LEVITATE: Road safety impacts of Connected and Automated Vehicles[1]

Authors: Wendy Weijermars (SWOV), Andreas Hula (AIT), Amna Chaudhry (LOUGH), Sasa Sha (LOUGH), Rins de Zwart (SWOV), Celina Mons (SWOV), Hitesh Boghani (LOUGH)

Connected and automated transport systems (CATS) are expected to be introduced in increasing numbers over the next decades. Moreover, they are expected to have considerable impacts on mobility, safety, the environment and society as a whole. One of the aims of LEVITATE is to forecast these impacts.

Deliverable 3.1 (Elvik et al, 2019) presents a taxonomy of potential impacts of CATS. The taxonomy 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 (rebound impacts) are generated by a primary impact.

Within LEVITATE, impacts are discussed for various so-called sub-use cases (SUCs). These SUCs reflect applications or interventions -related to passenger vehicles, urban transport or freight transport- that can be implemented by policy makers. Table 1 provides an overview of the SUCs that are considered within LEVITATE.

Table 1: Sub-use cases (SUCs) investigated in LEVITATE.

Passenger vehicles	Urban transport	Freight transport
Provision of dedicated lanes for AVs	Point to point automated urban shuttle	Automated freight consolidation
Replace on street parking with…	Point to point automated urban shuttle in a large network	Automated urban freight delivery
Road use pricing	On demand automated urban shuttle	Hub to hub automated delivery
Parking pricing		
GLOSA		
Automated ride sharing		

The impacts for the SUCs are estimated by comparing the situation with intervention to the situation without intervention, i.e. the baseline scenario. The baseline scenario reflects increasing penetration levels of connected and automated vehicles (CAVs).

One of the systemic impacts that is considered in LEVITATE is road safety. Road safety is affected in various ways by increasing penetration levels of CAVs and the sub use cases.

[1] Updated version: July 2021. Please refer to this web article as: Weijermars et al. (2021) Levitate: road safety impacts of Connected and Automated vehicles. Web-article, updated version July 2021. H2020 Levitate project.

This article discusses in which ways road safety is affected by developments related to CATS and how the impacts are quantified within LEVITATE.

Identification of road safety impacts of increasing penetration levels of CAVs

Connected and Automated Vehicles (CAVs) are expected to affect road safety in a number of ways, both directly and indirectly. Moreover, the impacts of CAVs on road safety are expected to develop over time. This section discusses the different ways in which road safety is expected to be affected by increasing penetration levels of CAVs.

Improved driving behaviour

Most crashes involve some form of human (driver) error. The essence of (C)AVs is that the driving task is transferred from the human driver to the vehicle itself. Automated vehicles do not get distracted or tired and have multiple sensors to detect other traffic. Moreover, automated vehicles are expected to have lower reaction times and less variability in driving behaviour, especially if they are able to communicate with each other, i.e. in case they are connected. In addition, automated vehicles can (and should) be programmed in such a way that they obey all traffic rules and therefore do not speed or negate a red traffic light.

Various microsimulation studies (e.g. Bahram et al., 2014, Morando et al, 2018, Padadoulis et al, 2019) have estimated impacts of reduced reaction time and driver variability on safety critical events and report reductions in safety critical events up to 99% in case all vehicles are automated.

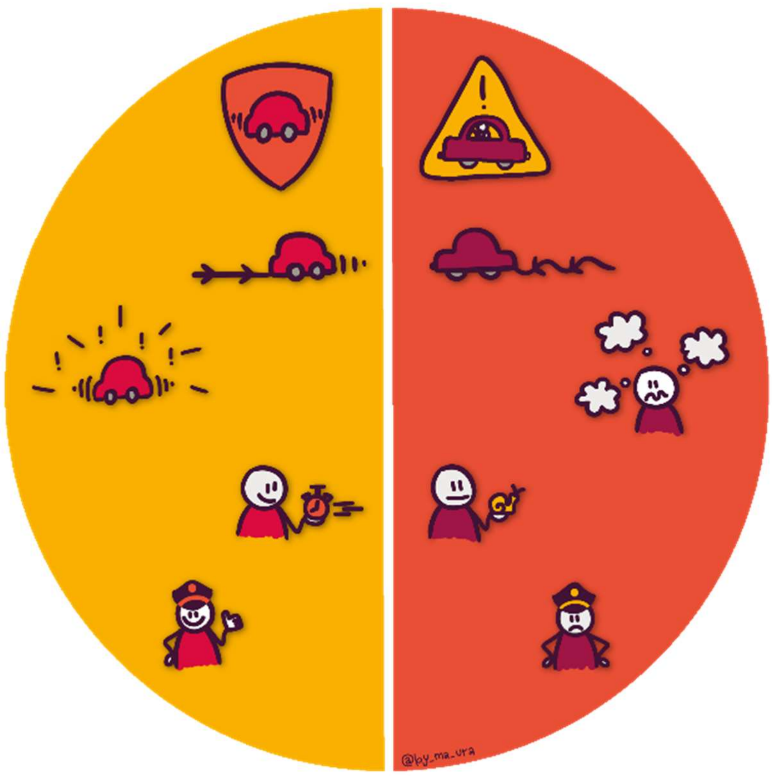


Figure 1 Improved driving behaviour of automated vehicles compared to human drivers. Illustration by Maura van Strijp.

New risks

On the other hand, new risks might be introduced by automated vehicles. First of all, the system might fail due to for example broken detectors or software malfunctioning. Moreover, CAVs might have difficulties with detecting (actually recognizing) other road users, traffic signs or road markings, especially in case of poor visibility due to for example bad weather conditions. More in general, human drivers are probably better in dealing with unexpected or new situations. We should expect CAVs to be well-designed and to have gone through a rigorous design process considering its entire lifecycle before being allowed on the roads. However, it cannot be expected that the system is 100% safe; also airplanes

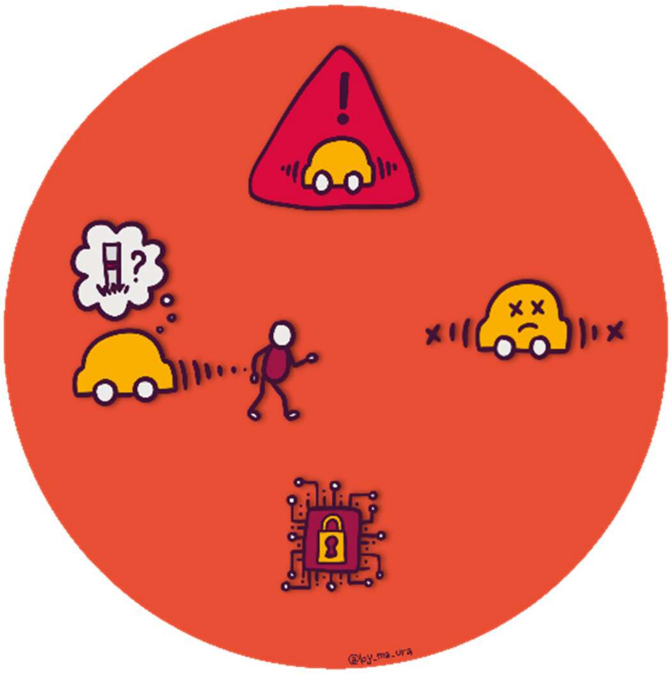


Figure 2 Potential new risks that are introduced by automated vehicles. Illustration by Maura van Strijp

still crash despite of all measures that are taken to prevent crashes. There is no information on the probability of crashes due to system failures related to CAVs.

Another relevant new risk is the risk of hacking or cyber-attacks. Due to the inherent vulnerabilities in CAVs it will be difficult to prevent all cyber-attacks. It is not feasible to quantify risks of cyber-attacks, but by means of a security risk assessment, insight into potential risks and impacts of these risks can be obtained. Elvik et al., 2020 conduct a security risk assessment of CAVs and conclude that it seems improbable that any of the discussed scenarios should result in more fatalities than currently occur annually in traffic.

Transition of control

In case CAVs are not (yet) fully automated, drivers may need to take over the driving task in specific conditions or in case of system failure. Literature shows that take over requests lead to increased reaction times, reduced time-headways and an increase in collisions (Radlmayr et al.,2014; Rudin-Brown & Parker, 2004).

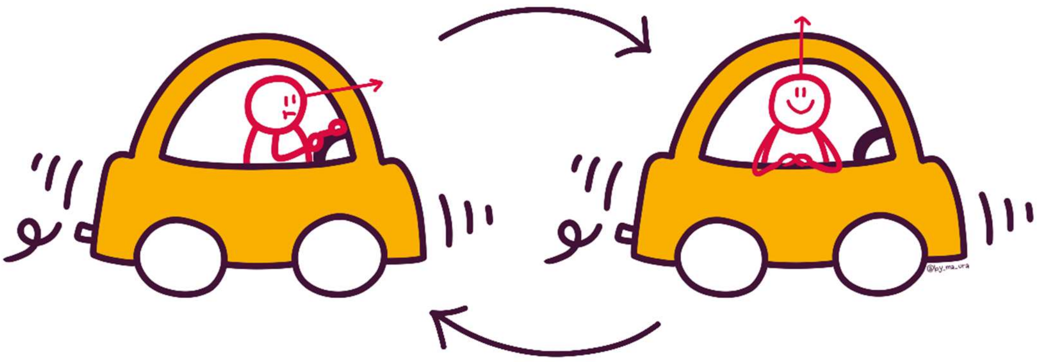


Figure 3 Transition of control. Illustration by Maura van Strijp

Another potential risk related to transition of control is mode confusion. In that case, the human driver is unsure about the current capabilities of the vehicle. Studies show that drivers think the vehicle is in self-driving mode, even when the interface indicates otherwise (Banks et al., 2018; Wilson et al., 2020). Moreover, there are also indications that systems designed to check if the driver is engaged such as hands-on-wheel detection are being circumvented (Wilson et al., 2020).

Rebound effects

Next to the direct impacts on road safety, CAVs also affect road safety indirectly, via impacts that in their turn have an effect on road safety. These rebound effects are summarized in Table 2.

Table 2: Rebound impacts that influence road safety indirectly.

Rebound effect	Description
Behavioural adaptation	Other road users probably adapt their driving/crossing behaviour due to automated vehicles. Human drivers for example adopt smaller time headways when driving next to a platoon of freight vehicles (Gouy et al., 2014).
Induced demand	The introduction of CAVs might result in more distance travelled, e.g. because CAVs drive around empty instead of parking. This results in an increase in exposure and therefore an increase in the number of crashes (in case the crash rate does not change)
Changes in modal split	The introduction of CAVs might also have an impact onf modal split, e.g. it might result in less use of active travel modes. As crash rates differ between transport modes, changes in modal split have an impact on the number of crashes.
Changes in route choice	CAVs could also provide new opportunities for traffic management and as such might result in changes in route choice. As crash rates differ between routes, changes in route choice might in their turn impact road safety
Infrastructural changes	To be able to deal with CAVs, the infrastructure needs to meet certain requirements (Farah et al., 2018). These improvements might also help other road users to prevent errors. In addition, other infrastructural changes that in their turn might impact road safety might occur, e.g. reduction of on street parking.

Developments of impacts over time

The impacts of CAVs on road safety is not a static figure, but is expected to develop over time. Firstly, CAVs are expected to become safer over time as the development work in autonomous vehicles field progresses with increased reliability in hardware (e.g. sensors, actuators) and operating software. Secondly, the penetration level of different types of CAVs is expected to increase over time.

Within LEVITATE, the development of impacts over time is taken into account by means of deployment scenarios in which two types of CAVs are distinguished: 1st generation, more cautious CAVs and 2nd generation more ambitious CAVs that are expected to for example adopt lower time headways, react more quickly and are more capable at interpreting the driving scenario. Table 3 presents the deployment scenarios.

Table 3: CAV Deployment scenarios used within LEVITATE.

CAV Deployment Scenarios								
Type of Vehicle	A	B	C	D	E	F	G	H
Human-Driven Vehicle	100%	80%	60%	40%	20%	0%	0%	0%
1st generation CAV	0%	20%	40%	40%	40%	40%	20%	0%
2nd generation CAV	0%	0%	0%	20%	40%	60%	80%	100%
Human driven freight vehicle	100%	80%	40%	0%	0%	0%	0%	0%
Freight CAV	0%	20%	60%	100%	100%	100%	100%	100%

Identification of road safety impacts for SUCs

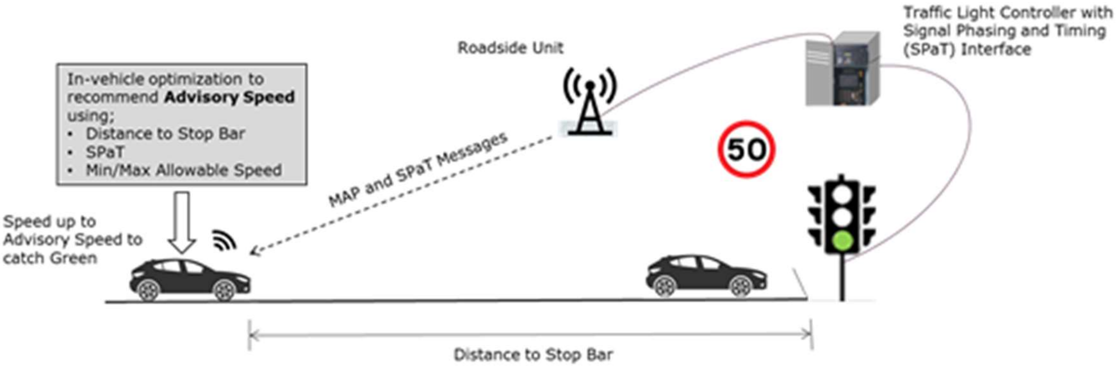
In addition to the general road safety impacts of CAVs that are described above, the specific Sub-use cases (SUCs) can have additional impacts on road safety. For each SUC, described in Table 1, the impacts on road safety are identified based on expert knowledge and available literature. It is outside the scope of this article to discuss all SUCs in this article, yet to illustrate the approach, we describe the potential impacts of the GLOSA sub-use case below.

Road safety impacts of GLOSA

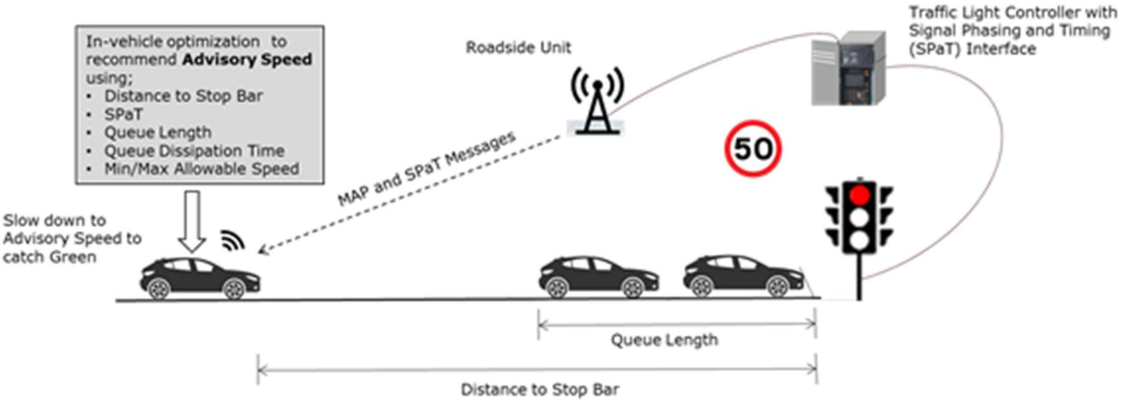
Green Light Optimal Speed Advisory (GLOSA) is an application that advises drivers about how to adjust their speed so they can pass the next traffic light within the green phase. To be able to provide that advice, the application combines traffic signal information with information on the current position of the vehicle. The GLOSA service can be provided by on-board computers of CAVs or via a smartphone app that is connected to the mobile network.

There is limited knowledge available in the literature related to impacts of GLOSA on road safety. As GLOSA is expected to result in a smoother traffic flow with less stop-and-go operation, it can be hypothesized that rear-end collisions will be reduced. However, a simulation research study (Stevanovic et al., 2015) has shown that the total number of conflicts only significantly decrease when GLOSA application works with fixed time signals and the penetration rate of GLOSA equipped vehicles is 100%. The study also reported decrease in rear-end while increase in lane-change conflicts with GLOSA system application. For lower penetration rate or mixed fleet scenarios, the study reported no significant change or in some cases even increased number of total conflicts as compared to 0% penetration; suggesting potentially negative safety impacts of GLOSA application under mixed fleet particularly when signal timings are not optimized.

Another, more indirect impact of GLOSA might be that drivers that are not equipped with GLOSA adapt their driving behaviour due to changed driving behaviour of GLOSA equipped vehicles. Whether or not non-equipped drivers adapt their driving behaviour, also depends on being informed about the GLOSA equipped vehicles. A driving simulator study (Preuk et al., 2018) showed that drivers mimicked the behaviour of GLOSA-equipped vehicles when they had received detailed information about the system. Preuk et al. (2018) also observed some safety issues as the informed drivers showed smaller minimum time-to-collision values when the GLOSA equipped vehicles slowed down while approaching green traffic lights.



(a). Communication initiated when current phase is Green



(b). Communication initiated when current phase is Red

Figure 4. GLOSA system and application concept

Finally, there could be additional impacts if the GLOSA service is provided to human drivers by means of a smartphone app. Monitoring the GLOSA app and adapting speed accordingly might increase workload and cause distraction of human drivers, resulting in a potential risk for road safety. Additionally, humans would likely need more time to respond to potentially changing speed advice than CAVs, which might compromise the accuracy of GLOSA and result in dangerous situations.

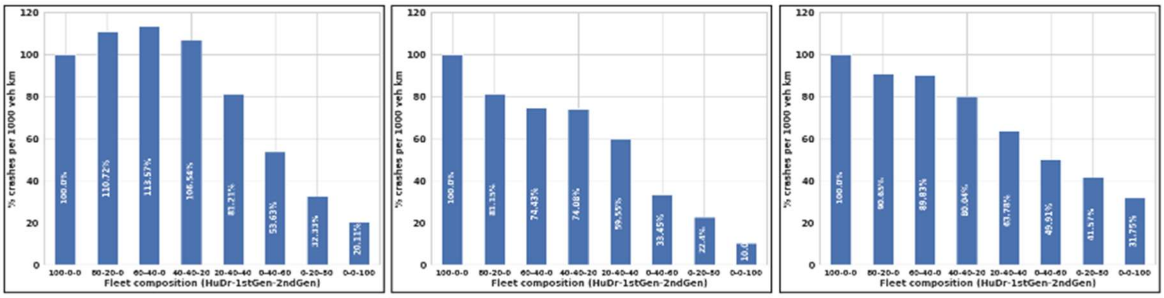
Quantification of expected road safety impacts in LEVITATE

Within LEVITATE, expected road safety impacts related to CATS are quantified as far as possible by combining different methods. Impacts on crashes between motorized vehicles are estimated by means of microsimulation. Impacts on crashes between vulnerable road users and motorized vehicles are estimated by a statistical approach and some of the rebound effects are estimated by combining information on crash rates and changes in distance travelled by various traffic modes.

Impacts on crashes between motorized vehicles, microsimulation

Within LEVITATE, the microsimulation environment AIMSUN NEXT is used to estimate impacts of CATS on traffic (speeds, volumes, congestion). AIMSUN NEXT can also be used to estimate the impacts of reduced reaction times and driver variability on road safety. The road safety impacts are analysed by using the Surrogate Safety Assessment Model (SSAM) that performs statistical analysis on vehicle trajectory data and provides information about the expected number and severity of conflicts. In case of a conflict, the so-called Time To Collision (TTC) is lower than a threshold value. As CAVs are expected to have a lower reaction time than human driven vehicles, the threshold value for TTC should be lower for CAVs than for human driven vehicles. On the basis of literature (Sinha et al., 2020; Virdi et al., 2019; Morando et al., 2018), the TTC thresholds are set to 1.5s for human-driven vehicle, 1.0s for 1st generation AVs and 0.5s for 2nd generation AVs.

Policy makers measure road safety impacts in terms of crashes or crash rates, not in terms of conflicts. Therefore, the estimated numbers of conflicts are converted into estimated numbers of crashes, using an approach based on that developed by Tarko (2018).



(a) **(b)** **(c)**

(a). Manchester network (b). Leicester network (c). Athens network

Figure 5. Preliminary results of the number of crashes for test networks

Figure 5 shows the preliminary results of the number of crashes calculated based on above-mentioned approach for the mixed fleet market penetration rate from three networks i.e. Manchester, Leicester and Athens. As can be seen in Figure 5, the number of crashes was normalised by every 1000km travelled. The overall trend is shown to be consistent as the number of crashes decreases as the market penetration rate increases for all three networks. At a 100% penetration rate of 2nd generation CAVs, crash rates are expected to decrease by 80% in the Manchester network, 90% in Leicester, and 68% in the Athens network. It is worth noting that the number of crashes increases in a lower market penetration rate scenario i.e. 80-20-0, 60-40-0 and 40-40-20 for the Manchester network. This is consistent with the findings from some previous studies which show that the introduction of autonomous vehicles (AVs) with mixed traffic flow may be more dangerous (Shi et al., 2020), especially when the market penetration of AVs is lower than 40% compared to traffic flow consisting of human drivers only (Yu et al., 2019). This is believed to be due to inhomogeneous traffic arising due to difference in driving behaviour.

Impacts on crashes between Vulnerable road users and motorized vehicles

Vulnerable road users (VRUs) are not included in the microsimulation model and therefore, crashes involving VRUs are not taken into account in the impacts discussed above. However, developments related to CATS are expected to impact road safety of VRUs as well. Therefore, another approach based on accident statistics was taken to estimate the impacts on crashes with VRUs.

This approach is based on three main assumptions:
1. It is assumed that all crashes that were caused by human driven vehicles (car is 'at fault') can be prevented by CAVs
2. It is assumed that the remaining crashes (VRU is 'at fault') are less severe when CAVs are involved instead of human driven vehicles, because CAVs are expected to respond faster than human drivers and therefore the impact speed is assumed to be lower in case of CAVs.
3. The CAV systems are highly developed and reliably operational across all relevant real-world scenarios.

The share of crashes for which the pedestrian or cyclist is registered to be 'at fault' differ between cities and countries. In 2016 injury crash data for Vienna (obtained from Statistik Austria), in 20% of the pedestrian-car crashes, the pedestrian is 'at fault' at initial assessment and in 18% of the cyclist-car crashes, the cyclist is 'at fault' at initial assessment. Based on these shares and the first assumption discussed above, 80% of the VRU-car crashes can be prevented in case of a 100% penetration level of CAVs. Taken into account the extra reduction in (severe) crashes due to the reduced impact speed, it is estimated that more than 90% of all fatal crashes between VRUs and cars can be prevented in case all cars are fully automated.

Rebound effects

Concerning the rebound effects, only changes in distance travelled and changes in modal split are taken into account in the quantification of impacts. Impacts of increasing penetration levels and SUCs on distance travelled and on modal split are estimated within other method groups of LEVITATE and the results of those analyses are used as input for the estimation of the road safety impacts of those changes.

Final impacts on the number of crashes are estimated by combining the expected changes in crash rates (crashes per km travelled) that result from the microsimulation and VRU approach with expected changes in distance travelled for the different traffic modes.

Conclusions

Connected and Automated Vehicles (CAVs) are expected to impact road safety in a number of ways:

- In normal circumstances, CAVs are expected to have a lower crash rate than human driven vehicles; CAVs make less errors than human drivers, are assumed to respect all traffic rules and are expected to have lower reaction times and less variability in driving behaviour

- Some new risks will likely be introduced by CAVs; the system might fail or cyber security/hacking problems might occur and in case CAVs are not fully automated (yet), risks related to transition of control or mode confusion might occur.
- Some rebound effects can be expected; mobility behaviour (distance travelled, mode choice, route choice) will likely be affected by the introduction of CAVs and this subsequently influences road safety. Other rebound impacts concern infrastructural changes and changes in travel behaviour of other road users.

It should be noted that policy makers can influence the road safety impacts of CAVs, for example by regulations concerning the conditions that must be met by CAVs to be allowed on the public roads. Moreover, measures like urban shuttles, provision of dedicated lanes or automated freight consolidation have additional impacts on road safety. These impacts are also identified in LEVITATE.

Some of the identified impacts are quantified within LEVITATE, by combining the following approaches:

- Microsimulation is used to estimate impacts of decreased reaction times and driver variability on crash rates between motorized vehicles
- The impact of improved driving behaviour on crash rates between motorized vehicles and vulnerable road users is estimated by using accident data and assumptions concerning types of crashes that can be prevented by CAVs and reduced reaction times
- The estimated impacts on crash rates are combined with estimated impacts on distance travelled that are determined via other methods within LEVITATE to estimate the overall impact on the number of crashes.

It should be stressed that not all impacts are quantified within LEVITATE and many assumptions were needed for the estimation of impacts. Possible new risks for example are not taken into account in the impact estimates since there is currently insufficient quantitative data available. Finally, it should also be stressed that, even if CAVs function perfectly and no crashes occur with CAVs, crashes would still happen. Not all crashes involve motorized vehicles that are likely be automated. In the Netherlands for example, more than half of the serious injuries are due to bicycle crashes in which no motorized vehicles are involved. These crashes cannot be prevented by CAVs.

References

Bahram, M., Ghandeharioun, Z., Zahn, P., Baur, M., Huber, W., & Busch, F. (2014). Microscopic traffic simulation based evaluation of highly automated driving on highways. *2014 17th IEEE International Conference on Intelligent Transportation Systems, ITSC 2014*, 1752-1757. doi:10.1109/ITSC.2014.6957946

Elvik, R. et al. (2019). A taxonomy of potential impacts of connected and automated vehicles at different levels of implementation. Deliverable D3.1 of the H2020 project LEVITATE.

Elvik, R., Meyer, S., Hu, B., Ralbovsky, M., Vorwagner, A., & Boghani, H. (2020). *Methods for forecasting the impacts of connected and automated vehicles Deliverable D3.2 of the H2020 project LEVITATE*.

Farah, H., Erkens, S. M. J. G., Alkim, T., & van Arem, B. (2018, 2018//). *Infrastructure for Automated and Connected Driving: State of the Art and Future Research Directions.* Paper presented at the Road Vehicle Automation 4, Cham

Gouy, M., Wiedemann, K., Stevens, A., Brunett, G., & Reed, N. (2014). Driving next to automated vehicle platoons: How do short time headways influence non-platoon drivers' longitudinal control? *Transportation Research Part F: Traffic Psychology and Behaviour, 27*, 264-273. doi:10.1016/j.trf.2014.03.003

Morando, M. M., Tian, Q., Truong, L. T., & Vu, H. L. (2018). Studying the Safety Impact of Autonomous Vehicles Using Simulation-Based Surrogate Safety Measures. *Journal of Advanced Transportation, 2018*, 1-11. doi:10.1155/2018/6135183

Papadoulis, A., Quddus, M., & Imprialou, M. (2019). Evaluating the safety impact of connected and autonomous vehicles on motorways. *Accident Analysis & Prevention, 124*, 12-22. doi:10.1016/j.aap.2018.12.019

Preuk, K., Dotzauer, M., & Jipp, M. (2018). Should drivers be informed about the equipment of drivers with green light optimal speed advisory (GLOSA)? Transportation Research Part F, 58, 536-547.

Radlmayr, J., Gold, C., Lorenz, L., Farid, M., & Bengler, K. (2014). How Traffic Situations and Non-Driving Related Tasks Affect the Take-Over Quality in Highly Automated Driving. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 58*, 2063-2067. doi:10.1177/1541931214581434

Rudin-Brown, C. M., & Parker, H. A. (2004). Behavioural adaptation to adaptive cruise control (ACC): Implications for preventive strategies. *Transportation Research Part F: Traffic Psychology and Behaviour, 7*, 59-76. doi:10.1016/j.trf.2004.02.001
Shi, Y., Li, Y., Cai, Q., Zhang, H., & Wu, D. (2020). How does heterogeneity affect freeway safety? A simulation-based exploration considering sustainable intelligent connected vehicles. Sustainability (Switzerland), 12(21), 1–18. https://doi.org/10.3390/su12218941

Sinha, A., Chand, S., Wijayaratna, K. P., Virdi, N., & Dixit, V. (2020). Comprehensive safety assessment in mixed fleets with connected and automated vehicles: A crash severity and rate evaluation of conventional vehicles. Accident Analysis and Prevention, 142(January), 105567. https://doi.org/10.1016/j.aap.2020.105567.

Stevanovic, A., Randivojevic, D., Stevanovic, J., Ostojic, M. & Kergaye, C. (2015). Impact of Green Light Optimized Speed Advisory Systems on Surrogate Safety Measures of Arterials. Road Safety & Simulation International Conference (RSS), 6-8 October, 2015, Orlando, Florida USA.

Tarko, A. P. (2018). Estimating the expected number of crashes with traffic conflicts and the Lomax Distribution – A theoretical and numerical exploration. Accident Analysis and Prevention, 113(November 2017), 63–73. https://doi.org/10.1016/j.aap.2018.01.008.

Virdi, N., Grzybowska, H., Waller, S. T., & Dixit, V. (2019). A safety assessment of mixed fleets with Connected and Autonomous Vehicles using the Surrogate Safety Assessment

Module. Accident Analysis and Prevention, 131(December 2018), 95–111. https://doi.org/10.1016/j.aap.2019.06.001

Wilson, K. M., Yang, S., Roady, T., Kuo, J., & Lenné, M. G. (2020). Driver trust & mode confusion in an on-road study of level-2 automated vehicle technology. *Safety Science, 130*, 104845. doi:https://doi.org/10.1016/j.ssci.2020.104845

Yu, H., Tak, S., Park, M., & Yeo, H. (2019). Impact of Autonomous-Vehicle-Only Lanes in Mixed Traffic Conditions. Transportation Research Record, May. https://doi.org/10.1177/0361198119847475