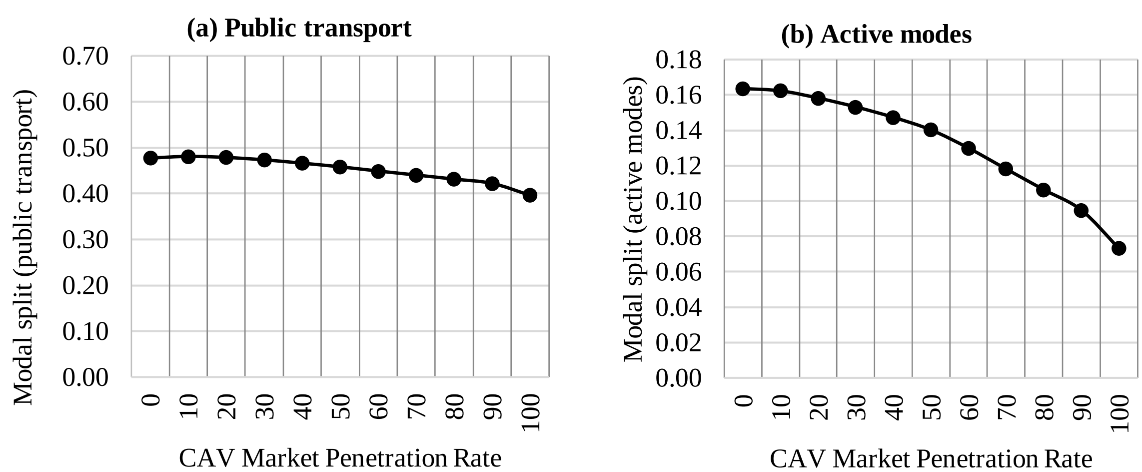


Figure 6 Impact on modal split for public transport and active modes

Wider Impacts

Road Safety

Overall, in all the networks, the investigation of conflicts between different vehicle types showed a significant share of conflicts involving freight vehicles which could potentially be due to added heterogeneity in vehicular interactions as well as due to the limitation of comprehensively modelling behaviours of these vehicles. The analysis based on only the passenger car fleet showed further reduction in conflicts. The estimated reduction in crashes (using Tarko Method (*28*)) was found to be almost 87% in the Manchester network, almost 92.85% in Leicester, 66.93% in Santander, and 58.93% in the Athens network at 100% MPR of CAVs (**Figure 7**).

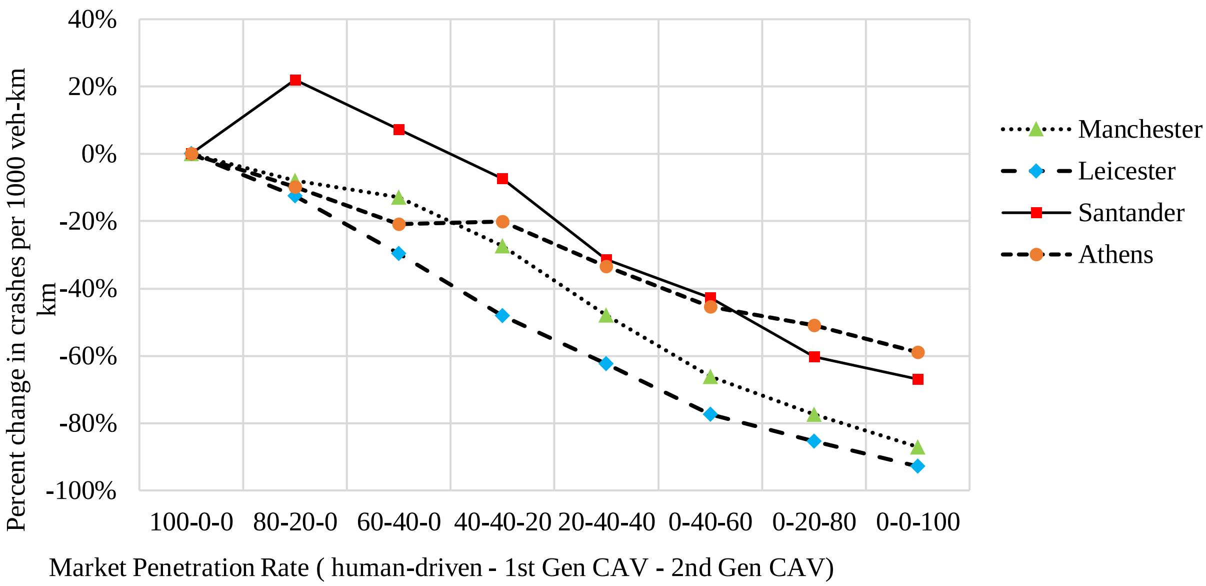


Figure 7 Impact on crashes per 1000 veh-km travelled based on test networks

Accessibility in Transport

The accessibility in transport is the degree to which transport services are used by socially disadvantaged and vulnerable groups including people with disabilities (10 points Likert scale). Based on the 1st round results experts suggested that the introduction of CAVs with no other intervention will improve accessibility in transport by 18.3% for 100% market penetration rate. Similarly, to public health, accessibility in transport has not been widely addressed in literature. Experts in the Delphi method suggested that the implementation of automated urban shuttle services will improve accessibility in transport. The majority of the 2nd round participants stated that they agree definitely (28%) or moderately (49%) with the first-round outcome.

Energy Efficiency

Energy efficiency is defined as the average rate (over the vehicle fleet) at which propulsion energy is converted to movement (%). According to the Delphi method results the introduction of automation in the urban environment will improve energy efficiency up to 14.7% when the CAV market penetration rate reaches 100%. This outcome is supported by the literature since CAVs in urban transport have a great potential of improving energy efficiency and decreasing pollution generated by conventional road transport. The majority of the 2nd round participants stated that they agree definitely (41%) or moderately (49%) with the first Delphi round trend.

Parking Demand

The System Dynamics model was used to forecast the impacts on parking demand due to increasing automation. The impact is presented as relative demand, in percentage of public (street) space within the inner-city area (zone 2). A value of 30% has been taken as initial value (in case of no automation) here. The results indicate an increase in demand for parking with increasing MPR of CAVs, reaching more than 40% at full fleet penetration (**Figure 8**).

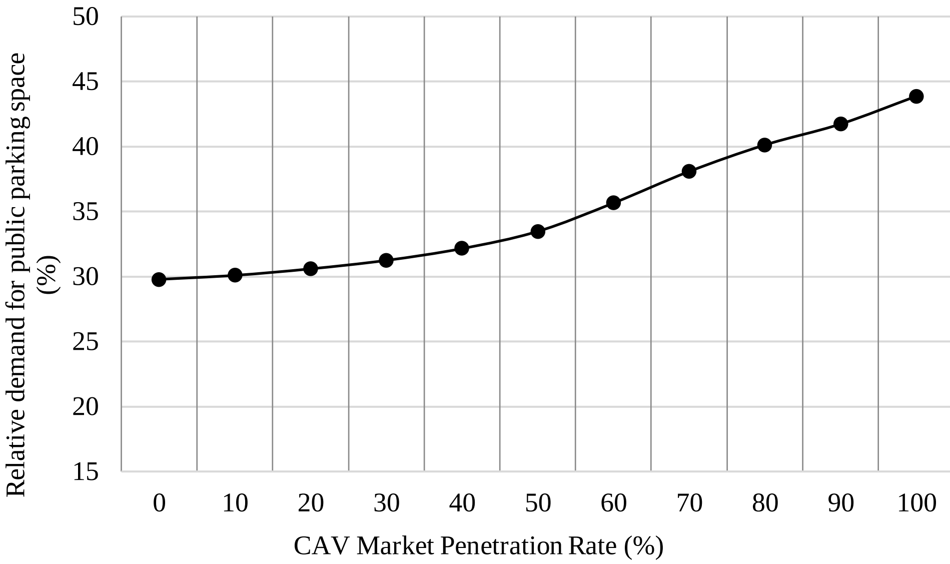


Figure 8. Impact of automation on demand for public parking space

Public Health

Public health (subjective users' rating of public health state, related to transport, such as air quality, noise pollution) is also an impact estimated using the Delphi method. The general experts' opinion in the 1st round was that the introduction of CAVs in the urban environment will lead to a small improvement of public health, which is compatible with the reduced emissions resulted in microsimulations. More precisely, it is estimated that for CAVs MPR up to 100% public health improvement will reach a maximum of 6%. The potential effect of CAVs on physical activity, and by extension public health, is not widely addressed in the literature. On the one hand the aforementioned reduction of the pollution could also improve public health, on the other hand the adoption of CAVs for all kinds of transport could cause people to spend more time in the CAVs and consequently less time being physically active. In the 2nd round the majority of experts commented that they agree definitely (44%) or moderately (38%) with the resulted trend. 13% of the experts stated that they do not at all agree with the 1st round outcome, and proposed that given the negative impact on modal split using active travel (walking, cycling) automation will not improve public health but instead reduce it by 10%.

DISCUSSIONS AND POLICY IMPLICATIONS

The results on various direct, systemic, and wider impact analysis of connected and automated vehicles illustrate a mixture of positive and negative societal impacts. Policy measures should be based on a full impact assessment in order to identify improved opportunities to achieve city policy goals or set measures to mitigate negative impacts.

The results show variations in the expected impact on congestion based on network characteristics; however, during the transition phase, with presence of human-driven vehicles and early generations of automated vehicles, which operate below the level of human driven vehicles, there may not be reduction in congestion levels delays rather in some cases a further increase can may be expected. Only when human-driven vehicles are no more part of the traffic mix and larger vehicular fleet is replaced with higher percentage of second-generation automated vehicles, a consistent reduction in congestion can be expected. In this respect, particularly during the early phases, parking policies related to space usage and pricing are important to carefully devise as some measures can potentially further enhance the adverse impact on congestion. For example, policies encouraging drivers to drive around (not to park) until pick-up can likely increase congestion in that area.

Depending upon network characteristics and fleet compositions, the early phases of CAV deployment with a mixed fleet of automated vehicles and vehicles with human drivers in the transport system can result in marginal decrease and in some cases increased conflicts and collisions. Local and national policies will be essential to monitor and mitigate these detrimental impacts during the transition phase.

As advanced automated vehicles form the largest part of the vehicle fleet, it is anticipated that crash rates will reduce substantially below the current levels. When these vehicles meet or exceed the performance of humans it is expected that traffic impacts may improve beyond existing levels.

Commonly any improvement in passenger car mobility through the increased automation will have the effect to reduce the use of public transport and active travel. Similarly, improvements in public transport will reduce personal car use and active travel. In this regard policies promoting services like automated ride sharing and last mile shuttle are likely to negatively impact active travel due to providing pick-ups and drop-offs closest to the origins and destinations of passengers, where last mile shuttles can potentially have much stronger impact on active travel than automated ride sharing. The adoption of CAVs as well as services further promoting their usage can eventually affect public health as also indicated in the Delphi study results which showed only small improvement in public health due to adoption of CAVs, primarily due to its environmental benefits, while physical activity (active travel) being strongly affected due to ease of traveling through CAVs. This decreased level of physical activity increases the risk of adverse health impacts (*33*). Additionally, AVs in the urban environment might lead to an increase in vehicle-miles travelled, which might in turn lead to lack of physical activity and increased obesity rates (*5*).

Vehicle operating costs are expected to increase in short-term with introduction of automated vehicles but reduce with higher MPR, potentially due to the the fact that during the early transition period, it will be more expensive to own a CAV than a conventional vehicle. Another potential factor could be due to the improved traffic flow when fully automated CAVs are the large majority, which will lead to less fuel consumption, as well as fewer collisions as a result of more law-abiding vehicles and will lower demand for auto repair, and insurance (*34*). Introduction of automated ride sharing services can potentially have a strong impact in reducing vehicle operating costs.

Experts predict small influence on access to travel in the early phases (up to 40% MPR) primarily due to trust issues in adopting CAVs, while increase in access to travel can be expected with higher MPRs of CAVs. In this regard, public opinion and adoption of CAVs is highly critical in the early phases. In several studies, neutral or negative public opinion regarding CAVs has been reported proved (*35*). Additionally, CAVs will be more expensive than a conventional vehicle and thus economically unapproachable, as willingness to pay is a factor that influences adoption of CCAM. According to the survey conducted by the global market research company Power and Associates (*36*), 37% of the participants (17400 vehicle owners), would purchase an automated driving mode. However, this percentage dropped to 20% when they were informed that the estimated market price would be 3000$. In terms of policy making, automated ride sharing services can potentially have a significant impact as well as increasing access to travel.

The accessibility in transport is predicted to increase with increasing MPR of automation and particularly at higher levels. Experts in the Delphi method suggested that the implementation of automated urban shuttle services will improve accessibility in transport. A number of authors have stressed the potential CAVs have to improve accessibility for a range of people. Many authors report that the use of AVs could enable elder persons, disabled and non-drivers, such as underage children, to become more mobile (*5*, *37*). Furthermore, Alessandrini et al. (*38*), argue that shared AV shuttles have the potential to improve accessibility for people living in areas that are not well connected to collective transport. In terms of policy making, introduction of automated ride-sharing services can also positively impact accessibility in transport. Policies on road use pricing can potentially negatively impact accessibility in transport.

Majority of experts predicted improvement in energy efficiency with higher penetration of CAVs in the urban environment. This outcome is supported by the literature since CAVs in urban transport have a great potential of improving energy efficiency and decreasing pollution generated by conventional road transport. Additionally, changes in vehicle design could include using lighter, less energy demanding materials for building the vehicles, since vehicles are less likely to crash; this would allow energy saving gains (*39*). However, research also notes that this change would only occur under high CAV penetration scenarios, once all manually driven vehicles have been phased out of the urban environment (*40*) and very high levels of safety assurance have been achieved.

Demand for parking is estimated to increase gradually with increasing automation with higher increasing rate with higher MPR (more than 50%) of automated vehicles. In this regard, policies on road use and parking pricing can strongly reduce the demand for public parking spaces.

Close monitoring of the manner in which CAVs move, their interactions within the transport network and a calibration of the societal impacts is essential to improve future impact forecasts and to prepare more effective interventions so that city goals can be achieved.

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