Delivery Report for

MeBeSafe

Measures for behaving safely in traffic

Deliverable Title	Final Measures
Deliverable	D5.5
WP	WP5 Field evaluation
Task	Task 5.6 Data analysis

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Acronyms

ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance Systems
ANOVA	Analysis of Variance
CARE	Citizens Consular Assistance Regulation in Europe
CPU	Central Processing Unit
EGO	Road user/participant with nudge potential
EU	European Union
Euro NCAP	European New Car Assessment Programme Advanced
GIDAS	German In-Depth Accident Study
HGV	Heavy Goods Vehicles
HMI	Human Machine Interface
HUD	Head-up Display
OEM	Original Equipment Manufacturer
PTW	Power Two Wheelers

1 Executive Summary

The main objective of WP5 has been to run a set of field trials with naïve users (i.e. not experts involved in the development of the measures) for all nudging and coaching measures developed in WP2-4. Then, given the outcome of the field trials, the task has been to analyse which impacts these measures may have on road safety along with the cost of implementing them in vehicle fleets and/or infrastructure. All these activities have taken place in Tasks 5.4 (Data collection) and 5.6 (Data analysis).

1.1 Field Trial results

For Objective 1 - driver alertness feedback, a fleet of *N* = 49 drivers were provided with an additional incentive (a gift card type of reward) to stop and take a break when the Driver Alert Control (DAC) system indicated that a break would be beneficial, that is, when high levels of drowsiness had been detected in the driver. The incentive offer was displayed on an additionally installed in-vehicle screen whenever DAC triggered.

The results from the field trial showed a clear positive effect on driver behaviour. The proportion of drivers who stopped within 20 minutes after getting a DAC drowsiness warning nearly doubled in the treatment phase, i.e. it went from 44 % in Baseline to 87 % in Treatment. For drivers who received DAC warnings in both baseline and treatment, the average stopping time after receiving the warning was reduced with 8 minutes in the treatment phase. The offered incentive to stop thus had a large impact on driver behaviour when combined with the drowsiness warning.

For Objective 2 - usage of safety ADAS to prevent close following, a fleet of *N* = 49 drivers were provided with nudging that consisted of different types of visual in-vehicle feedback on the extent to which they were using Adaptive Cruise Control (ACC) while driving. Two types of visual feedback were tried: A) an Ambient Display concept and B) a Competitive Leader Board concept.

Both concepts had significant effects on driver behaviour. For the ambient display nudge, the average ACC use of 14.24 % in baseline rose to 20.82 % in treatment. In other words, drivers on average increased their ACC usage level with about 46 % when nudged with the Ambient Display concept. For the Competitive Leader Board nudge, the average ACC use of 14.48 % in baseline rose to 30.67 % in treatment. Drivers thus on average increased their ACC usage level with 118 % when nudged with the Competitive Leader Board concept.

For Objective 3 - Attention to potential hazards (i.e. to improve timely attention to a potential hazard in intersections), the field trial involved a total of $N = 22$ naïve drivers who twice drove a prescribed 1-hour route through central Eindhoven (NL). Each driver received a nudge at unsignalized intersections, to direct their attention towards areas of the intersection where view obstructions would hide a possibly approaching bicyclist.

With the nudging HMI to direct driver attention, drivers spent on average 20% more time looking in the direction of a potential hazard at a distance of 20-30 m before entering the intersection. Out of $n = 18$ participants, $n = 10$ increased their gaze in the direction of the possible hazard when the HMI was activated. Additionally, $n = 13$ and 14 out of $N = 22$ participants decreased their speed while approaching an intersection in respectively the 30 km/h and 50 km/h zone. The nudge was thus successful both in enhancing visual attention toward relevant areas of the intersection and in making drivers proactively reduce speed, which in turn improves the situational safety margins.

For Objective 4 - behavioural change through online private driver coaching, it was determined that ACC oriented coaching would have its largest impact not on drivers who are already using ACC, but rather on drivers who do not use ACC at all. Since nudging toward increased ACC usage only can be applied on drivers who already use the function, non-users must first become users before nudging can be applied.

Experience from previous studies of non-users have shown that reluctance to use ACC often stem from underlying uncertainties about how to activate it as well as about what to expect if one does (i.e. what will happen?). To address such worries, an in-vehicle, app-based coaching concept was developed where drivers step by step are talked through how to activate ACC while driving, as well as what to expect from the car in each step. The in-vehicle coaching app was pilot tested in three different countries. The outcome of those pilots was successful, in the sense that many who previously characterized themselves as "determined" non-users successfully activated ACC.

A key assumption in the WP5 field trial planning for this app (based on previously collected driving data) was that 20-30% of the drivers in the fleet recruited for Objective 2 would be determined non-ACC users who would not respond to the ACC nudging concepts. These non-users would thus provide the test group for coaching.

As it turned out, this assumption did not hold. All drivers who participated in the Objective 2 field trial, including the ones who did not use ACC in Baseline, did use ACC during Treatment. While positive in the sense that the Objective 2 nudges were more successful than predicted, this also meant that there literally was no-one left to coach for an Objective 4 field trial. The latter therefore had to be cancelled, and efforts were instead focused on making the Objective 2 field trial more informative by deploying a second nudging concept, rather than just one as was the initial plan.

For Objective 5 - HGV driver behavioural change through online coaching, two fleets of company drivers were recruited, one in Norway and one in the UK. However, due to delays in the development of the coaching app, the field trial start was delayed until late February 2020. This in turn placed the field trial start right at the onset of the corona pandemic, which severely affected both the two companies recruited for the field trial and the traffic environment in which they normally drive.

This places severe restrictions on possible interpretations of the field trial outcome. While data indicates that the app was both well received and used by the drivers, and that peer-to-peer coaching is a viable approach, today it is not possible to conclude whether coaching does change HGV driver behaviour or not.

For Objectives 06 and 07 - Safe speed/trajectory on inter-urban roads, the field trial took place on an exit lane in Eindhoven, Netherlands, where roadside marking lights were installed in such a way that drivers who entered the exit lane at speeds above a predefined threshold could be exposed to systematically varying light patterns along the lane. Overall, *N* = 727,299 vehicles drove through the field test location, of which 67.2 % fulfilled nudging criteria. The results indicate that vehicles do slow down significantly when being nudged by the nudging system, reducing the ratio of speeding drivers by up to 40 %. Furthermore, drivers in the top speed segment, i.e. those who entered the exit lanes at the highest speeds during the field trial, were the ones most affected by the nudge.

An on-site survey (*N* = 20) and an online resident survey (*N* = 346) revealed a positive attitude of participants towards the nudging system and rated it as suitable to reduce driving speed. In both qualitative data collections, participants rated the nudging system as most effective to reduce speed in comparison to a regular speed sign or speed cameras.

For Powered Two-Wheelers (PTWs) taking the exit however, no systematic effect of the nudge could be found in the data. The analysis showed that this most likely was due to the PTWs entering the exit lane at a much later point than cars, which means they either failed to activate the visual nudging completely, or only were exposed to a limited part of it.

For Objective 8 - Cyclists' speed reduction the field trials involved a random sample of cyclists passing two test sites implemented in Gothenburg, Sweden, and another random sample of cyclists who passed a test site implemented in Eindhoven, the

Netherlands. In both instances, passing cyclists were visually nudged by transverse lines on the bicycle lane that got closer to each other as the distance to the respective intersection decreased.

Both trials showed positive effects on cyclist behaviour. In the Gothenburg trial, 9-17% more cyclists reduced their speed in treatment depending on location and other factors. In the Eindhoven trial, cyclist speeds were reduced, and deceleration rates were also higher during treatment.

1.2 Safety and socio-economic impact assessment

To estimate the safety impact of the nudged developed in MeBeSafe, the Euro NCAP Advanced method was applied. This gives an estimate of how many persons might avoid negative traffic accident related outcomes in the EU-27 if MeBeSafe measures were to be deployed, depending on both user acceptance and the extent to which the measures are able to penetrate the market.

A number of scenarios were investigated. In what was judged to be the most realistic scenario with plausible market penetration rates, the MeBeSafe measures together address 0,9 % of all fatally injured persons. That corresponds to 189 fatalities annually by 2025 and 366 fatalities (1.9 %) annually by 2030 (Figure 1-1). In addition, the MeBeSafe measures would address 16,584 seriously and slightly injured persons in 2025 and 40,053 persons in 2030. This corresponds to a share of 1.2 % in 2025 and 2.5 % in 2030 respectively, for the group of seriously and slightly injured persons.

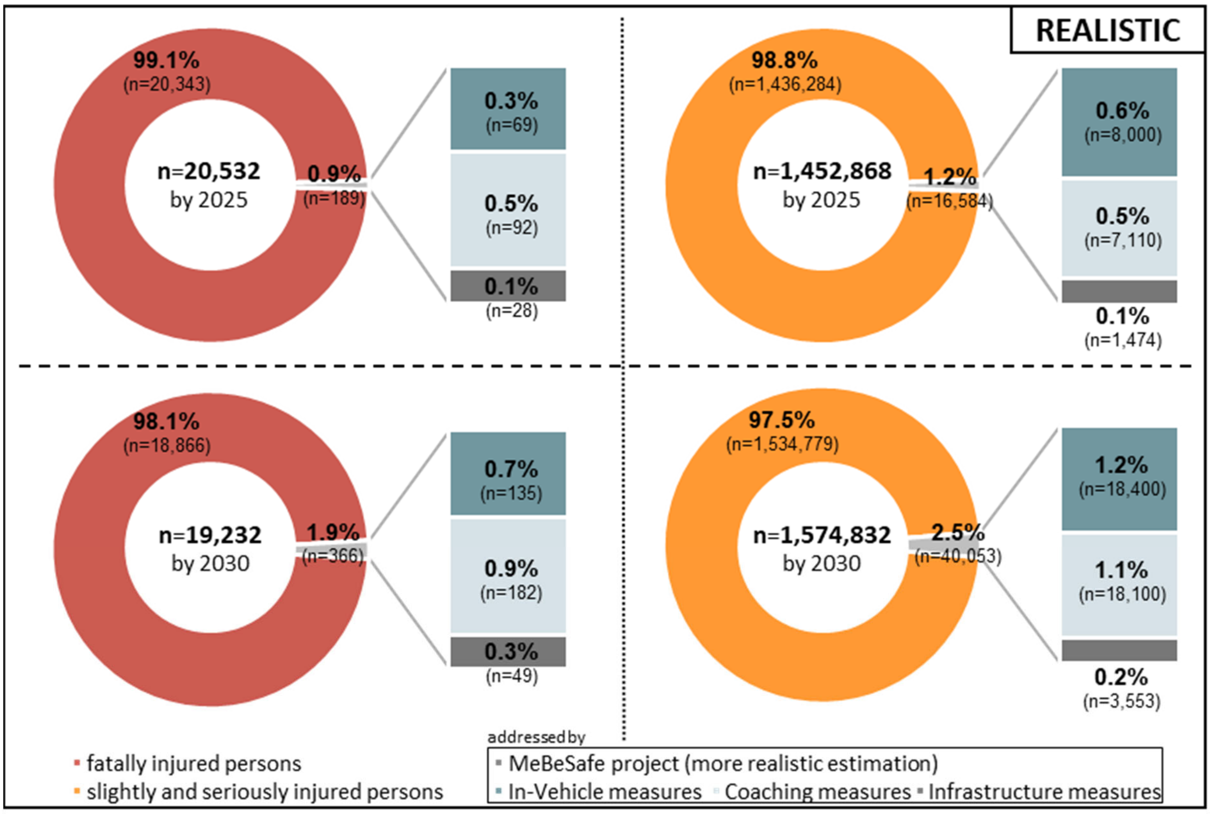

Figure 1-1: Impact assessment according to the realistic estimation of the MeBeSafe project to the EU-27 for fatally injured persons (left) and slightly/seriously injured persons (right) in 2025 and 2030

The socio-economic impact assessment translates the predicted reduction in the number of fatalities and injuries in the safety impact assessment above to potential financial savings for the EU-27. Socio-economic costs of road traffic accidents in the EU-27 represent 1.8 % of the Gross Domestic Product (GDP). These costs include healthcare costs for the management and treatment of injuries, administration costs of liability settlements, damage to public goods, and loss of output from those injured or killed.

Based on the realistic market penetration scenario, it was estimated that the measures of the MeBeSafe project could potentially save socio-economic costs of €1.9 billion annually by 2025 and of €2.2 billion annually by 2030.

It is also important to note that while new safety measures in vehicles usually result in higher market prices, the MeBeSafe in-vehicle measures use components already present in the vehicle for other purposes, so probably will not result in higher costs.

2 Contribution by each Partner

This deliverable was written by Mikael Ljung Aust (VCC), with contributions from Niccolò Baldanzini (UFI) Bram Bakker (Cygnify), Moritz Berghaus (ISAC), Sabine Bertleff (IKA), Ayse Cetin (IKA), Saskia de Craen (SWOV / Shell), Marianne Dyer (Shell), Adrian Fazekas (ISAC), Pär Gustavsson (VCC), Ines Güldenberg (IKA), Maren Klatt (IKA), Jordanka Kovaceva (SAFER), Anna-Lena Köhler (IKA), Stefan Ladwig (IKA), Henrik Liers (VUFO), Matin Nabavi Niaki (SWOV), Norah Neuhuber (Virtual Vehicle), Olaf Op den Camp (TNO), Alberto Perticone (UFI), Muriel Schnelle (IKA), Cedrik Sjöblom (SAFER), Elizabeth Uduwa-Vidanalage (Shell), Johann Ziegler (VUFO), Vincent de Waal (HEY), Pontus Wallgren (SAFER), Marijke van Weperen (TNO), Anders af Wåhlberg (Cranfield University).

All other partners in WP5 contributed by giving their feedback on this deliverable. All partners have fulfilled their tasks in time and with satisfactory quality.

3 General introduction

The main objective of MeBeSafe has been to develop a set of nudging/coaching countermeasures that were expected to have a significant positive impact on traffic safety if widely implemented, and then run a set of field trials with naïve users for all measures developed to verify that these expectations can be met in reality.

This deliverable describes the results of all the Field Trials that were set up to evaluate the effectiveness of the nudging and coaching measures. It also describes the impact on traffic safety, which these measures would have if implemented on the EU-27 level, along with suggestions for improvements as well as predicted costs for implementing them in practice.

First, the final results from each Field trial are described in detail (Chapters 4- 10). Next comes the Safety and Socio-economic Impact Assessment (Chapter 11), an evaluation of what could be improved with the Measures (Chapter 12) and finally an estimation of the costs involved in deploying these measures (Chapter 13).

4 Final results for O1: Driver alertness feedback

For driver alertness feedback, the nudging concept consists of providing the driver with an incentive to stop and take a break when the Driver Alert system indicates that a break would be beneficial (i.e. when a high level of drowsiness has been detected). The details and results of this field trial are described below.

4.1Participants

The field trial test fleet had *N* = 49 participants. All were Volvo Cars employees driving Volvo XC60 MY 2020 company cars. A gender- and aged-balanced test population was targeted in recruitment. The final fleet consisted of n = 26 women and 23 men in the age span 39 - 62 (*M* = 50.4, *SD* = 6.07). Driving experience ranged from 20 to 44 years (*M* = 32.0, *SD* = 6.25).

Note that these are the same participants that were nudged to increase their usage of ACC more, as described in chapter 5 below. While it was not predicted that there would be any interaction effects between the two nudging types (i.e. receiving an incentive to stop when drowsy versus being nudged to engage ACC more often) as they address very different events and mechanisms, this still deserved to be explicitly mentioned.

4.2 Materials, procedure and test design

All participants were given the same written information stating that the purpose of the test was to examine a new platform for driving feedback. Participants were informed that their company car would be fitted with an additional screen (in the form of an iPhone 6 or 7 where they would receive visual feedback related to their driving and use of vehicle systems. Participants were asked to keep the phone "alive" and visible at all times when driving and report any problems that occurred.

Note that DAC was not explicitly mentioned in the information drivers received, to avoid influencing driver behaviour in any way except by the nudge itself. The field trial used a within-group design, i.e. baseline and treatment data were collected from the same 49 cars in a sequential manner.

4.3 Nudging measure

In order to nudge drowsy drivers to take a break by providing an incentive to do so, a *Driver Alert Control nudge app* was implemented. When a driver received a Driver Alert Control warning from the car, the app informed the driver that s/he would receive a surprise gift if s/he took a break within 20 minutes. A timer then started to count down. If the driver did not stop within that time, the app would tell them that they missed their chance to receive a gift.

If the driver did stop, the app would reveal what the surprise gift was and inform that it would be delivered by email. The gifts were vouchers valid in different online/physical stores, restaurants or recreational attractions, at values between 30 and 90 €. A driver could not receive more than one voucher per 24 hours. Furthermore, a driver could not get the same voucher type twice. The different views of the app are shown below.

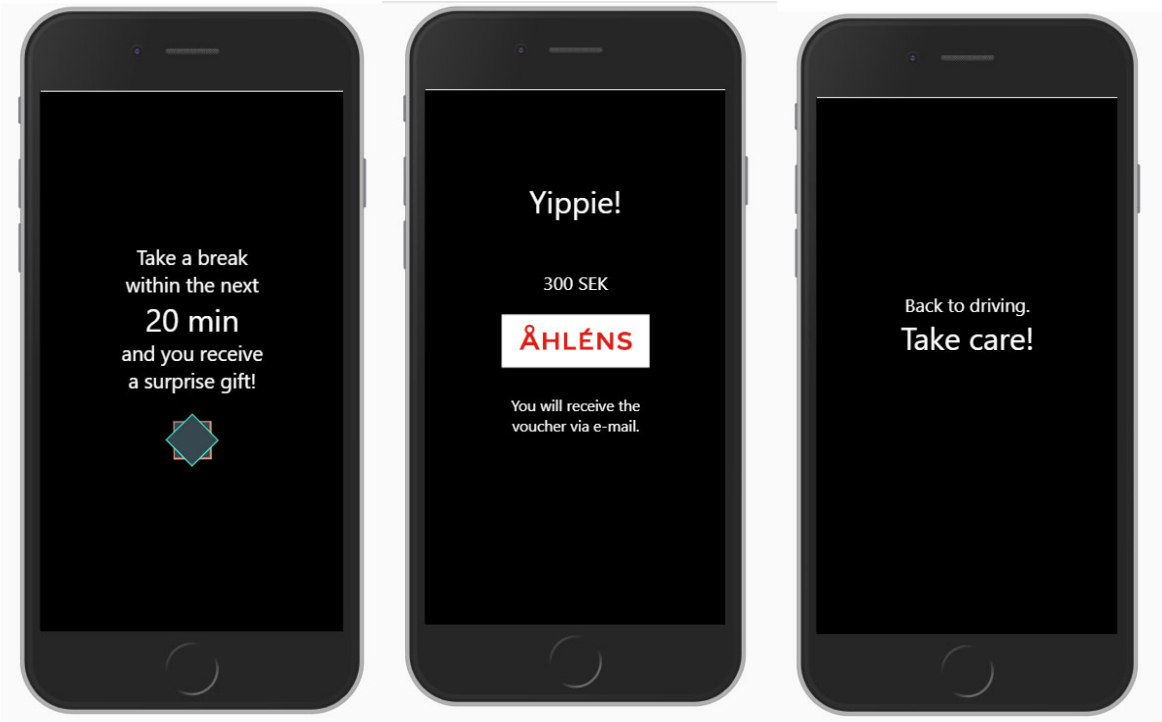

Figure 4-1: Screen shots from the Driver Alert Control Nudge app

4.4 Data collection

The participants' cars were equipped with remote data acquisition units set up to record vehicle data including engine status, vehicle speed, DAC status and standalone GPS-data. Data recording was triggered at every engine start and continued until engine shutdown. The general baseline data collection lasted between October 2019 mid-April 2020. Treatment data was collected from mid-April to August 2020.

4.5 Dependent variable

DAC stopping time was calculated for each trip by calculating the duration from DAC warning status until the vehicle was at standstill (i.e. vehicle speed = 0). For trips including several DAC warnings, the first warning was used as the time reference point.

4.6 Results

During baseline, *N* = 23 drivers received at least one DAC warning and there was a total of 59 trips which included at least one DAC warning. In 44 % of the trips where a driver received a warning, they stopped within 20 minutes. During treatment, *N* = 11 drivers received at least one DAC warning and there was a total of 15 trips which included at least one DAC warning and an incentive offer to the driver. In 87 % of the trips where a driver received a warning and the incentive was offered, the drivers stopped within 20 minutes and received the incentive. In other words, the proportion of drivers who stopped within 20 minutes of a DAC warning almost doubled when drivers were offered an additional incentive.

Looking at a within driver comparison, there were *N* = 9 drivers who received at least one DAC warning in both baseline and treatment. For these *N* = 9 drivers, their stopping time was on average reduced with 8 minutes. The highest decrease in stopping time between baseline and treatment was 32 minutes.

5 Field trial results for O2: Usage of safety ADAS to prevent close following

For usage of safety ADAS to prevent close following, the nudging consisted of providing the drivers with different types of visual feedback on the extent to which they were using Adaptive Cruise Control (ACC) while driving. The details and results of this field trial are described below.

5.1Participants

All *N* = 49 participants were Volvo Cars employees driving Volvo XC60 MY 2020 company cars. To the extent possible, a gender- and aged-balanced test population was targeted. The number of females were 26 and males 23 aged between 39 and 62 (*M* = 50.4, *SD* = 6.07). Driving experience ranged from 20 to 44 years (*M* = 32.0, *SD* = 6.25).

Note that these are the same participants that were given an incentive to stop if receiving a DAC warning, as described in chapter 4 above. While it was not predicted that there would be any interaction effects between the two nudging types as they address very different events and mechanisms (i.e. receiving an incentive to stop when drowsy versus being nudged to engage ACC more often) this still deserved to be explicitly mentioned.

5.2 Materials, procedure and test design

All test participants were given the same written participant information stating that the purpose of the test was to examine a new platform for driving feedback and driver behaviour. The participants were informed that their company car would be fitted with an additional screen (in the form of an iPhone 6 or 7) to which software would be remotely downloaded that would give them visual feedback related to their driving and their use of the car's systems. Furthermore, participants were asked to keep the phone alive and visible at all times when driving and report any problems that occurred.

The terms *Adaptive Cruise Control* (ACC) or *Driver Alert Control* (DAC) were not explicitly stated anywhere in the information the drivers received, in order to avoid influencing drivers in other ways than through the app design.

The field trial used a within-group design, where baseline and treatment (i.e. driving with the app) data were collected from the same 49 cars. One driver participated during baseline and the ambient design concept treatment phase but not in the competitive Leader Board concept treatment phase and was hence not included in analysis of the latter.

5.3 Nudging measures

ACC nudging was tried in two different versions, one using an ambient design concept and the other a Competitive Leader Board concept. The *ACC ambient design nudge* was designed based on the assumption that many humans prefer order over chaos in their lives. Thus, the design aimed to nudge drivers into using ACC by continuously transforming the visuals from a chaotic to an orderly pattern, with the transformation continuing as long as they drove with ACC engaged. The concept provided drivers with a daily goal of 10 minutes of ACC use. The app informed the drivers whether ACC was available or not, as well as indicating if the function was active or inactive.

The structure of the ambient display nudge is as follows: the start-view of the app (when the engine is turned off) shows a yellow ACC symbol and the text “Adaptive Cruise Control” and “Not started”. When the engine is turned on, the symbol changes to grey and the text changes to “Not available” as long as vehicle speed is below 15 km/h. When ACC is available (speed exceeds 15 km/h), ten grey dots start to move with random speeds on the screen and the text states “Available”.

When the driver activates ACC, the dots lower their speeds and turn white while the text changes to "Active". For each minute of ACC driving one dot will move into the centre of the screen, turn yellow and slowly circulate. If the driver temporarily deactivates ACC, the yellow dots will stay in the centre while the others will behave as they did before ACC was activated and the text states "Paused". When the drivers have driven with ACC for ten minutes all the dots will centre and slowly circulate together in what is perceived as harmony and the text "Goal reached" is shown. Following 10 minutes of ACC driving the only visual difference is the colour of the ACC symbol (yellow when ACC is active and grey otherwise).

The corresponding screen views of the app are shown below in Figure 5.1.

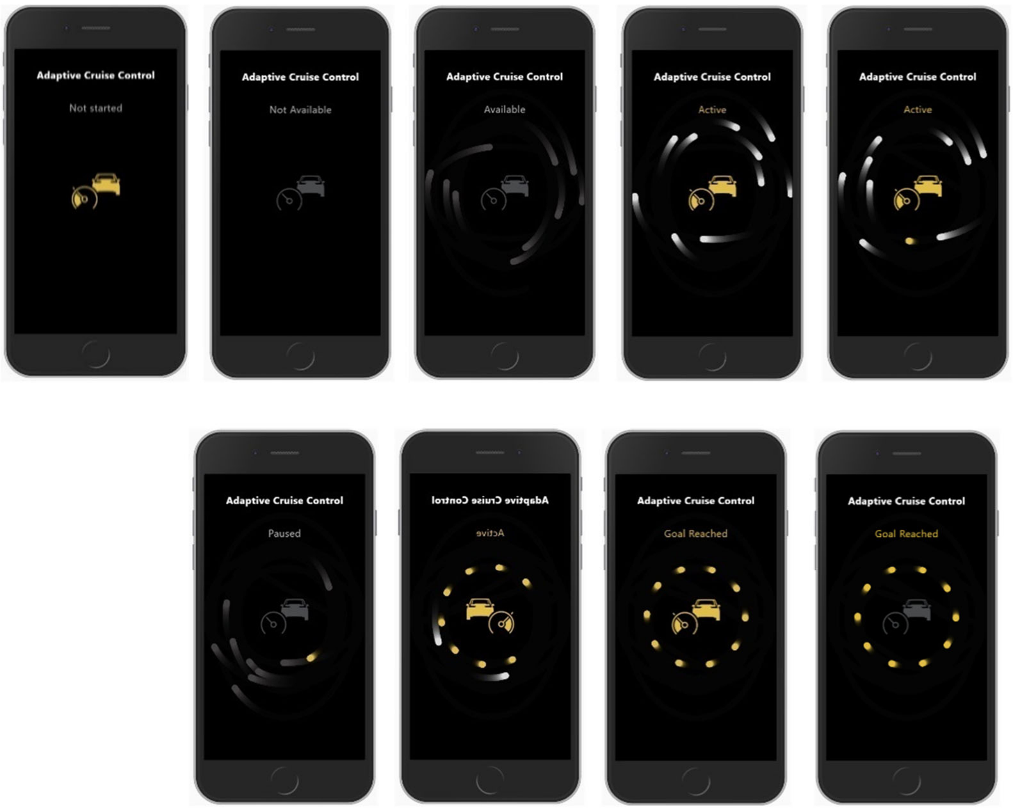

Figure 5-1: Screen shots from Ambient Display nudging concept

The *ACC Competitive Leader Board Nudge* was designed to test another nudging approach – social comparison and competition. This app presented the drivers with a Leader Board ranking all the participants by weekly ACC minutes.

The structure of the Competitive Leader Board Nudge is as follows: during driving the visuals show a Volvo XC60 either at standstill (when ACC is not activated) or driving (when ACC is active) and the minutes of ACC use today. Whenever vehicle speed is zero or the engine is turned off the app displays the Leader Board. The Leader Board shows your rank, your weekly ACC minutes, your daily ACC minutes and trend (position change since the Leader Board was last shown). In addition to this, the leader and his/her minutes as well as other drivers around your rank is shown. All participants were assigned a fake name that was shown in the app. Every Sunday night the Leader Board was reset, and the participants received an email with their weekly rank and ACC minutes as well as the name of the weekly winner. The different views of the app are shown below.

Figure 5-2: Screen shots from Competitive Leader Board nudging concept

5.4 Data collection

The participants' cars were equipped with data acquisition units set up to record vehicle data including engine status, vehicle speed, ACC status, DAC status as well as standalone GPS-data. Data recording was triggered at every engine start and continued until engine shutdown.

The general baseline data collection lasted between October and November 2019 and the general treatment data collection between December 2019 and July 2020. The baseline data included in the analysis below consists of *N* = 16,604 trips, adding up to a total of 4,342 hours of driving. The treatment data consists of *N* = 41,012 trips, with 30,189 trips (7,399 hours of driving) for the ambient ACC concept and 10,823 trips (2,529 hours of driving for the competitive ACC concept. Data files not including any driving data (i.e. only ignition on and off without any speed increase) were filtered out.

5.5 Dependent variables

ACC use percentage was calculated for each trip by dividing the duration of ACC status ON with the trip duration (the time between engine start and stop). Furthermore, average ACC use on an individual level was calculated by summing all ACC status ON duration and divide that by total trip duration.

To calculate the effect of the respective nudge on ACC usage, the percentage of ACC usage over total trip time was first calculated for each driver in the baseline (no nudge) and treatment (nudge active) phase, and then summed on a group level. This was done for both nudging concepts.

5.6 Results on Ambient display nudge

For the ambient display nudge, the average ACC use was 14.21 % in baseline and 20.82 % in treatment. This means that drivers on average increased their normal level of ACC usage with about 46 % when being nudged with the Ambient Display concept. A paired t-test showed that this increase was significant ($t(48) = 5.25$, $p < .001$).

In Figure 5-3 below, the difference between ACC use in baseline and when being nudged with the Ambient Display concept for all drivers are visualised, ranked from largest increase to lowest.

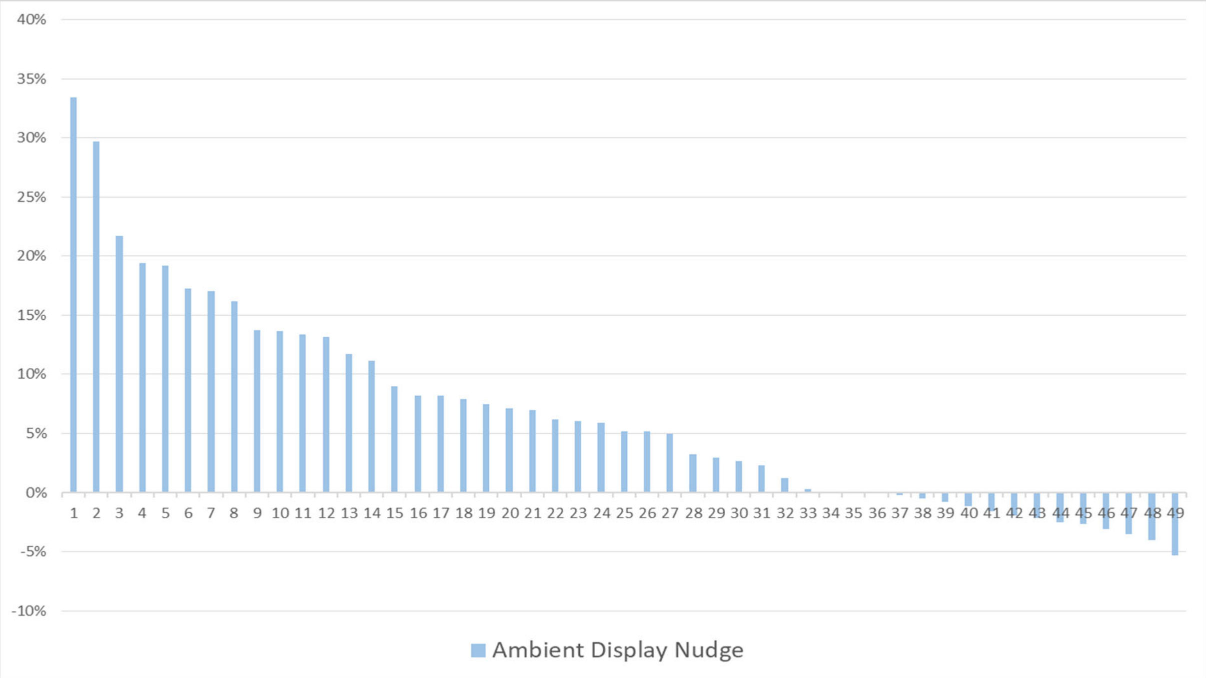

Figure 5-3: The relative change in ACC usage between baseline and treatment for each driver participating in the field trial when exposed to the Ambient Display nudge. Each vertical bar represents one driver.

As can be seen, when using the *Ambient Display nudge*, *N* = 26/49 drivers increased their ACC use by at least 5 %. However, it should also be noted that there were some drivers for whom ACC usage decreased in treatment. This illustrates the need to keep track of nudging impacts in real time if possible, so one can remove the nudge, or switch to a different paradigm, if drivers are negatively affected.

5.7 Results on the Competitive Leader Board nudge

For the Competitive Leader Board nudge, the average ACC use was 14.48 % in baseline and 30.67 % in treatment. This means that drivers on average increased their normal level of ACC usage with about 118 % when being nudged with the Leader Board concept. A paired t-test showed that this increase was significant ($t(47) = 6.64$, $p < .001$).

In Figure 5-4 below, the difference between ACC use in baseline and treatment II for all drivers are visualised, ranked from largest increase to lowest.

Figure 5-4: The relative change in ACC usage between baseline and treatment for each driver participating in the field trial when exposed to the Leader Board nudge. Each vertical bar represents one driver.

5.8 Comparing the effects of Ambient Display and Competitive Leader Board nudges

An obvious question to ask when deploying two different nudging concepts targeting the same population is whether drivers were affected similarly or differently by the two concepts. In Figure 5-5 below, the relative change in ACC use is shown for both the Ambient Display concept and the Competitive Leader board concept, on a per driver basis. As can be seen, the answer to the question seems to be that the two different nudging concepts have affected most drivers differently, i.e. there are very few instances where the two bars per driver are of exactly the same height. Some drivers have responded better to the Ambient Display concept, but most drivers seem to have responded the best to the Competitive Leader Board nudge.

This provides interesting learnings for the future, in the sense that if one wants to create a particular type of change in a large driver population, quite a bit of experimentation will need to be applied to find the right concepts. Also, the final result is likely to include more than one type of nudge if the outcome is to be robust across the whole population.

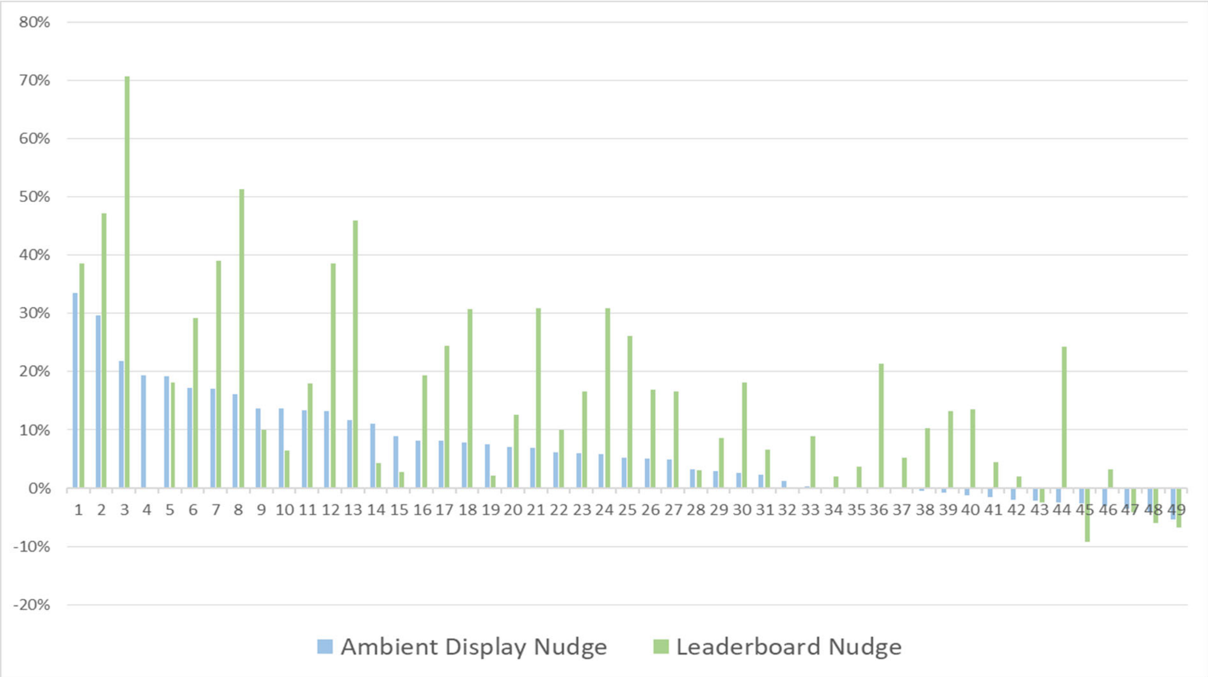

Figure 5-5: Relative change in ACC usage for all drivers under the Ambient Display Nudge and the Leader Board nudge respectively.

6 Final results for O3: Attention to potential hazards in intersections (TNO)

6.1 Introduction

Accidents between cars and cyclists are often attributed to the fact that the car driver did not see the cyclist crossing an intersection in time to avoid the accident. "Failure to look properly" has been shown to be a major causation factor in 30% of accidents[1]. To direct the attention of the driver towards these hazardous situations, an in-vehicle nudging solution has been developed in MeBeSafe. Nudging stimulates the driver to perform desired behaviour in a subtle way, without enforcing it. The driver has the possibility to make an own choice. In deliverables D2.1 (Op den Camp, et al., 2018) and D2.2 (Kirchbichler, et al., 2019), detailed descriptions of the nudging system for directing driver attention towards potentially hazardous situations with cyclists in intersection are found.

In a simulator study of CRF reported in deliverable D2.3 (Op den Camp, et al., 2019), the effectiveness of three HMI designs as part of the in-vehicle nudging solution have been evaluated. In continuation of this simulator study a Field Operational Test (FOT) has been performed to evaluate the most promising and feasible HMI solution in real traffic. The in-vehicle nudge solution is an abstracted intersection which is displayed on a Head-Up Display (HUD) at every approach of an intersection in an urban area with a speed limit of maximum 50 km/h. This abstracted intersection, a cross, escalates from green to orange to red while simultaneously increasing in size during the approach of an intersection. A detailed description of the implementation of the nudging solution can be found in D2.3 (Op den Camp, et al., 2019). In this chapter the design of the FOT and its results are described.

In a 2 hours' drive through the inner city of Eindhoven, the velocity and gaze of 22 naïve participants have been recorded while driving with and without the nudging HMI

[1] Reported Road Casualties GB 2014.

in 30 km/h and 50 km/h zones. Velocity and gaze adaptation while approaching intersections have been measured to evaluate the effectiveness of the nudging solution towards more timely attention of potential hazards. Subjective measures have been used to evaluate the acceptance of the HMI by the participants.

The basic research question to be answered in this study is: “Can the HMI increase the timely attention to a forecasted hazard by at least 20% of test subjects?”

6.2 Method and approach

The FOT is designed to reveal how well the nudging HMI is capable to direct the direction of attention towards a potential hazard under realistic driving conditions. In other words, the results are used to quantify how well the drivers respond in case the HMI is triggered. To keep the FOT as specific and simple as possible, in order to be able to draw well-founded conclusions on the basis of the results, it is designed such that all triggers are staged up front. This ‘Wizard of Oz’ method is an experimental method to evaluate the effect of vehicle functions or interfaces that are not yet available for production. In this study the GPS-locations of the intersections and side roads for HMI escalation have been hardcoded in the HMI software. The HMI escalates while approaching the pre-programmed intersections and points into the pre-programmed direction of a potential hazard.

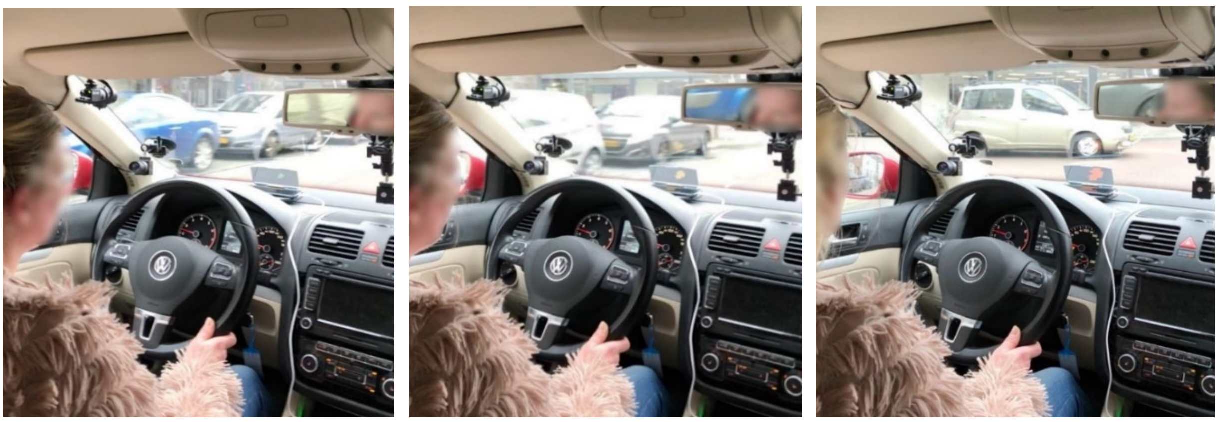

Figure 6-1: True positive escalation of the HMI for a hazard from the left

To evaluate the effectiveness of the HMI, the HMI is activated in the approach of 74 intersections (true positive triggers) and in 5 non-hazardous situations (false positive triggers). A false positive trigger is defined as an escalation of the HMI while not approaching a hazardous situation or intersection. False positive triggers indicate how well the HMI is capable to direct the attention of the driver, even in cases where it is not necessary from traffic perspective. True and false positives are compared to the baseline effect or also called false negatives: no activated HMI on the locations of the 74 true positives and the 5 false positives.

The effectiveness of the HMI is analysed using the driven velocity and gaze direction while approaching an intersection and the subjective measures. Eye-tracking is used for analysis of gaze behaviour. The gaze direction has a direct relation with the driver's direction of attention. The speed of the vehicle (selected by the driver) is also monitored, especially in the approach of intersections. It is assumed that the selected speed by the driver is an indicator for the level of attention of the driver, or the level of awareness of the possible presence of a hazardous situation. In case the results of the FOT show a clear relation between the triggering of the HMI and a reduction of speed by the driver, we have another indicator for the effectiveness of the HMI to direct driver attention.

The subjective evaluations are analysed to understand the participants comprehension and experience with the HMI, their experience of the driving task and suggestions of improvements regarding the HMI.

It is hypothesized that the HMI influences the gaze direction into the direction of the potential hazard in real traffic, which has already been proven in the simulator study of CRF (Op den Camp, et al., 2019). As an additional measure the speed adaptation has been included in this study. If drivers recognize the potential hazard earlier, they might adapt their speed accordingly. Therefore, it is additionally hypothesized that the speed while approaching an intersection decreases as a result of increased attention by the driver from the activation of the HMI; especially in cases where the speed is not appropriate for the situation.

This study is designed as a within-subjects study: all *N* = 22 participants drove the same route through Eindhoven twice. The baseline and treatment conditions were evenly distributed between the first and second round and between morning and afternoon sessions, decreasing the probability of learning effects and disadvantages of HMI visibility due to sun position. All driving sessions were scheduled outside rush hours, to prevent participants from encountering too much other traffic that bias their level of attention. Nevertheless, the participant could encounter traffic at every intersection, making this a realistic environment without too much disturbance to test the HMI.

Since the HMI is designed to nudge people to look into a certain direction subconsciously, the participants were kept naïve on the system, and they got very little or no information from the TNO test leader about the meaning of the HMI before or during driving. The only information the participant was given was the size and colour of the cross indicate the level and direction of a potential hazard. More information could have caused bias in the results as participants might have consciously tried to interpret the HMI and act appropriately.

6.3 Metrics

6.3.1 Dependent variables

Velocity: the velocity of the vehicle with the HMI is controlled by the test participant. The velocity in the approach of each intersection has been analysed from the moment the HMI starts escalating until the intersection is reached.

Gaze direction: The horizontal gaze direction, indicating whether the driver is looking straight, to the right or the left, has been analysed from the moment the HMI starts escalating until the intersection is reached. To analyse whether the HMI correctly directs the attention of the driver in the direction indicated by the HMI, a metric is needed with respect to the gaze in the direction of the potential hazard, which is either from the right or the left at an upcoming intersection. A relation between the direction of the potential hazard and the distance to the intersection is derived, in order to determine a corridor of gaze direction positively attributed to the right or left area of interest at an intersection. Far away from the (potentially hazardous) intersection, the driver looks almost straight ahead to look at the area of potential hazard. When the driver is at the intersection, he/she has to look far left or right to get a view on the area of potential hazard. Therefore, the relation between the 'correct' gaze direction and the distance from the intersection is represented with the positive part of a reciprocal function. Due to the camera position, the functions for left and right potential hazard direction are slightly different. The corridors relating the 'correct' gaze direction to the distance to the intersection are given by:

$y = [-\left(\frac{3000}{x+6}\right) + 500, -\left(\frac{3000}{x+6}\right) + 600]$ for the potential hazard from the left (1)

$y = [\left(\frac{6000}{x+8}\right) + 400, \left(\frac{6000}{x+8}\right) + 500]$ for the potential hazard from the right (2)

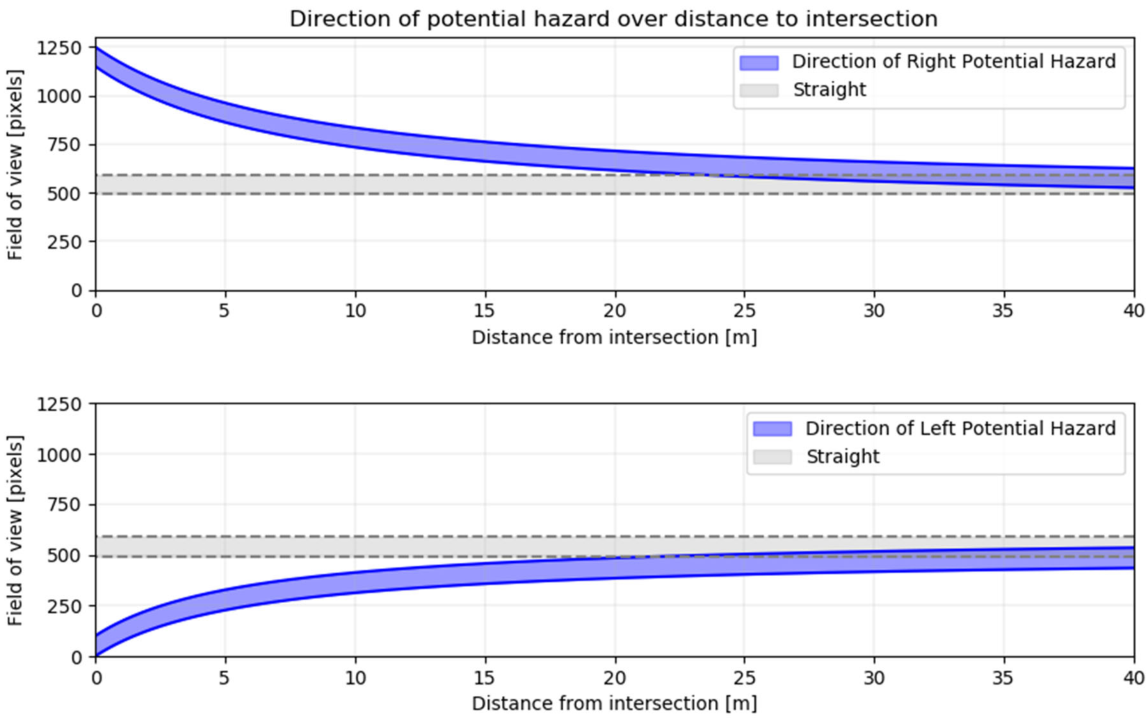

Figure 6-2: Direction of potential hazard over distance to intersection

In these equations, *x* represents the distance to the intersection in meters and *y* represents the field of view of the camera in pixels. The width of the corridor is selected to be 100 pixels in our analyses, shown in blue in

Figure 6-2. Changing the range (small increase or decrease of the size) only marginally influences the results of the analyses of the gaze direction and does not influence the conclusions based on those analyses.

6.3.2 Independent variables

Distance to an intersection: The velocity at different distances x of 40, 20, 15, 10, 5 and 0 meters before the intersection have been selected to cover the velocity profile during the approach of an intersection for correlation purposes. These discrete points are expected to cover the most important region just before the intersection in both the 30 km/h zone and the 50 km/h zone.

Also, the HMI status (on/off) and the speed limit in the different zones (30 km/h and 50 km/h) are considered independent variables.

6.3.3 Statistical analysis

The effect of the HMI on the velocity of the participants has been analysed with a Linear Mixed Effect Model (LMM). This model allows for differences in overall driving speed between participants as well as for differences in approach speed for different intersections by modelling these as random effects. The model also accounts for the fact that the data contains more intersections in 30 km/h zones than in 50 km/h zones. All independent variables, HMI status (On/Off), maximum velocity in the zone (30 km/h, 50 km/h) and distance to each intersection have been modelled as fixed effects. This model is used to test if the null hypothesis: 'The velocities while driving with and without HMI are the same' can be rejected. For estimation of the parameters of the model, a Restricted Maximum Likelihood estimation has been used. The Satterthwaite approximation for degrees of freedom has been used to correct for inflated type 1 errors (rejection of a true null hypothesis).

The effect of the HMI on gaze direction distributions has been analysed using the Kolmogorov–Smirnov test. This test determines whether the 2 distributions (with and without HMI) can be drawn from the same dataset.

6.4 Test description

6.4.1 Test vehicle and equipment

This study was conducted using a TNO laboratory vehicle (VW Jetta), with the following equipment:

- GPS sensor combined with a Global Navigation Satellite System - Inertial Measurement Unit (OxTS GNSS-IMU) for accurate ego-vehicle positioning/localization/heading, installed on the back of the car, recording at 100 Hz

- One ELP industrial machine vision camera, looking forward for mapping the gaze of the driver to the environment, recording at 32,5 Hz
- One inward-looking ELP industrial machine vision camera to track the gaze of the driver, recording at 32.5 Hz
- Context camera for mapping the gaze of the driver to the vehicles interior, recording at 32.5 Hz
- Pointgrey front right and left context cameras for analysis purposes, recording at 100 Hz
- CAN Bus data to track velocity, acceleration and steering angle of the participant, recording at 100 Hz.
- A smartphone connects to a ROS based laptop computer to display the HMI integrated with a retrofit head-up display at the windshield in front of the driver, recording at 10 Hz.

Cygnify installed two ELP industrial machine vision cameras into the vehicle. One of the cameras is mounted to the windshield next to the rear-view mirror, with a forward-looking field of view. This camera provided images of the driver's view through the windshield. The other camera is also mounted to the windshield but closer to the driver, next to the steering wheel, and is looking at the driver's face. The information from this camera assesses driver gaze. Neither camera obstructs the view of the driver looking towards the road and traffic situation in a significant way. The third camera is a low-resolution context camera. This context camera provides information about the view of the participant on the car's interior.

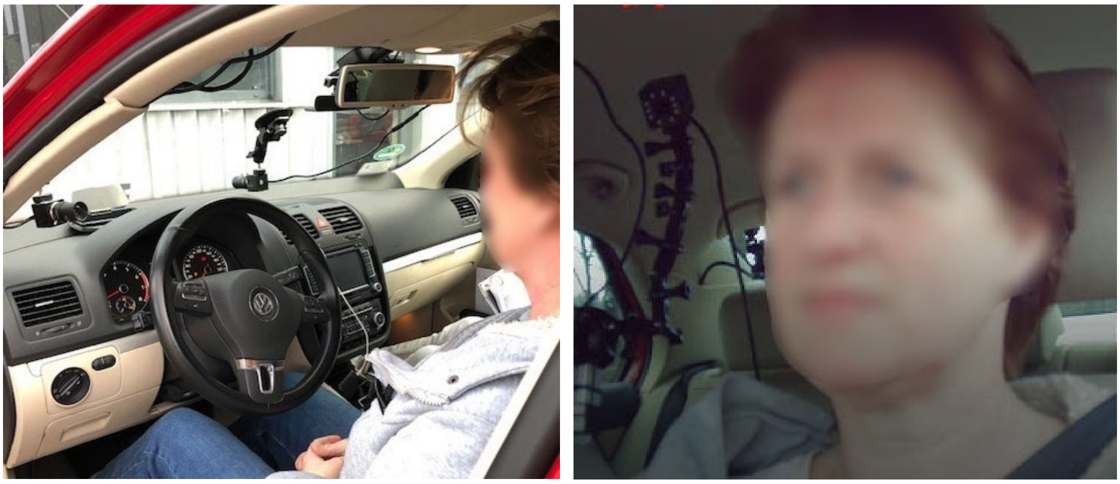

Figure 6-3: Set-up of the 3 Cygnify camera's: 1 facing forward, 1 facing the driver and 1 context camera

Figure 6-3 shows the positioning of these three cameras: one close to the steering wheel facing inward, one close to the rear-view mirror facing forward and one context camera behind the participant facing the instrument panel.

To map the gaze direction of the participant on the images of the context and forward-facing cameras, a calibration procedure was used. During this procedure, the participant was requested to look at the instrument panel, the rear-view and side mirrors and the HMI in a pre-defined order. The test leader pushed a button when the participant was looking at a certain system, capturing his gaze direction at that moment. Using this calibration, the gaze direction of the participant measured with the inward facing camera has been mapped on the images from both forward-looking cameras, as shown in Figure 6-4. The red circle represents the uncertainty of the gaze direction. This x,y-mapping of the gaze direction to the inward and outward facing cameras provides meaning to the gaze direction.

Figure 6-4: Mapping from the eye-tracking algorithm on the interior and outward facing camera images

A Head Up Display (HUD) has been selected to be the most safe and intuitive option to provide the in-vehicle abstract cross nudging solution as designed by OFFIS. The HUD consists of a mobile phone and a vertical partial transparent mirror, as shown in Figure 6-5. The HUD is attached onto the dashboard, just behind the steering wheel, such that it does not block the view of the driver. A mobile phone with the HMI is placed onto the horizontal part of the HUD. The screen of the mobile phone is reflected in the mirror, such that it is visible for the driver when he/she looks straight. This makes the placement of HMI very intuitive: the abstract cross on the HMI is shown close to driver's view onto the real intersection when the participant looks straight.

Figure 6-5: Head Up Display consisting of mobile phone and partial transparent mirror

The escalation of the HMI is programmed to start approximately 6 seconds before entering the intersection. So, if the intersection is located at a 30 km/h zone, the escalation starts 50 meters before the intersection, for a 50 km/h zone this is 83.33 m. Since the heading with respect to the middle of the intersection changes rapidly in the last few meters before the intersection, the escalation of the HMI is stopped before entering the intersection. The escalation of the HMI is shown in Figure 6-6. In the 30 km/h zone, the HMI starts escalating at distance 46 m of the middle of the intersection and stops when the front of the car reaches the middle of the intersection (0 m).

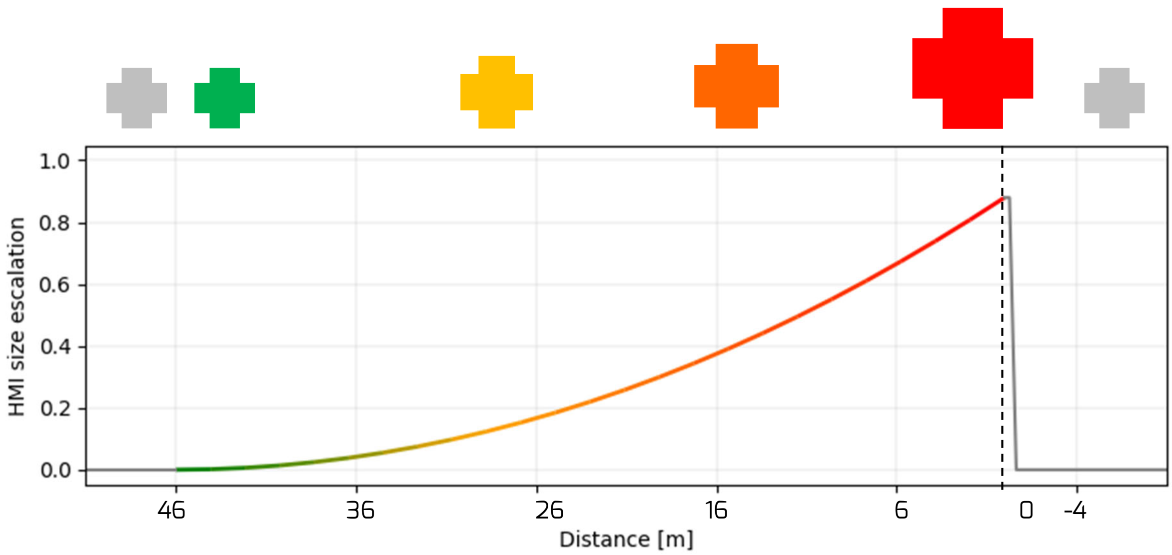

Figure 6-6: Escalation of the HMI over distance towards an intersection

When the HMI does not escalate, a grey cross is shown on the HUD, as shown in Figure 6-5 (upper most figure). During escalation of the HMI, the colour changes with decreasing distance from grey (no intersection within next 6 seconds) to green, to orange to red, as shown in Figure 6-6. Meanwhile, the size of the abstract cross changes with distance as well, as shown in the same figure. Arriving at the intersection, the cross instantly changes to a grey small-sized cross again.

6.4.2 Participants in the FOT

The following requirements have been used in selecting participants for the study:

- In possession of a driving license for at least 5 years;
- Driving at least 5.000 km last year;
- Having at least an MBO 4 degree;
- Not using drugs that influence alertness or balance;
- Having experience with navigation systems;
- Having no problem using an automatic gearbox.

These requirements are to exclude participants who had too little driving experience or might get too distracted by the HMI. Since a medium effect in this study is expected, a population of 20 participants was aimed for (Ljung Aust, et al., 2019). From the 27 participants invited, *N* = 22 subjects actually participated in this study. All have been recruited by an external agency. These participants have a mean age of 43.8 (*SD* = 10.9) years and were in possession of a driving license for 24,9 (*SD* = 11,2) years on average. They drive on average 17,000 (*SD* = 1000) km per year on different road types. 87 % of the participants drive on city roads at least once a week. All participants are used to come across bicyclists in traffic at least once a week and 69 % of them regularly ride a bicycle themselves.

6.4.3 Route

A route through the city centre of Eindhoven has been selected. To get familiar with the car, the participant first had to drive 10 minutes from the TNO office in Helmond to the starting point of the route. The route contains visually obstructed intersections in both 50 km/h zones and 30 km/h zones, as shown in Figure 6-7.

Figure 6-7: Visual obstructions on the route at 50 km/h zone (left) and 30 km/h zone (right)

The route contains 94 intersections, of which 20 were not used for analysis since the participant had to turn or the intersections was controlled by traffic lights. From the 74 intersections used in the analysis, 21 are located in a 50 km/h zone, where the test vehicle has priority. All other intersections were located in a 30 km/h zone, where the test vehicle has to give way to traffic coming from the right. The route is shown in Figure 6-8 (from start to finish).

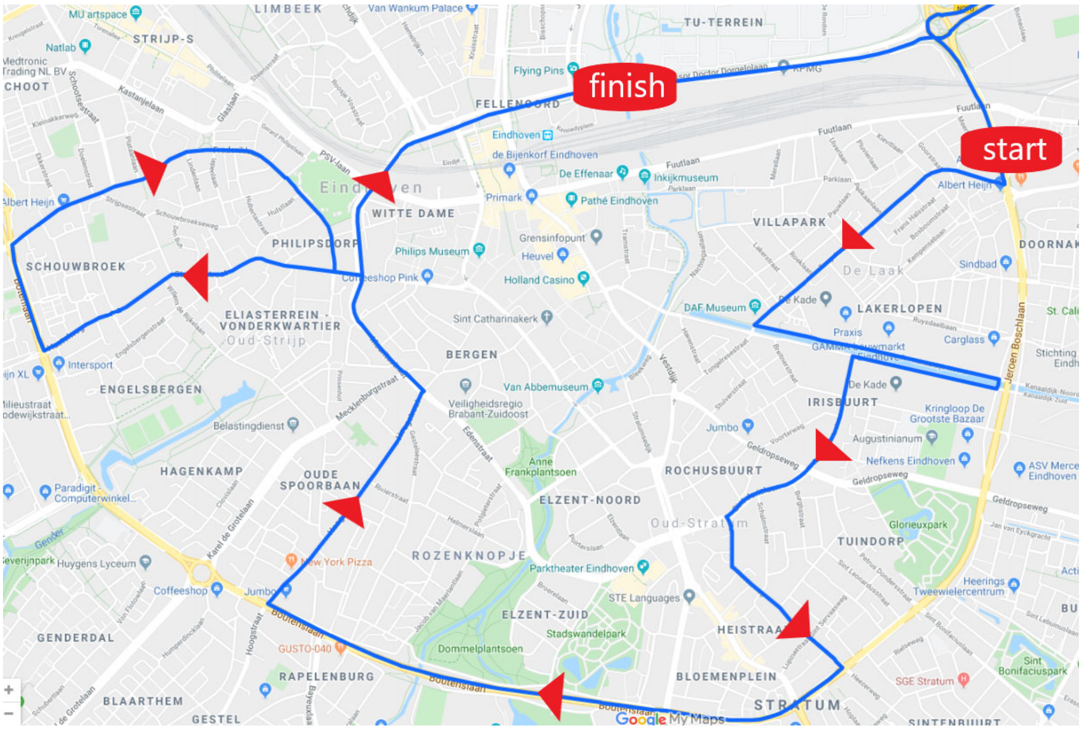

Figure 6-8: Route through the inner city of Eindhoven

6.4.4 Test procedure

Prior to the instructions, participants knew about the field trial in general, but not about the HMI design to keep them unbiased. The participants were generally informed about the experiment in the TNO office in Helmond.

Figure 6-9: Indicational figures showing the escalation of the HMI towards an intersection

The information included figures of the HMI, as shown in Figure 6-9 and little information about what these signs mean: the size and colour of the cross indicate the level and direction of a potential hazard. The arrow points in the direction from which the hazard is expected to be largest. Additional questions about the meaning of these signs were not answered, because this could influence the nudging effect. Questions regarding the experiment were answered as long as answers would not disturb the results.

When the participants were informed and had no further questions, they were requested to complete a questionnaire on their personal vehicle use and experiences. After completing the questionnaire, the participant was taken to the car standing outside, requested to take the driver seat and adjust the seat and mirrors for maximum comfort and safety. A safety driver (test leader) took the passenger seat and stayed there for the whole drive to give instructions, make the participant feel comfortable, and make sure all measurement systems are up and running and the intended HMI activation is provided to the driver according to the test plan. For calibration of the gaze direction, the participant was asked to look in the rear mirror, both side mirrors, the instrument panel and the HMI.

After completing the calibration, the drive to Eindhoven was started. This drive consists of 10 minutes highway driving towards the starting point; this part of the drive does not qualify for analysis. During the highway drive towards the Eindhoven city centre, the participant was given the opportunity to get familiar with the car. When the participant reached the starting point, the recording was started. The participant was not aware when the experiment started or ended.

After the drive, the participants were requested to fill out a questionnaire regarding the driving task and HMI experience.

6.5 Results

To have the same sampling frequency for all measurements, but to not throw away important data, the data is interpolated to the nearest sample with a frequency of 30 Hz. This frequency is close to the sampling frequency of the cameras (32.5 Hz), the lowest sampling frequency of the equipment used in the car, such that the collected gaze data can be used in the analysis. Lowering the frequency of velocity is assumed to have negligible influences on the results.

6.5.1 Results based on velocity data

For all 22 participants in the test, a full set of velocity measurements is available during the complete test drive, both baseline and treatment. The velocity profile in the approach of the intersections is shown in Figure 6-10 and 6-11, for the 30 km/h and 50 km/h zones respectively. In Figure 6-10 (for the 30 km/h zone), it can be seen that participants first decrease their velocity while approaching an intersection and increase their velocity the last 10 meters before the intersection. In 6-10 (for the 50 km/h zone), there is no clear decrease of velocity visible in the approach of an intersection.

In general, the HMI does not have a significant effect on the velocity (combining the results for the 30 km/h and 50 km/h zones). However in the 50 km/h zone, as shown in Figure 6-10, activating the HMI does result in a decrease of velocity towards the intersection that is statistically significant. The participants drive approximately 1 km/h slower when the HMI is activated in the 50 km/h zone.

Although there is not a clear overall difference in speed when the HMI is activated at 30 km/h, the HMI does cause a difference when looked at participants one by one. This influence per participants, although it might be small, is shown in Table 6-1. Interestingly, a large part of the participants decreases their speed while approaching an intersection in the 30km/h zone. However, this effect is not significant over all participants.

Effect of HMI on velocity at 30km/h zone	Number of participants
Decrease in speed in the approach	13
No effect	6
Increase in speed in the approach	3

Table 6-1: Effect of HMI on velocity at 30km/h zone

The effect of the HMI on the velocity while approaching a potential hazard in the 50 km/h zone is shown in table 6-2**Fehler! Verweisquelle konnte nicht gefunden werden.**. A decrease in approaching speed when the HMI is active is seen for a majority of the participants.

Effect of HMI on velocity at 50km/h zone	Number of participants
Decrease in speed in the approach	14
No effect	1
Increase in speed in the approach	7

Table 6-2: Effect of HMI on velocity at 50km/h zone

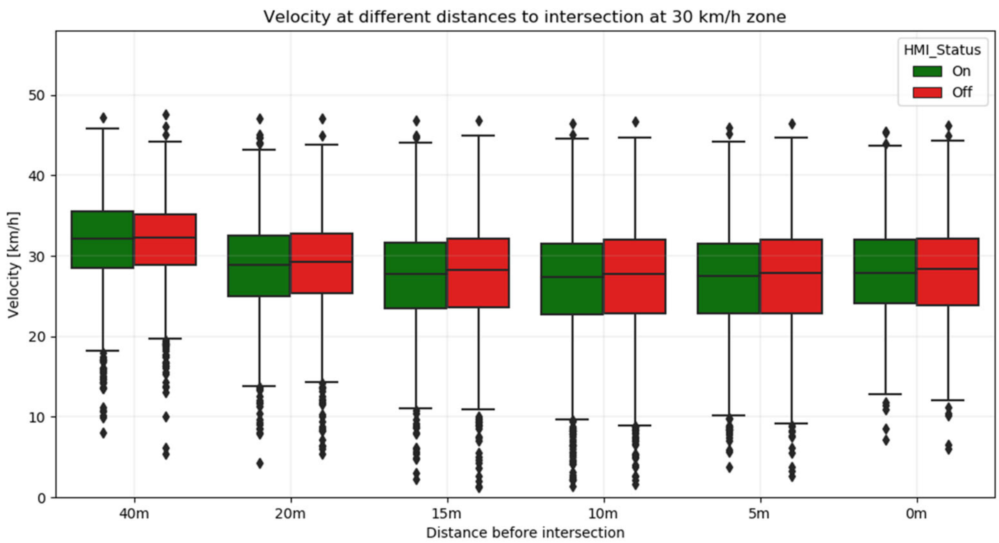

Figure 6-10: Velocity at different distances to intersections at 30 km/h

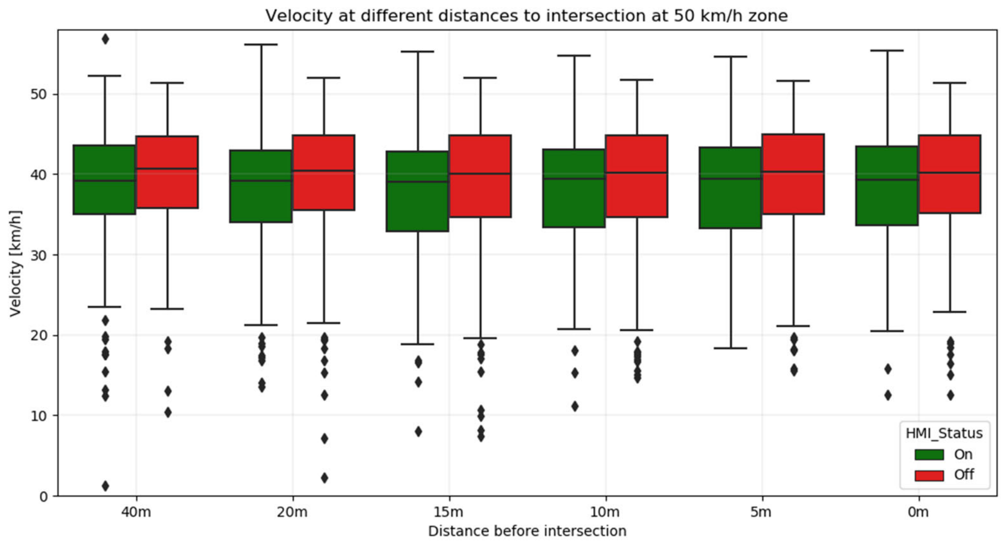

Figure 6-11: Velocity at different distances to intersections at 50 km/h

6.5.2 Results based on analyses of the gaze direction

Cygnify analysed the camera images for all drives to determine the gaze direction of the drivers with time using machine learning techniques. The percentage of gaze in the direction of the potential hazard over different parts of the approach is shown in Figure 6-12. The direction of the potential hazard and the distance to the intersection have an inverse relation as shown in

Figure 6-2. In this part of the analysis, both right/left potential hazards and 30/50 km/h zones have been analysed together.

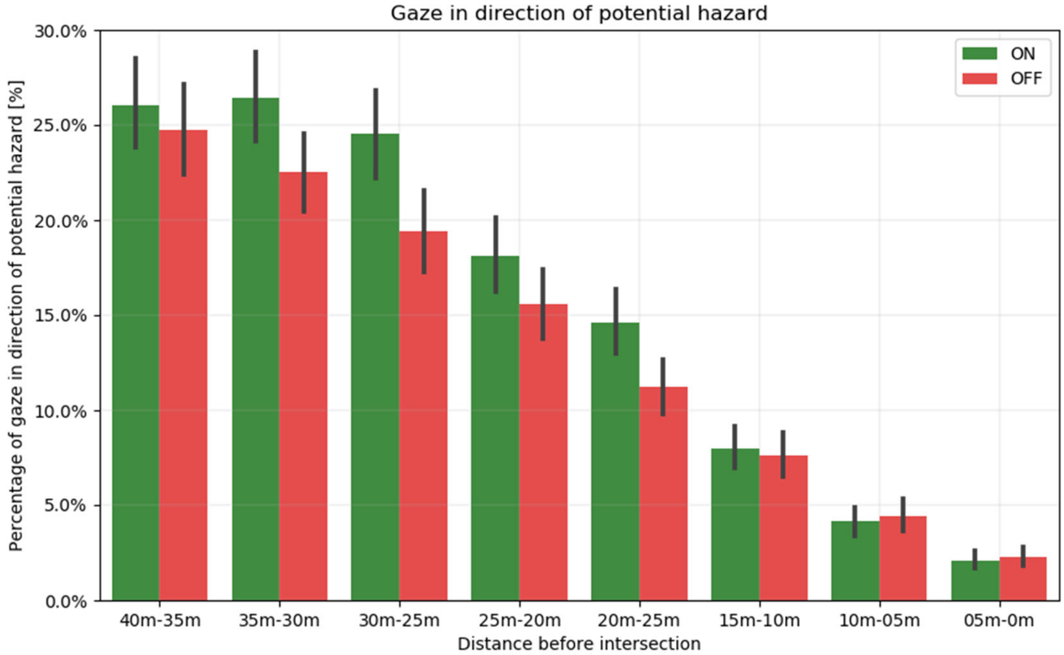

Figure 6-12: Gaze in direction of potential hazard for all intersectionsFigure 6-12 shows that the HMI positively influences the gaze direction towards the direction of the potential hazard as indicated by the HMI in the majority of the approach. This influence is minor or negative in the last few meters before the intersection. The region from 40 to 15 m before the intersection is the most interesting, as nudging the direction of attention of the driver needs to happen well in advance of reaching the intersection. Up to 15 m before the intersection, the gaze in direction of the potential hazard with HMI has increased with 2-5 % compared to driving without HMI. The influence of the HMI on the gaze direction in the 30 km/h and 50 km/h zone is shown separately in Figure 6-13 and Figure 6-14. The gaze in the direction indicated by the HMI is influenced in both zones to a different degree. In the 50 km/h zone, the gaze in the direction indicated by the HMI is about 33 % of the time when the intersection is 35-40 meters away, where in the 30 km/h zone, this is only 26 %. When the intersection is closer, about 10-15 meters, the difference in gaze direction between the two zones is negligible.

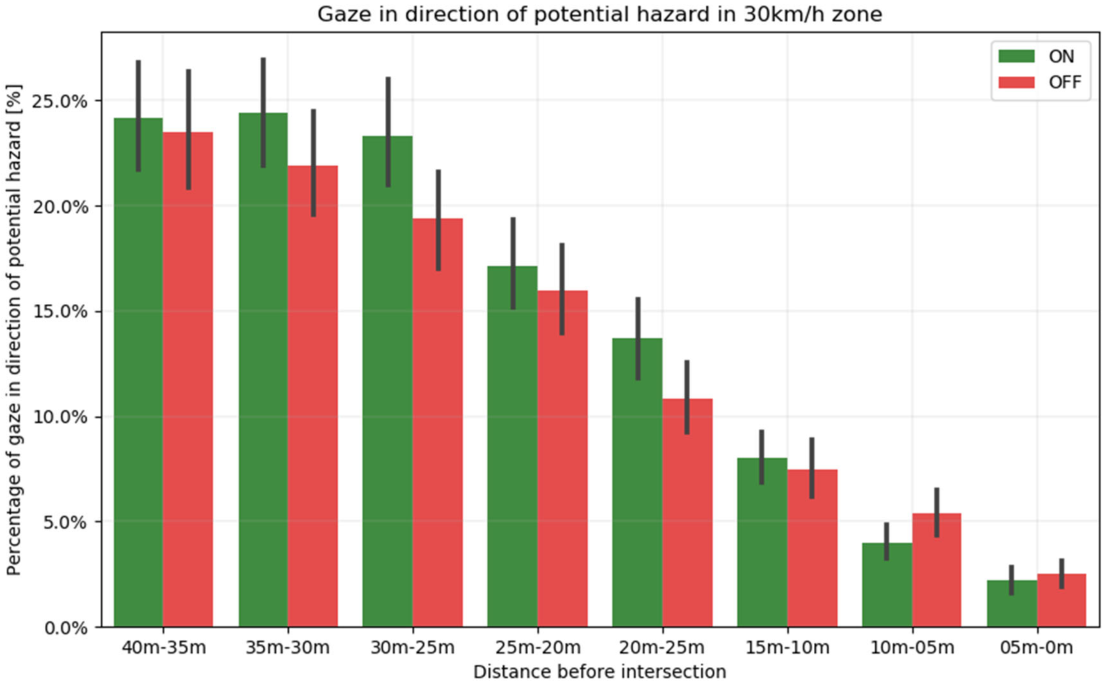

Figure 6-13: Gaze in direction of potential hazard in 30km/h zone

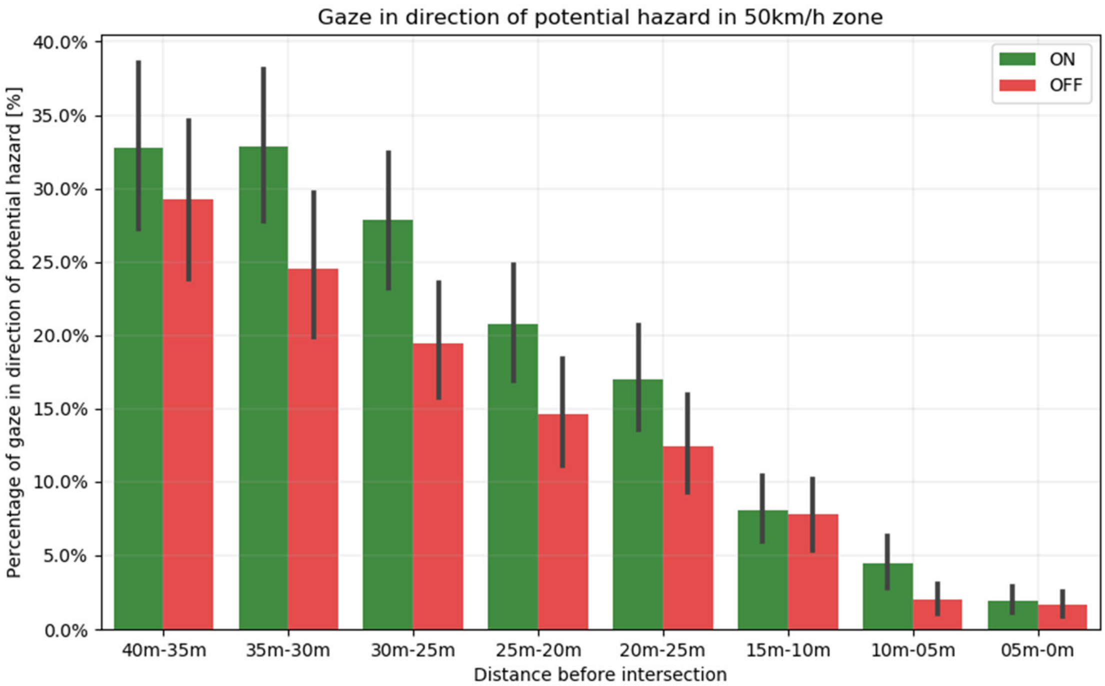

Figure 6-14: Gaze in direction of potential hazard in 50km/h zone

To understand the influence of the HMI better, the percentage of gazing in the direction of the potential hazard as indicated by the HMI has been determined for every participant separately. The results of this analysis have been categorized in three groups: the first group shows a higher percentage of time gazing into the direction of the potential hazard when the HMI is activated, the second group shows no difference or alternating effects in the gaze direction due to activation of the HMI and the third group shows a lower percentage of time gazing into the direction of the potential hazard when the HMI is activated. Examples of participants for all three groups are shown in Figure 6-15, Figure 6-16 and Figure 6-17.

The differences in the effect of activating the HMI on gaze direction are large. Some participants look more and others look less toward the potentially hazardous intersection. For some participants it is hard to state whether they look more or less towards the potential hazard and no clear effect is shown. An overview of the number of participants showing a certain effect is given in Table 6-3.

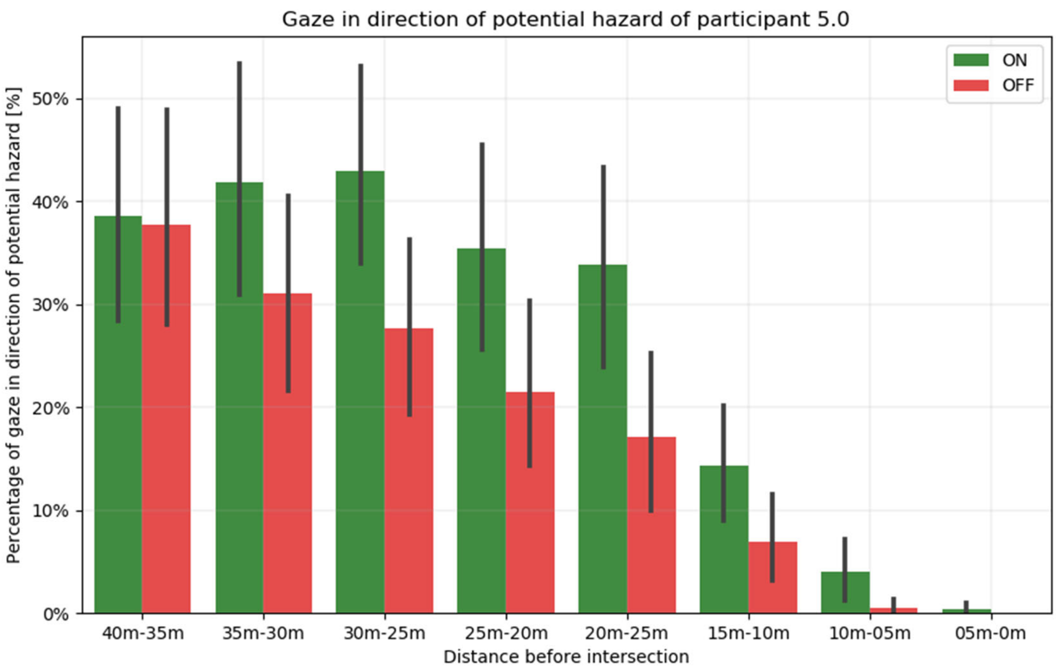

Figure 6-15: Example of participant who pays more attention to the direction of potential hazard when HMI is activated

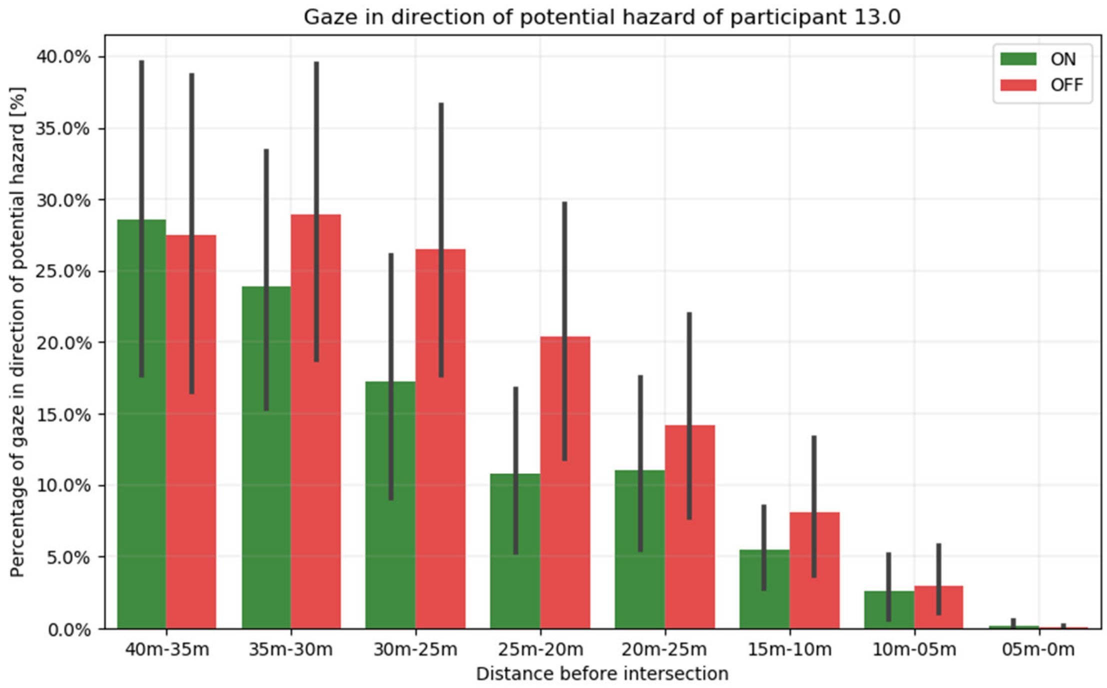

Figure 6-16: Example of participant with less attention in the direction of the potential hazard

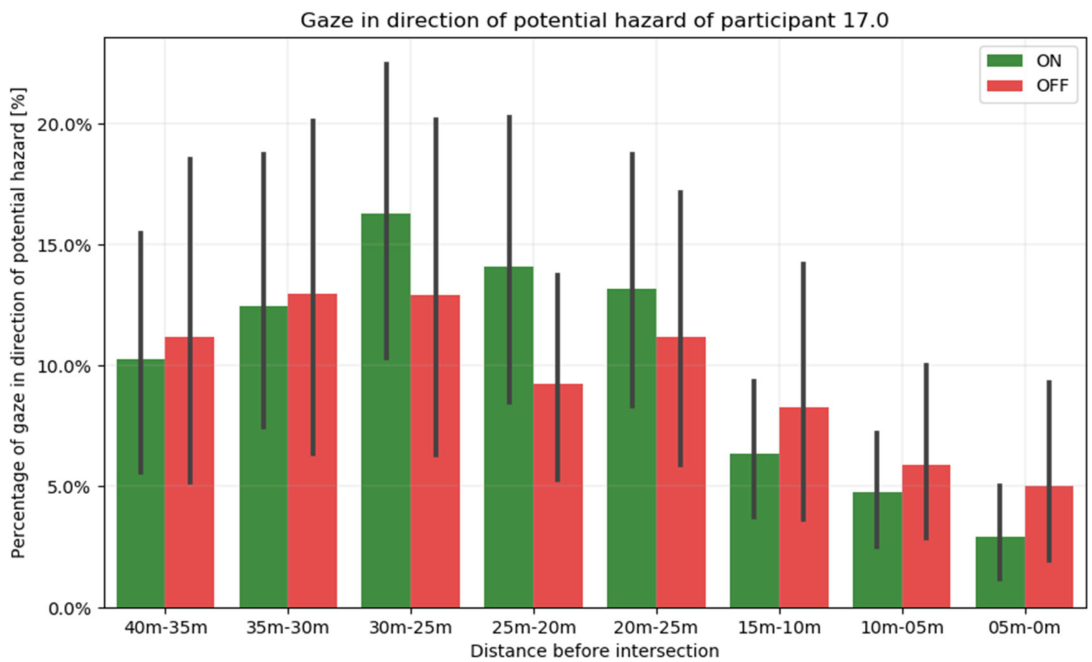

Figure 6-17: Example of participant with alternating more and less attention to potential hazard

Effect of HMI on gaze direction	Number of participants
Increase in attention in the direction of a potential hazard	10
No clear effect	3
Decrease in attention in the direction of a potential hazard	5

Table 6-3: Number of participants showing more attention, less attention or no clear effect in percentage of gazing in the direction of potential hazard as indicated by the HMI

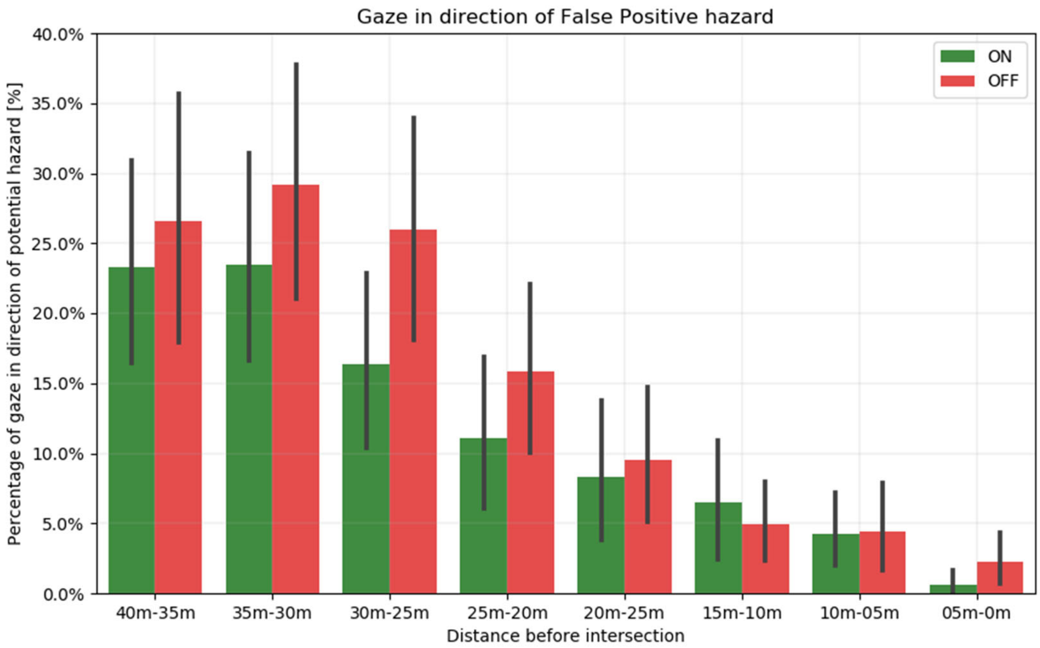

Figure 6-18: Gaze in direction of potential hazard for false positive signals

The percentage of time that the driver looks towards the potential hazard for a false positive signal is shown in Figure 6-18. When a false positive signal is presented on the HMI, the participant in general does not look more in the indicated direction. Especially at the start of the approach, the participant looks less in the indicated direction than when no HMI signal is present. At the end of the escalation this difference becomes less. False positive escalations (HMI is escalated to indicate the approach of an intersection, where the intersection is actually not present) have only been provided 5 times to each participant more towards the end of the treatment cycle, to prevent "alarm degradation". The number of false positives is so small that we cannot derive statistically sound conclusions to this part of the analyses, especially since surrounding traffic has a large influence on the direction of attention during the approach and cannot be cancelled out for the responses to the false positives.

6.6 Discussion

The aim of this study was to evaluate whether the nudging HMI is capable to increase the timely attention to a forecasted hazard (an upcoming intersection with potentially crossing bicyclist) by at least 20% of test subjects in real traffic. Additionally, it was checked whether the HMI influences drivers to adjust speed in the approach of an intersection. Subjective measures have been used to evaluate the acceptance and comprehension of the system by the drivers that participated in the test.

Results show that participants are very positive about the nudging HMI. The information displayed on the HMI is a pleasant way to make them aware of intersections. They experienced this study as relaxing, safe and easy. More than 70 % of the drivers would leave the system active, as they think it could warn them for possibly hazardous intersections.

Drivers decrease their speed when the HMI is activated in a 50 km/h zone with 1 km/h in average given an average speed in this zone of 39 km/h. This decrease in speed in 50 km/h zones is statistically significant. This result is believed to indicate that drivers are more aware of possible hazards in a 50 km/h zone with the HMI activated. From 22 drivers, 14 participants decrease their speed (which is 64 % of the drivers.) In the 30 km/h zone the HMI does not seem to affect the speed in the approach of intersections significantly. Nevertheless, in 30 km/h zones, 13 participants seem to decrease their speed, though this decrease is not statistically significant.

Results show that drivers change their gaze direction when the HMI is active in both 30 km/h and 50 km/h zones. Especially, it seems that drivers increase time looking to the potentially hazardous side, when indicated by the HMI. This conclusion is supported by the increase in percentage of time that drivers looked in the direction of the potential hazard during the approach. 10 out of 18 drivers looked more in the direction of the potential hazard when the HMI was activated, which represents 56% of the drivers. Only 5 (out of 18) participants showed a decrease in time looking towards the potential hazard indicated by the HMI (28 % of the drivers.)

Both speed adaptation and increasing the time gazing in the direction indicated by the HMI are considered indicators for increased driver attention. Based on the quantitative results of the FOT, it seems fair to state that certainly more than 20 % of test subjects increase their level of attention in the approach of a potentially hazardous intersection as a result of the implemented in-vehicle nudging HMI.

False positive signals of the HMI do not seem to influence the approaching speed, but the results show a decrease in the amount of time that participants look in the direction of the potential hazard. The latter might be caused by the fact that drivers (subconsciously) start searching for the potential hazard in case the HMI escalation is not in agreement with the actual road layout. Since there is no hazard but the HMI does escalate, participants start looking around, not necessarily in the direction of the potential hazard. This means that the attention level of the drivers still might have been raised as a result of the false positive HMI escalation, though there is no way of confirming this based on the recorded data.

6.6.1 Traffic and priority

In this study, effects of other traffic on the velocity and gaze have not been considered. It has been assumed that traffic and environment is the same under both treatment and baseline conditions, such that the effect does not cause biases in any of the two conditions. To ensure as little traffic on the road as possible, the study was performed outside rush-hours. However, still periods occurred with larger traffic density in which the driver had to give more priority to other traffic in one of the conditions. To test the assumption, for one participant who increased gaze in direction of the potential hazards and decreased speed while approaching intersections when the HMI was activated, traffic influenced intersections have been removed from the dataset. Removing this data did not have a large impact on the results and consequently, it is assumed that traffic does not have a large impact on the results and conclusions of this study.

Differences between speed profiles in 30 km/h and 50 km/h zone are probably due to the fact that the participants have priority at the 50 km/h zone. The participants do not have priority in the 30 km/h zone and therefore had to stop or slow down to watch out for other traffic. This effect could also have been caused by an average lower speed at 30 km/h, making braking less required.

6.6.2 Learning effects

The route with the treatment, the HMI being active, only lasted 50 to 60 minutes for each participating driver. Consequently, there has been no possibility to address the learning effect from the data collected during the FOT. All drivers are naïve users of the HMI and within the hour, they will hardly be able to get used to the HMI. Learning effects take place over days, even weeks. To see the change in effect of the HMI on the longer term, a much longer FOT needs to be run. This was outside the scope of the current project. However, results discussed in this report show the potential of the driver direction of attention nudge, which provides perspective to a longer and more detailed trial to include studying the learning effect of using the HMI.

6.6.3 Gaze direction

The gaze direction distributions are calculated by using all gaze data during the approach of an intersection. No filtering steps have been performed to filter out effects from drivers which had to give way to other road users and therefore had a longer approach. An unequal approach time of intersection could lead to a bias in the percentage of time that the driver gazes in the left and right direction, as they tend to spend more time looking into the direction of road users to which they have to give priority.

Large peaks on the far left and right side of the gaze distribution indicate that not the complete field of view of the driver could be measured. Gazes exceeding the far right outside the interior and exterior camera view, were included in the data as far as right as possible. Distinction between gaze direction in that area is no longer possible. Additionally, the camera measuring the gaze direction was placed on the left side of the driver, which might have caused a bias in the eye-tracking performance. To measure the complete field of view of a driver the camera has to cover at least 120 degrees field of view. In a next study, it is advised to have a camera with larger field of view right in front of the driver (without distracting the driver or blocking the view).

The test leader might also have caused bias in gaze direction of the participant. The test leader was seated in the passenger seat to guide the participant through Eindhoven and make them feel comfortable. Some participants were looking towards the test leader when approaching an intersection, which might have caused a bias in gaze direction to the far right. However, as this is the same in all conditions, it is expected not to influence the comparison between driving with and without HMI.

Vertical eye- and head-movements were not considered in the analysis, since the video quality was insufficient to recognize these movements. Therefore, the horizontal gaze direction distribution includes looking of the drivers at the rear-view mirrors, the dashboard and the HMI.

Due to the limited resolution of the camera images and the framerate of 32.5 Hz, very fast head and eye-movements could not be included in the analyses. As fixations of eye-movements take range from 50ms to several seconds (Unema, Pannasch, Joos, & Velichkovsky, 2005), this framerate is too small to capture short fixations. Consequently, scanning frequency and fixations could not analysed with the current setup. The gaze analysis is therefore based on the cumulative percentage of time that drivers look into a direction. Fast eye- and head-movements are expected to have very little influence on the percentage of time the driver looks in a certain direction, as these movements are very short. However, these short fixations are an essential part of the attention being paid by the driver to other road users, objects and situations.

A large part of the drivers were influenced by the HMI and increased their attention in the direction of the potential hazard or decreased their approaching speed. However, the influences differ per participant. Four participants increased their direction of attention towards the potential hazard and decreased speed. Two participants increased their direction of attention towards the potential hazard and increased speed. Only one of the participants decreased the direction of attention towards the potential hazard and increased speed. The other participants showed ambiguous influences. These results show that drivers adapt their driving behaviour due to the HMI, but the way in which they adapt differs greatly.

6.7 Conclusion

In the simulator study of CRF a positive influence of the nudging HMI on timely attention to a forecasted hazard has already been found. Although a simple HMI escalation design without real-time hazard detection has been used in this field trial, our results support this conclusion in real traffic. When the HMI is activated, the drivers in the field trial spend on average 20 % more time in looking into the direction of a potential hazard at a distance of 20-30 m before entering the intersection. Out of 18 participants, 10 of them increased their gaze in the direction of the possible hazard when the HMI is activated. Additionally, 13 and 14 out of 22 participants decrease their speed while approaching an intersection in respectively the 30 km/h and 50 km/h zone. In general, a statistically significant decrease of speed of 1 km/h in a 50 km/h zone has been found. All effects are attributed to an increased level of attention of the driver and more awareness of the possible hazards.

Based on the quantitative results of the FOT, it seems fair to state that certainly more than 20 % of test subjects increase their level of attention in the approach of a potentially hazardous intersection as a result of the implemented in-vehicle nudging HMI. A positive influence of the HMI on timely attention (more attention in the direction of the potential hazard or a decrease in speed) is seen for 19 out of the 22 participants.

Further development of this proof-of-concept is needed to combine information regarding static hazards such as intersections with view-blocking obstruction (currently indicated by the HMI) with information on the dynamic hazards. Dynamic hazards result from road users (here we considered mainly bicyclists) that are in direct view of the driver. Within MeBeSafe a cyclist prediction model has been developed to get a reasonable estimate of the cyclist's behaviour several seconds in advance of such behaviour. If provided with this information, drivers might be able to better anticipate to the dynamics of traffic. In case tests show it is possible to predict cyclist behaviour using the cyclist prediction model, such information can be used as an additional input for HMI escalation. Of course, going that direction would also require additional studies addressing e.g. how to design the combination of static and dynamic hazard information in HMI escalation without overloading the driver with information and maintaining the HMI as a nudging solution rather than a warning function. Also, the effectiveness of the nudging HMI over time needs further study to determine what usage looks like when the driver is exposed to the nudge over a longer period of time (weeks, rather than hours).

7 Final results for O4: Behavioural change through online private driver coaching (Volvo Cars)

7.1 Field trial setup

As previously detailed in WP4 (see Deliverable 4.3), when it comes to ACC usage, the overall picture of ACC usage levels indicated that ACC users could be grouped into three types; the intensive users, the modest users and the non-users, where the last group does not use ACC at all. Furthermore, a clear difference in mind-set could be identified between users and non-users. Both the intensive and modest users were well aware of how ACC operates and comfortable with using it while driving. Drivers in the non-user group on the other hand were afraid of activating ACC, because they did not trust it to be capable of actually regulating speed and the distance to lead vehicles.

From that analysis, it was determined that ACC oriented coaching would have its largest impact not on drivers who are already using ACC, but rather on drivers who do not use ACC at all. In principle, since nudging toward increased ACC usage only can be applied on drivers who are already function users, non-users must first become users before nudging can be applied. It was thus decided that coaching would be applied primarily toward non-users, with the goal of turning them into users, and hence become available subjects for nudging efforts.

Ways of coaching non-users using an in-vehicle app was developed and tried out in WP4 (see Deliverable 4.5). In total, three development studies were performed, one in Sweden ($N = 30$ test persons), one in the US ($N = 10$ test persons) and one in England ($N = 6$ test persons). These studies lead to three important insights.

First, the app as developed was not robust and natural enough in its speech interaction, especially for users with limited interest in technology (i.e. the target group for coaching). To reach this level, a natural speech-based app with performance much closer to common speech recognition systems like Siri©, Alexa©

etc. and a high level of dialogue localization in the driving support domain would have to be developed.

Second, for the results of the field trial to be clear, it is important to avoid possible confounders. One MeBeSafe research question is whether non-users of ACC can be turned into users through coaching. In that perspective, it would be unfortunate if technical activation difficulties were to interfere with the effects of coaching.

Third, while the coaching toward ACC usage was successful in development pilots, it cannot be ruled out that the presence of a test leader in the vehicle might have had an increased influence. In other words, even if the App was perfectly built, some drivers who now activated functions may have refrained from doing so in absence of a test leader in the vehicle.

Given these conclusions, it became quite clear that the best way forward was to employ a Wizard of Oz approach in the field trial. Wizard of Oz testing is commonly used to understand interaction patterns for functionality which is not yet fully developed. The test participant is led to believe to be interacting with a computer-based function of some type (such as a self-driving car), while in reality an experimenter (the "wizard") is simulating the behaviour of the application (in the case of self-driving cars, a hidden back seat driver is controlling the vehicle).

7.2 Field trial cancelled

A key foundation of this field trial setup was the assumption (based on previously collected data) that among the test participants recruited to the ACC nudging field trial, 20-30 % would be determined non-ACC users who would not be affected by the ACC nudging concepts, and who therefore could benefit from coaching.

This assumption did not hold. When processing the data from the ACC nudging concepts, it turns out that all participants in the field trial were nudged into some level of ACC usage by the nudging concepts. In other words, there is no-one left to coach.

There is also no immediate way to remedy the problem. At a minimum, a new ACC nudging field trial with a significantly larger test population would have to be carried out, where one monitors test participants actively during the treatment phase to make sure there is a sufficient group of non-users left to coach at the end of the trial. For certainty reasons, the field trial should likely apply some form of staggered release design, with groups of N = 15-20 drivers entering a treatment with 3-4 weeks delay between groups, and the field trial is kept going until a set target level of non-nudged users will be reached. This is not feasible within MeBeSafe, so the assessment of the potential for coaching non-users will not come further than the work carried out in WP4.

On the positive side regarding the ACC nudging, there was enough time and competence around to roll out an additional in-vehicle ACC nudging concept (reported above), so the field trial on ACC nudging actually was doubled in size compared to what was initially planned.

8 Final results for O5: HGV driver behavioural change through online coaching (Shell)

In WP4 of MeBeSafe, a coaching system for truck drivers was developed, as well as a first version (V1) of the DriveMate app, which was to measure driver behaviour by in-phone sensors and deliver feedback and coaching material. V1 was field tested at the company Litra in Norway by four drivers starting in December 2018 and found to exhibit a high number of bugs. After the shift of funds within the project, V2 of Drivemate was developed in WP5, starting in November 2019. In February 2020, field tests were started at Litra (*N* = 13 drivers) and at Bertschi in the UK (*N* = 20 drivers). This deliverable reports on preliminary results of this field trial.

Principles of the MeBeSafe coaching system

DriveMate and the coaching to be delivered were designed to address issues which had been identified as associated with similar systems in WP1. This, however, also lead to the system differing from others, and the guiding principles will be therefore briefly described here.

- The drivers are anonymous. The account of a driver is associated with a phone ID, but the owner of the phone is not known to the researchers.
- The data is not shared with the company unless aggregated over all drivers.
- There is no real control as to whether the drivers actually read the material, or what they do in the coaching sessions. This is due to the principle of supplying the drivers with a support tool, and not to introduce further surveillance.
- All data is gathered by the phone from its internal sensors, and it is thus not connected to the vehicle CAN-bus.
- Very little information is displayed by the app during driving, due to the risk of distraction.
- Coaching is based mainly upon cognitive-behavioural principles.

- Coaching is peer-to-peer, i.e. drivers are paired and instructed in coaching and deliver this themselves.

8.1 Field trial setup

8.1.1 Groups

Two companies supplied drivers who had volunteered for the project; Litra (*N* = 13 drivers, Norway) and Bertschi (*N* = 20 drivers, UK). There was no control group, as those companies approached to participate in the project declined their participation. However, as there was a baseline period of measurement of at least 18 days when no intervention was delivered (no feedback and no coaching), and drivers would proceed at different paces through this period, a sort of staggered design was used.

The Litra drivers were issued with new Android© phones specifically for DriveMate, while the Bertschi drivers installed the app on their company phones.

8.1.2 Timeline

The introduction to DriveMate and coaching was held on the 27th of February 2020 for the Litra drivers in Bergen (Norway) and on the 7th of March 2020 for Bertschi in Middlesbrough (UK). The timeline thereafter became individual for each driver, as it was dependent upon how fast the driver undertook the sessions. After eighteen sessions of onboarding (coaching techniques material), the actual coaching was started.

Due to the developmental level of the app, the onboarding was not delivered once a day (or rather 22 hours after the completion of the previous session) as planned, and the onboarding was therefore delayed beyond the expected three to four weeks. To speed up the pace, on 4th of June 2020 the onboarding setting was changed so that a new session could be delivered once a minute.

8.1.3 Data processing and storage

In V2 of DriveMate, raw data was gathered by the app and sent to the Cygnify server for processing of feedback values on the three parameters of smoothness, harsh braking and harsh acceleration. These calculated values were stored in a database hosted by Shell, along with the raw data files for each trip.

Summary values for each trip were calculated by Cygnify, which were then rendered as coloured bars in the app and added to average values for the driver and the company (also shown as bars).

8.1.4 Intervention

The intervention has two distinct parts; the DriveMate app and the coaching material. The app has a simple setup where the drivers start DriveMate when they are driving their truck, and then save the trip afterwards. The app uses GPS and time to calculate smoothness of driving (the average of all speed changes when moving), and harsh acceleration and braking (further described below).

Timewise, there are also two distinct phases to the intervention. First, drivers only receive written instructions in the app about how to do peer-to-peer coaching (onboarding), with a time period of at least 22 hours in between sessions. After 18 sessions, during which driving data is gathered but not displayed (baseline data), the drivers move to the second phase, and coaching is started including feedback in the form of driving data after each trip. Drivers pair up and meet for discussions when the app indicates this to be due (every two weeks at the beginning). Discussion subjects are suggested by the app, including summaries of the user's driving behaviour since the last session. These driving data are compared to previous behaviour and that of all drivers of the same company.

Also, there are events which have been recorded by the app and saved for coaching by the driver, safety topics and videos of truck driving events (gathered from the web). Some coaching alerts invite the drivers to take a survey about a road safety topic (e.g. speeding, dangerous overtaking, distraction, etc.). If the results of a survey indicate that a driver lacks awareness or competence, the topic is suggested for discussion in a coaching session.

8.1.5 Dependent variables

The project used the three parameters of smoothness of driving, harsh braking and harsh acceleration, both as feedback to the drivers and as outcome variables. The goal was to reduce these values (with zero as the absolute minimum value for all variables).

Smoothness was calculated as the average of all absolute acceleration values during movement (given by GPS position and time). This variable has been found to be associated with crash involvement for car (Lajunen & Summala, 1997; Quimby, Maycock, Palmer, & Grayson, 1999) and bus drivers (Khorram, af Wåhlberg, & Tavakoli, 2020; af Wåhlberg, 2006; 2007; 2008).

Harsh braking events have no single physical definition and goes by many different names in research (e.g. Duarte, Gonçalves & Farias, 2013; Klauer et al., 2009; Tapp, Pressley, Baugh, & White, 2013). In MeBeSafe, preliminary analyses on the UDRIVE database had indicated that there existed differences in what could be considered harsh braking at different speeds; at low speeds, most strong braking was found to be due to traffic lights turning red, i.e. not a situation of some kind of risk. Therefore, two different criteria for harsh braking events were implemented; 1.4 m/s^2 when speed was <40 km/h and 0.9 m/s^2 when speed was >40 km/h. Acceleration events were calculated in a similar manner.

8.1.6 Analysis

Due to the quasi-experimental setup of the trial, and the individual delivery of the intervention, the arrangement of the data became complex. As each driver pair would start the intervention at different times, and record different numbers and lengths of trips, a separate arrangement was needed for each driver pair.

8.2 Results

8.2.1 Number of drivers and trips

Litra: A total of $N = 705$ trips had been recorded by the Litra drivers, of which $N = 668$ (93.4%) were error-free and could be used. One driver reported that his MeBeSafe phone had stopped working because it could not be charged. Due to corona, this problem could not be resolved. Three drivers did not record any trips. This left nine drivers who recorded trips during the whole intervention period. However, due to corona, Litra experienced a strong setback in business and many drivers were laid off, while the remaining worked less than their usual hours. Also, the onboarding did not proceed as expected, due to technical problems the onboarding sessions were not presented to the drivers as planned. By early June 2020, only one driver had proceeded to the coaching stage.

Bertschi: This company continued business rather much as before corona. By early June 2020, $n = 4$ drivers, out of $N = 20$, had proceeded to the coaching stage. These drivers recorded 1615 trips, of which 1398 (86.6 %) were error-free.

None of the drivers had reached a coaching session that included a driver-competence survey.

8.2.2 Driver behaviour change

The effect of the intervention was calculated as the differences in means between before and after the coaching intervention started for each driver. This means that differing numbers of trips were used for each driver. The length of the trips could also differ strongly.

Table 8-1 and Table 8-2 show the results by 2020-06-10 (means and standard deviations on the outcome variables). For both companies, the number of drivers in coaching are too small for further analysis to be meaningful.

	Litra, N=1			Bertschi, N=4		
	Before	After	d	Before	After	d
	Mean/std	Mean/std	-	Mean/std	Mean/std	-
Smoothness	0.264/0	0.273/0	-	0.226/0.070	0.203/0.087	-
Harsh braking	0.524/0	0.584/0	-	0.439/0.407	0.449/0.596	-
Harsh acceleration	0.397/0	0.446/0	-	0.339/0.399	0.365/0.578	-
Number of trips	172	24	-	96	21/14	-

Table 8-1: Mean values of smoothness, harsh braking and acceleration events, before and after coaching started for the drivers who passed beyond the onboarding stage. Lower values indicate better driving.

	Litra			Bertschi		
	Coaching, N=1	No coaching, N=8	d	Coaching, N=4	No coaching, N=16	d
	Mean/std	Mean/std	-	Mean/std	Mean/std	-
Smoothness	0.273/0	0.254/0.031	-	0.203/0.087	0.356/0.161	-
Harsh braking	0.584/0	0.400/0.087	-	0.449/0.596	0.410/0.010	-
Harsh acceleration	0.446/0	0.286/0.074	-	0.365/0.578	0.338/0.022	-
Number of trips	24/0	59/72	-	21/14	58/37	-

Table 8-2: Mean values of smoothness, harsh braking and acceleration events, compared for drivers who did and did not pass beyond onboarding. Cohen's d values were computed for the differences

8.2.3 Covid-19

The field trial was started at the very moment when the corona crisis was acknowledged in most European countries, and lockdown and other measures restricting movement where put in place. This had the direct effect upon the coaching trial that all drivers in Norway had their driving strongly reduced. Also, the focal point manager was put on part time and could no longer support MeBeSafe or the drivers.

Furthermore, the driver behaviour measurements of MeBeSafe assume an unchanging driving environment, a condition which has been violated by the changes in traffic due to the corona crisis. There are also seasonal changes in driving environment which were planned to be handled by statistical controls in these data. The change due to corona, however, is currently not possible to estimate in the areas where the field trial is taking place. Any changes in measured truck driver behaviour in the MeBeSafe project can therefore be due to different factors, which can currently not be disentangled. Although drivers who did not reach the coaching stage of the intervention could in principle be used as a control group for the same time period as the drivers who started coaching, the amount of data was deemed too small to be used for this end. Also, these drivers were probably to some degree self-selected, and any difference therefore not really reliable due to the intervention.

Also, feedback from the drivers concerning the use of the app was limited. An explanation could be that the corona crisis might have had an impact in the sense that drivers would see the project as less important than many other factors in their lives, and therefore have abstained from responding to surveys and queries.

8.2.4 Summary and outlook

The limited test period and the corona pandemic places restrictions upon the possible interpretations of the field trial results. Conclusions on whether coaching changes driver behaviour can therefore not be drawn at this stage. However, conclusions can to some degree be drawn about the feasibility of delivering peer-to-peer coaching in trucking companies, the technical standard of the DriveMate app, as well as whether the users are satisfied with the app. For the latter point, we may conclude that most drivers where probably reasonably satisfied, as they continued to record trips during the whole field trial time period, despite technical problems and the corona crisis.

Supporting that hypothesis, whenever we have had meetings with truck drivers about the coaching and the app, they have been very positive about the concepts behind the app and this approach to coaching. Thus, our careful conclusion is that there is potential for the approach and technology we have developed, even though due to the limitations and issues we have encountered, and which are described above, at this point in time it is too early to say whether it leads to statistically significant benefits in the KPIs we have identified.

9 Final results for O6/O7: Safe speed/trajectory on inter-urban roads (ika/ RWTH Aachen)

This chapter targets the results of the field trial of the Infrastructure Driver Nudge. First, we give an overall introduction (chapter 9.1), including the hypotheses regarding the expected behaviour of drivers driving through the field trial location depending on the respective nudging scenarios. Secondly, we describe the set-up of the Infrastructure Driver Nudge in detail (chapter 9.2). Subsequently, different means of data collection and –analysis are reported, starting with an overall descriptive traffic analysis (responsible: ISAC, chapter 9.3). Following this, we state the analysis of driver behaviour of especially fast drivers (with velocities that are at least 2SD over the mean of the baseline, see chapter 9.4.1.1 for details) according to the derived hypotheses by means of inferential statistical analyses (responsible: ika, chapter 9.4). We evaluated the effectiveness of the Infra Driver Nudge based on the velocities recorded using thermal imaging cameras. Furthermore, we outline the results of qualitative data collection by means of an on-site survey (responsible: ika, chapter 9.5) and a resident survey (responsible: ika, chapter 9.6). Concluding, the potential effectiveness of the system on PTWs is investigated (responsible: UFI, chapter 9.7), which was investigated independently from its potential influence on car drivers as described in chapters 9.3 to 9.6. A general discussion on the field trial results targeting especially car drivers at the field test location in Eindhoven is given in chapter 13.6.

9.1 Introduction

For Objectives 6 and 7 - Safe speed/trajectory on inter-urban roads, the field trial took place on an exit lane in Eindhoven, Netherlands. We installed roadside marking lights in such a way that drivers who entered this exit lane at velocities above a predefined threshold could be exposed to various light patterns along the lane. Both, field trial set-up and hypotheses, built directly on the results of WP3 – Driver nudge as described in deliverable D3.2. In WP3, the stimuli have been developed and tested by means of driving simulator studies and traffic simulations, and further, the system including the vehicle detection system and decision-control logic has been developed. The hypotheses regarding driver behaviour in the four testing phases (see chapter 9.2) are stated in the following paragraph. Subsequently, implications on safe trajectory and overall traffic safety are outlined.

9.1.1 Hypotheses on Driver Behaviour

The field test aims at examining the effects of selected nudging measures on driving speed in a real traffic situation. In order to gain an understanding of how certain modifications of the nudging measure affect driving behaviour, different design elements were modified, thus resulting in four testing phases. These are described in the methodological section of chapter 9.2.

9.1.1.1 Testing Phase 1

In the first test phase, we investigate different (nudging) scenarios varying regarding the **movement of lights** as well as the **spacing between active lights** and test them against an initial baseline with no lights. These were the most promising measures from the simulator studies evaluated in WP3. Since humans are conditioned to respond to red lights with caution (Donald, 1988; Edworthy & Adams, 1996) we expect that drivers reduce their driving speed more in static light scenarios (scenarios 2 & 4) compared to an initial baseline (scenario 0; **H1.1**). As the optic flow is influenced by the frequency in which objects roll by, we expect that scenarios with lights moving towards the driver lead to a higher perceived driving speed (Gibson, 1950; Manser & Hancock, 2007). Therefore, we expect that lights moving towards the driver (scenarios 1 & 3) lead to a reduced driving speed compared to an initial baseline (scenario 0; **H1.2**).

As the scenarios with lights moving towards the driver combine the function of triggering caution (Donald, 1988; Edworthy & Adams, 1996) as well as affecting speed perception (Gibson, 1950; Manser & Hancock, 2007), we expect that the driving speed in scenarios with lights moving towards the driver (scenarios 1 & 3) is slower compared to static lights (scenarios 2 & 4; **H1.3**).

We vary the spacing between active lights to investigate whether implementing fewer lights in follow-up locations is possible as this would result in potentially lower implementation costs for the future. We do not expect the spacing between active lights to have an effect on driving speed as long as same number of the lights is displayed. A narrower spacing between active lights increases the salience of lights, as more stimuli are displayed on a shorter stretch of the road. That is, when every third light is activated, there is 18 m (3* 6 m) between two activated lights. Consequently, four activated lights lead to an overall stimulus length of 72 m (18 m * 4 gaps between each two of four activated lights). However, when every fourth light is activated there is a gap of 24 m (4 * 6 m) between two activated lights. Consequently, four activated lights lead to an overall stimulus length of 96 m (24 m * 4 gaps between each two of four activated lights). We do not expect salience to have an impact on speed choice. As a result, the driving speed in the scenario with static lights with a narrow spacing (oox, with x being an activated light and o being an inactivated light, scenario 2), and static lights with a wider spacing (ooox, scenario 4) is expected to not differ significantly (**H1.4**). Correspondingly, we also expect that driving speed in the scenario with the lights moving towards the driver with a narrow spacing (oox, scenario 1) does not differ from lights with a wide spacing (ooox, scenario 3; **H1.5**; Van Mierlo, 2017).

9.1.1.2 Testing Phase 2

Within the second test phase, we test whether the **movement speed of lights** has an influence on the driving speed. Here, **movement speed of lights** describes the movement velocity at which the lights are moving towards the driver. A higher movement speed of the lights leads to a higher frequency in which lights roll by.

According to the optic flow (see Gibson, 1950), the higher the frequency of the lights that are moving towards the driver, the higher is the perceived speed, which is then expected to result in lower driving speed. We therefore expect a linear relationship between the **movement speed of lights** and the (perceived) driving speed. Together with the driver's own velocity, the absolute subjectively perceived speed (driving speed + movement speed of lights) will be perceived differently depending on the speed of lights moving towards the driver. As a result, we expect the driving speed in scenarios with lights moving towards the driver at 80 km/h (scenario 7) to be lower compared to lights moving towards the driver at 50 km/h (scenario 1; **H2.1**). Further, we expect the driving speed in scenarios with lights moving towards the driver at 50 km/h (scenario 7) to be lower compared to lights moving towards the driver at 20 km/h (scenario 6; **H2.2**). Concluding, we expect driving speed in scenarios with lights moving towards the driver at 80 km/h (scenario 7) to be lower compared to lights moving towards the driver at 20 km/h (scenario 6; **H2.3)**

9.1.1.3 Testing Phase 3

Within the third test phase, we test whether the **movement of lights** and the **spacing between sets of activated lights** have an influence on driving speed. The levels of the **movement of lights** are the same as in the first testing phase (static lights vs. lights moving towards driver). In testing phase 3, we varied the spacing between two sets of activated lights, resulting in a narrow spacing (oxx) and a wider spacing (ooxx). The difference between the first and third testing phase is the different number of activated lights: while only one light in a row was activated in testing phase 1 (oox (scenarios 1 & 2) vs. ooox (scenarios 3 & 4), two lights in a row were activated in testing phase 3 (oxx (scenarios 9 & 10) vs. ooxx (scenarios 11 & 12).

As in the first testing phase, we expect that drivers slow down more when seeing red static lights with a set of two activated lights (scenarios 10 and 12) compared to an initial baseline (scenario 0, **H3.1**). Additionally, we expect that the lights moving towards the driver with a set of two activated lights influence optic flow in such way that the driver perceive the driving speed as higher (Gibson, 1950; Manser & Hancock, 2007). This eventually results in a reduced driving speed when lights in a set of two move towards the driver (scenarios 9 and 11) compared to baseline (scenario 0, **H3.2**). Similar to the expectations in testing phase 1, we hypothesize that the driving speed in scenarios with lights moving towards the driver with a set of two activated lights (scenarios 9/11, respectively) is even slower compared to static lights with a set of two activated lights (scenarios 10/12, respectively; **H3.3**). We explain this with the assumption that lights moving towards the driver combine the caution-triggering function of the colour red (Donald, 1988; Edworthy & Adams, 1996), as well as the expected effect on speed perception (Gibson, 1950; Manser & Hancock, 2007). Also, similar to the first testing phase, the spacing between two activated lights is not expected to have an effect on driving speed because only the salience is expected to be altered (Van Mierlo, 2017), but not the optic flow (Gibson, 1950). As a result, we expect the driving speed in the scenario with static lights with a narrow spacing between a set of two activated lights (oxx, scenario 10), and static lights with a wider spacing between a set of two activated lights (ooxx, scenario 12) to not differ significantly (**H3.4**). We also expect that the lights moving towards the driver with a narrow spacing between a set of two activated lights (oxx, scenario 9) do not differ from a set of two activated lights with a wide spacing (ooxx, scenario 11) in driving speed (**H3.5**, Van Mierlo, 2017).

When comparing the collected data from the first and third testing phase, we expect no difference in driving speed between the scenario with single activated lights moving towards the driver (oox, scenario 1) compared to sets of two activated lights moving towards the driver (oxx, scenario 9; **H3.6**). This is due to the assumption that more lights may result in an increased salience (Van Mierlo, 2017), but do not alter the optic flow itself. As this expectation is independent from the spacing between an activated set of two lights, it applies to single lights moving towards the driver with the pattern ooox (scenario 3) and a set of two activated lights moving towards the driver (ooxx, scenario 11) as well. Hence, we expect no significant difference between single lights moving towards the driver with a spacing ooox (scenario 3) and a set of two activated lights moving towards the driver (ooxx, scenario 11; **H3.7**).

9.1.1.4 Testing Phase 4

Within the fourth testing phase, we tested a Speed Indicator Device displaying an emoticon to study the effect of an already established measure on driving speed. For this evaluation, we do not expect the Speed Indicator Device displaying an emoticon to have an effect on human speed perception (Gibson, 1950), we expect that the Speed Indicator Device displaying an emoticon draws the attention to excessive driving speed in form of a mindful nudge (Kahneman, 2011; Karlsson et al., 2017). As a result, we assume that showing the Speed Indicator Device displaying an emoticon leads to a speed reduction, irrespective of the light-based nudging measure. Hence, we expect lower driving speed when a Speed Indicator Device without the nudging system is displayed (scenario 13) than in the initial baseline with no Speed Indicator Device displaying an emoticon (scenario 0).

Please note that a direct statistical comparison of our light-based system and the Speed Indicator Device displaying an emoticon is not possible due to the different ways the Speed Indicator Device and the nudging stimuli work. We explain this in detail in chapter 9.3.3. However, implementing a Speed Indicator Device at the field trial location can give valuable insights into how people would behave with a commonly known measure on site.

9.1.2 Implications on Safe Trajectory

Leading drivers along a safe trajectory can be achieved by reducing speed via the developed nudging measures, due to the close correspondence of speed and trajectory safety. This was deduced in deliverable D3.2. In a curve, the vehicle requires radial friction forces between the tyre and the road, which reduces the available tangential friction in case the driver has to brake suddenly. The difference between the available and the required friction coefficient is called margin of safety (Pratt et al, 2015). The margin of safety can be increased by reducing the radial acceleration, which depends on the speed. We will therefore evaluate whether the radial acceleration in scenarios where drivers have been nudged is lower than in the baseline. Furthermore, the influence of the nudge on the distribution of lateral positions (distance to the edge of the road) can be analysed.

9.1.3 Implications on Traffic Safety

Within all four testing phases, we hypothesise that the infrastructure nudge (or the Speed Indicator Device in testing phase 4 can reduce the speed of drivers. We expect that this also affects the speed distribution and the speed profile along the motorway exit. If fast drivers reduce their speed, the mean speed of all vehicles decreases. It also implies that the percentage of speeding vehicles decreases. It is widely accepted that there is a relationship between speed and traffic safety (Elvik 2009). Since drivers can be nudged from the beginning of the exit lane, we expect that nudged drivers decelerate earlier than non-nudged drivers with the same initial speed do. This reduces the risk of hard braking at the beginning of the curve.

9.2 The Nudge that was evaluated

This chapter gives an overview of the set-up of the field trial and the tested and evaluated scenarios. More detailed methodological information on sample and distinct stimuli is given in the respective sub-chapters as described in chapter 9.1. Please note that the trial design and location set-up were described in detail in deliverables D3.3 ("Infrastructure measures", confidential deliverable), D5.1 ("trial design", public deliverable), and D5.3 ("Locations ready for field trials", confidential deliverable").

For the field trial of the Infrastructure Driver Nudge, roadside marking lights were installed (40 LED road studs on each side of the exit lane for a total length of 240 m, see figure 9.1 on the left) in such a way that drivers who entered the exit lane with a speed above a predefined threshold (see Figure 9-1 on the right) could be exposed to various light patterns along the lane. We measured the vehicles' speed using thermal cameras along with computer vision algorithms. An intelligent decision control logic identified those vehicles that fulfil the nudging criteria (exceeding the speed threshold as shown in figure 9.1 on the right and a minimum distance of one stimulus length (72 m or 96 m) between two nudged vehicles) in order to display the light pattern only to relevant vehicles at the relevant position, thereby avoiding distraction of other drivers. More details about this set-up are described in deliverables D3.3 and D5.3 (chapter 7). For details on trial design, please see D5.1.

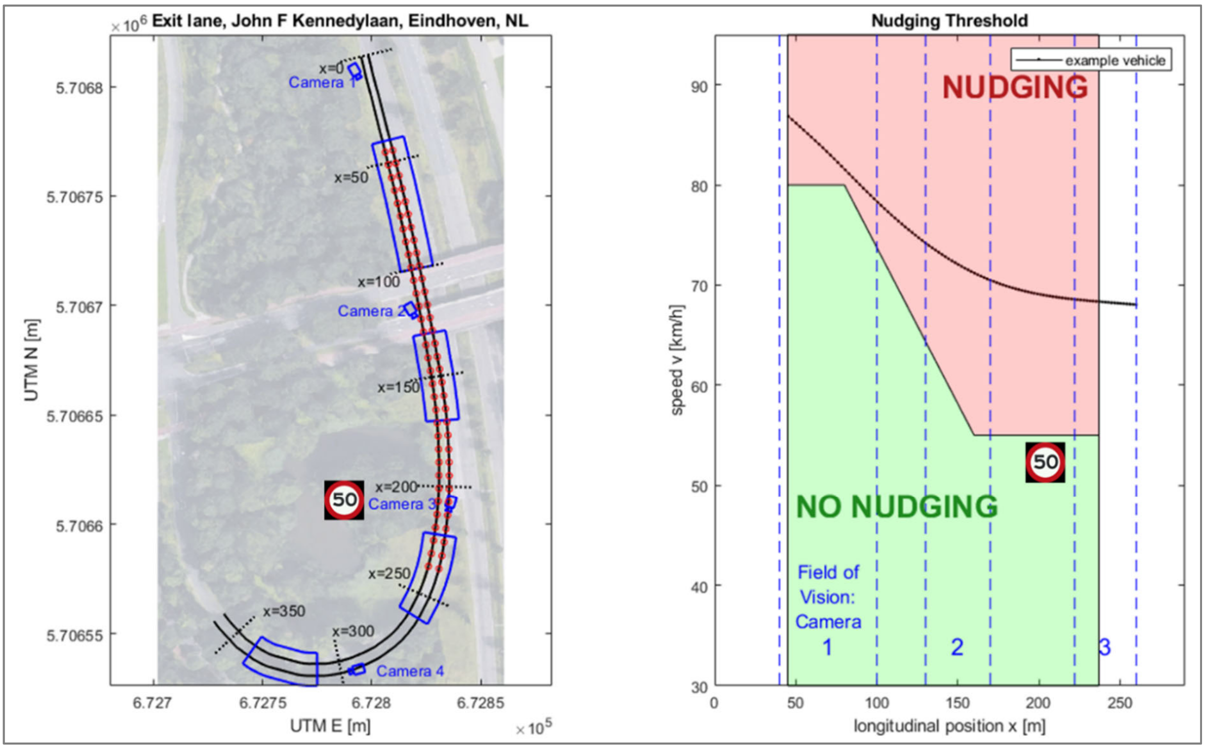

Figure 9-1: On the left: Set-up of the field trial with thermal cameras and roadside marking lights. The beginning of the lights is the beginning of the exit lane. On the right: Nudging threshold based on speed over the course of the exit lane.

Nine different light scenarios were tested based on the results of the driving simulator studies (see Deliverable 3.2) including variations of light pattern, spacing between activated lights, as well as light movement speed. Further, one emoticon-sign scenario and two baseline scenarios were tested for comparison reasons. Each scenario was typically tested for one week (Monday to Monday), some shorter due to technical problems. The scenarios were divided into different testing phases. Testing phase 1 compared a baseline to different movement of lights, including static lights and lights moving towards the driver. Both scenarios were tested in two different variations of spacing between activated lights, resulting in four scenarios plus a baseline (see table 9.1). Testing phase 2 tested different **movement speed of lights** and testing phase 3 scenarios with different **spacing between an activated set of two lights** and **numbers of lights activated**. Between testing phase 2 and testing phase 3, we conducted an intermediate baseline for control purposes. Furthermore, in testing phase 4, we compared the system to a traditional Speed Indicator Device displaying an emoticon placed right in front of the 50 km/h-sign while the nudging system itself was turned off. A mobile radar system normally used near road construction was used for this. The standard red/white striping was covered with black masking tape as the striping is normally not used for speed indicator devices and might lead to a misinterpretation. The lights of the driver nudge system were turned off. A positive emoticon ("☺") was shown when drivers where below the set speed threshold, or a negative emoticon ("☹") when they were above the set speed threshold. Figure 9-2 displays an example of how activated red lights without a Speed Indicator Device looked (on the left, the pylons had been set up for light installation and were removed for the field trial) and the set-up of the Speed Indicator Device (on the right), which was displayed without the lights.

Figure 9-2 On the left: Exemplary view on activated red lights while driving. On the right: Positioning of the speed indicator device.

Table 9-1 displays the detailed scenarios. After the first four test runs the brightness of the lights during day and night were adjusted based on feedback from users. During the day, the brightness was turned up and during the night, the brightness was lowered. Scenario 12 could not be tested as intended due to a camera failure.

Testing Phase	No.	Scenario			Time of testing (change initiated at noon)	Number of all vehicles on the exit during the testing time
		Colour	Movement	Spacing between lights		
	0	No nudge – baseline			Oct 21-Oct 28, 2019	N = 19,030
1	1	red	Moving towards the driver at 50 km/h		Nov 14-Nov 21, 2019	N = 10,059[2]
	2	red	Static lights		Nov 4-Nov 11, 2019	N = 18,458
	3	red	Moving towards the driver at 50 km/h		Nov 25-Dec 2, 2019	N = 19,417
	4	red	Static lights		Dec 2-Dec 9, 2019	N = 19,211
2	6[3]	red	Moving towards the driver at 20km/h		Jan 13-Jan 20, 2020	N = 19,492
	7	red	Moving towards the driver at 80km/h		Jan 20-Jan 27, 2020	N = 19,181
	8	No lights (intermediate 'baseline')			Jan 27-Feb 3, 2020	N = 18,780
3	9	red	Moving towards the driver at 50 km/h		Feb 3-Feb 10, 2020	N = 6,189[4]
	10	red	Static lights		Feb 10-Feb 18 + Feb 26-Mar 2, 2020	N = 28,702
	11	red	Moving towards the driver at 50 km/h		Feb 18-Feb 26, 2020	N = 19,790
	12[5]	red	Static lights		Not tested	

[2] Lower sample size due to technical problems.
[3] Scenario 5 was an internal test without any experimental variation.
[4] Lower sample size due to technical problems..
[5] Camera failure

4	13	-	Emoticon (sad smiley if speed above threshold, happy smiley if under threshold) – no lights	☺/☹	Mar 2-Mar 9, 2020	N = 18,336

Table 9-1: Tested scenarios (between-subjects) within the field trial of the Infrastructure Driver Nudge with specifications regarding light colour, movement, spacing between lights, time of testing, and overall number of vehicles on the exit during the testing time.

9.3 Traffic Analysis

This chapter first describes the data processing that is necessary for evaluating the effectiveness of the nudge. This chapter then states the results of the overall descriptive traffic analysis. This analysis includes all vehicles that used the motorway exit. The results give an overview over the field test of the infrastructure driver nudge and its implications on traffic safety, before behavioural hypotheses are answered in the subsequent chapter 9.4.

9.3.1 Data Processing

The raw data used for the analyses in chapters 9.3 and 9.4 consist of

- Vehicle ID
- Timestamp t (~30 Hz)
- Current position x, y (~30 Hz)
- Duration and timing of nudge (if applicable)
- current scenario (if applicable)

The positions of each vehicle are described in a road coordinate system, i.e. in coordinates measured relative to the road. The x-coordinate is the position along the road. The y-coordinate is the orthogonal distance to the (right) edge of the road (see Figure 9-3). This enables us to describe the trajectory of a vehicle relative to the road. Figure 9-4 shows an excerpt from the raw data in $t - x$ and $x - y$. It should be noted that there are gaps between the fields of vision (FOV) of each camera where positions are not available in the raw data. The first available positions of the vehicles were between x = 40 (beginning of the exit lane) and x = 50, the last available positions were approximately at x = 260. Camera 4 was not used due to the limited CPU (Central Processing Unit) load. This did not affect the operation of the system, because the FOV of camera 4 started behind the last light.

Figure 9-3: Detection of vehicle positions and speed in a road coordinate system, where the x-coordinate is the (longitudinal) position along the road and the y-coordinate is the lateral position, i.e. the orthogonal distance of the vehicle to the right edge of the road.

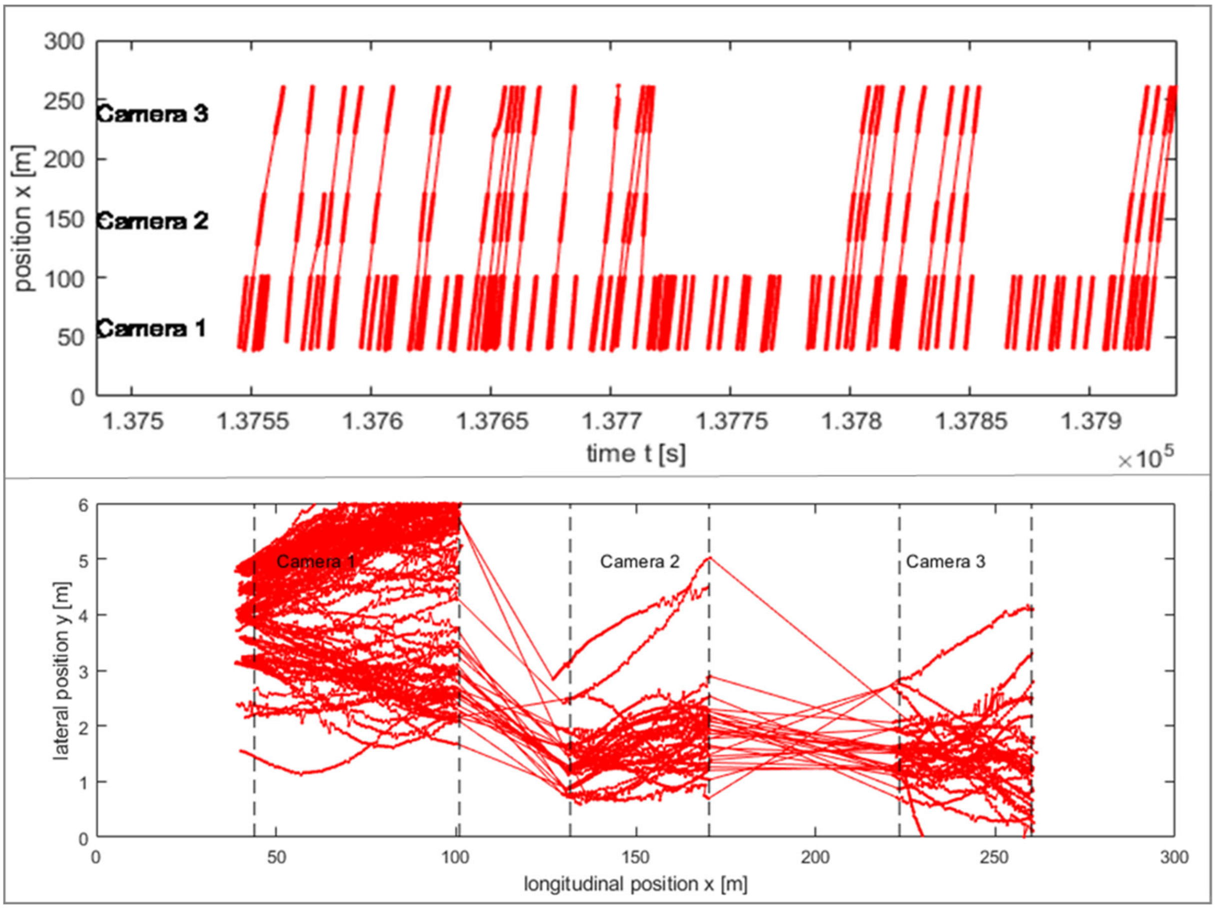

Figure 9-4: Excerpt from the vehicle trajectory data. t-x (top), x-y (bottom). The thick red lines represent the tracked vehicle positions, the thin red lines are interpolations in the gaps between the FOVs. Vehicles that do not use the motorway exit are only tracked in camera 1 and usually have a larger lateral position value.

The data processing has to be distinguished between the real-time decision of whether or not a vehicle is nudged and the analysis of the effectiveness of the nudging measure. In the real-time application, the vehicle speed had to be computed efficiently and based only on the previous positions and timestamps. To achieve this, the speed was averaged over the last second. Furthermore, the positions and speed in the gaps between the FOVs of the cameras had to be extrapolated by assuming that vehicles maintain their speed in both longitudinal and lateral directions while they are in the gaps.

For the data analysis, we were able to perform a more thorough data processing in order to remove obvious errors and implausible trajectories. The following steps were conducted:

- Filter the trajectories of vehicles that have taken the motorway exit.
- Smooth the trajectories in order to obtain realistic speed and acceleration values. First, the raw position data were weighted according to their distance from the camera. Vehicles with positions further away from the camera appear smaller in the image (see Figure 9-3); hence, these positions are less accurate and were assigned a lower weight. A smoothing spline was then fitted to the position data of each vehicle separately for x and y. From the smoothing spline, a continuous trajectory along the whole exit path (including the gaps between cameras) including positions, speed, and accelerations in x- and y-directions can be computed.
- Compute the headway between consecutive vehicles.
- Filter trajectories of vehicles that have been tracked until the end of camera 3 ($x \approx 260$).
- Filter trajectories of vehicles according to the following plausibility criteria:
    - If one or more headway values of a vehicle pair are negative, both vehicles are removed.
    - In order to exclude trucks that have been falsely detected as two passenger cars, vehicles with a headway to the leading vehicle of less than 40 m throughout the whole curve are removed.
    - If one or more position values of a vehicle are outside the bounds of the road (e.g. negative y values), the vehicle is removed.
    - In order to exclude vehicles that have not been matched correctly between the cameras, the average speed of each vehicle in five sections (FOV camera 1, gap between cameras 1&2, FOV camera 2, gap between cameras 2&3, FOV camera 3) is computed. If the speed

difference between two consecutive sections is larger than 10 m/s in x-direction and 2 m/s in y-direction, the vehicle is removed.

9.3.2 Results

During the analysis phase (21st Oct 2019 to 9th Mar 2020) the trajectories of *N* = 2,329,211 vehicles (*N* = ~16,600 per day) were gathered. As the likelihood that vehicles travelling in the left lane would exit was quite low, vehicles on this lane were not measured. Thus, the data gathered does not reflect the actual number of vehicles on the road. *N* = 727,299 (31.2 %) vehicles used the exit lane, on average *N* = ~5.200 per day. After running the plausibility check mentioned above, *N* = 374,449 (51.5 %) vehicles were usable for the analysis. *N* = 295,843 (79.0 %) of these vehicles took the exit while a scenario was active. *N* = 198,666 (67.2 %) of them fulfilled the criteria for nudging (speed above threshold, headway large enough to show the light pattern) for at least a short period of time. This number is not equal to the number of actually nudged vehicles: This is because in the two baseline scenarios (scenarios 0 and 8), vehicles were not nudged even if they fulfilled the nudging criteria, and in the other scenarios, some vehicles were nudged but excluded from the analysis due to obviously implausible trajectories. The most important characteristics of the scenarios considered in the analysis are presented in Table 9-2.

Scenario	Number of Vehicles (after Data Processing)	Number of Vehicles Fulfilling Nudging Criteria	Speed (km/h) at x = 50		Speed Reduction (km/h) between x = 50 and x = 205	
			Mean	Standard Deviation	Mean	Standard Deviation
0	19,030	12,317 (65 %)	71.7	8.7	15.5	7.7

1	10,059	6,365 (63 %)	71.1	8.9	15.8	7.6
2	18,458	11,162 (60 %)	70.6	8.8	16.0	7.9
3	19,417	11,183 (58 %)	71.4	9.0	17.0	8.4
4	19,211	10,818 (56 %)	72.0	9.1	17.9	8.4
6	19,492	12,256 (63 %)	72.6	9.0	17.2	8.1
7	19,181	11,612 (61 %)	73.5	9.1	18.5	8.2
8	18,780	11,757 (63 %)	73.1	8.9	17.5	8.0
9	6,189	4,025 (65 %)	73.6	9.3	18.4	8.2
10	28,702	18,352 (64 %)	73.0	8.7	17.7	7.9
11	19,790	12,535 (63 %)	73.7	8.6	18.4	7.9

Table 9-2: Overall number of vehicles, number of vehicles fulfilling the criteria for nudging, speed at the beginning of the exit and speed reduction between the beginning of the exit and the beginning of the curve. Each scenario (between-subjects) was tested for about one week.

For the following analyses, the vehicle trajectories were evaluated at cross sections every 5 m between x = 50 and x = 250. The first and last few metres of the vehicle trajectories were omitted because not all vehicles were tracked at these positions.

Since the computer vision algorithm typically detects fast vehicles later, the sample of vehicles at x < 50 would be biased. Recall that the first light was positioned at approximately x = 45, but drivers could already see the lights as soon as their vehicle was detected. The beginning of the curve and the 50 km/h speed limit are both located at approximately x = 205.

At first, we analysed the mean speed at the different cross sections in the different scenarios of **testing phase 1** (see Figure 9-5). The baseline scenario (0) was the scenario with the highest mean speed beyond x = 90. Nudging reduced the mean speed by up to 2.1 km/h (3.7 %) at the beginning of the curve. However, the differences between the nudging scenarios (1 to 4) were small and were therefore analysed further in chapter 9.4. The mean speed at the beginning of the exit (x = 50) differed between the scenarios. This cannot be attributed to the nudge as it is only 5 m behind the first light, and the mean speed of vehicles that are not exiting differs in the same way. This indicates that the speed differences at x = 50 were caused by external factors such as weather. It should be emphasised that the mean speed includes those vehicles that are already driving at a safe speed as well as those that are influenced by a vehicle ahead. Therefore, the change in mean speed must not be confused with the magnitude of the effect of nudging.

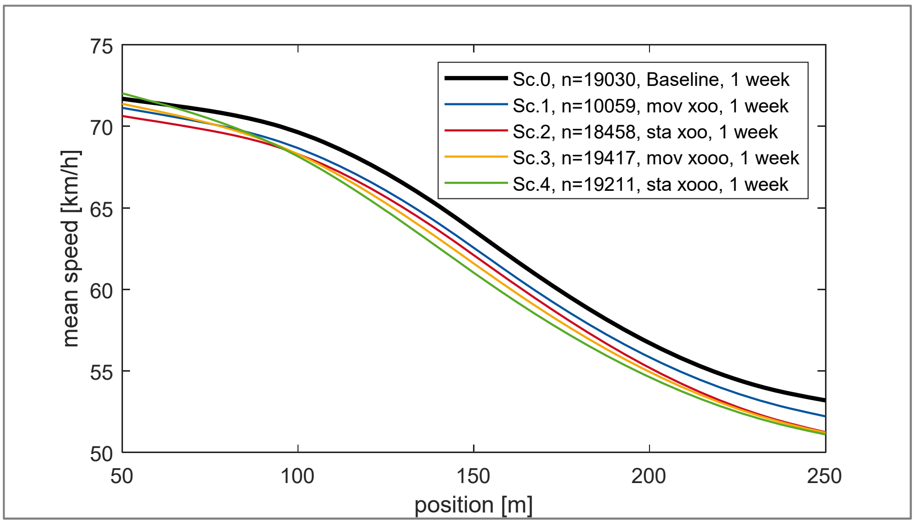

Figure 9-5: Mean speed of all vehicles taking the motorway exit. Each scenario (between-subjects) was tested for about one week.

The effect of the nudge can be analysed by selecting only those vehicles that are within the same speed range at x = 50 and that are not influenced by another vehicle throughout the whole exit. Thus, the speed differences at x = 50 can be controlled, and only vehicles that fulfilled the nudging criteria were analysed. Vehicles with an initial speed between 80 and 85 km/h at x = 50, i.e. vehicles slightly above the speed threshold, were selected as an example group. Figure 9-6 shows that these vehicles reduced their speed on average up to 3.0 km/h (4.9 %; x = 200) more if they are nudged. The differences between the baseline scenario 0 and the nudging scenarios 1-5 increased between x = 50 and x ≈ 150, which indicates that the effect of the nudging stimuli was strongest at the beginning of the exit. Figure 9-7 shows that the effect of nudging slightly increases with the initial speed by taking the example of scenarios 0 and 4. However, it has to be mentioned that the sample size of vehicles with high initial speed was very small.

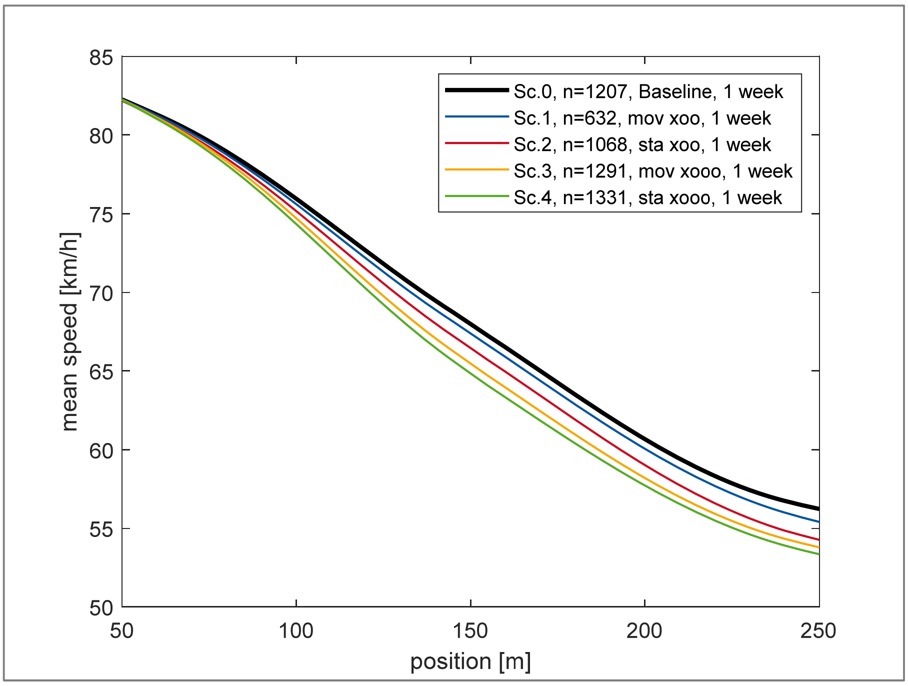

Figure 9-6: Mean speed of vehicles with an initial speed (at x = 50) between 80 km/h and 85 km/h and a headway larger than 90 m throughout the exit for testing phase 1. Each scenario (between-subjects) was tested for about one week.

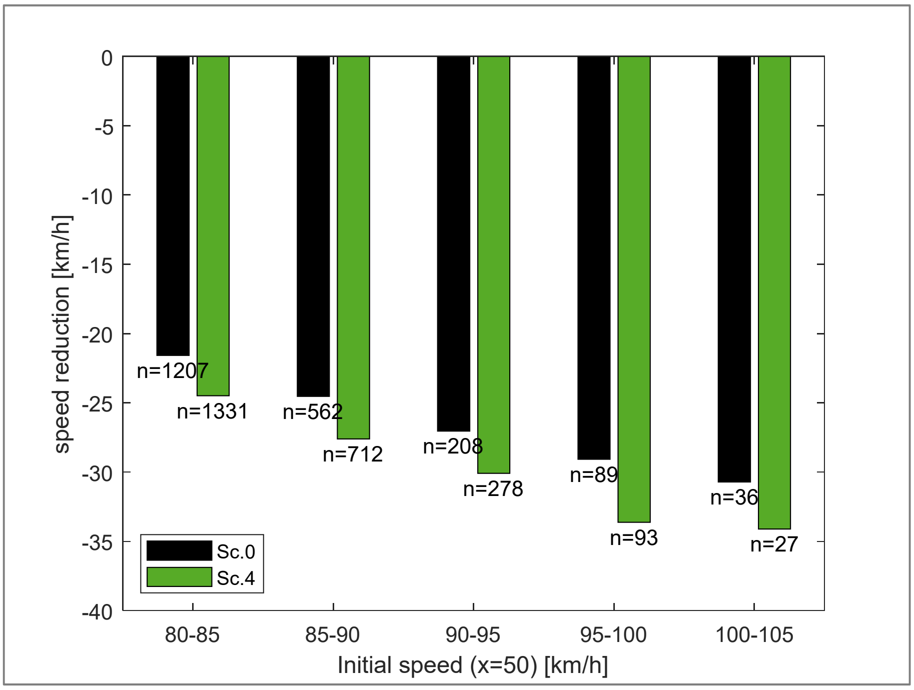

Figure 9-7: Speed reduction from x = 50 to x = 200, exemplary comparison of baseline scenario 0 and scenario 4. Each scenario (between-subjects) was tested for about one week.

The results presented so far are based only on mean values. The distribution of speed is also an important criterion to evaluate the effect of the nudging measure. Since the nudging measure only targets speeding vehicles, the distribution of speed can be described by the ratio of speeding vehicles. To define a "speeding vehicle", we use the 85 % quantile of speed "V85" (see Figure 9-8 on the left) which is commonly used in road design (Lippold, 1999). The V85 of the baseline scenario is used as a reference. Figure 9-8 (on the right) shows the ratio of vehicles faster than V85 of the baseline scenario. By definition, 15 % of all drivers are faster than V85 in the baseline scenario. In the nudging scenarios, the ratio of speeding vehicles decreases to approximately 9 % (scenario 4), which corresponds to a reduction of 40 %.

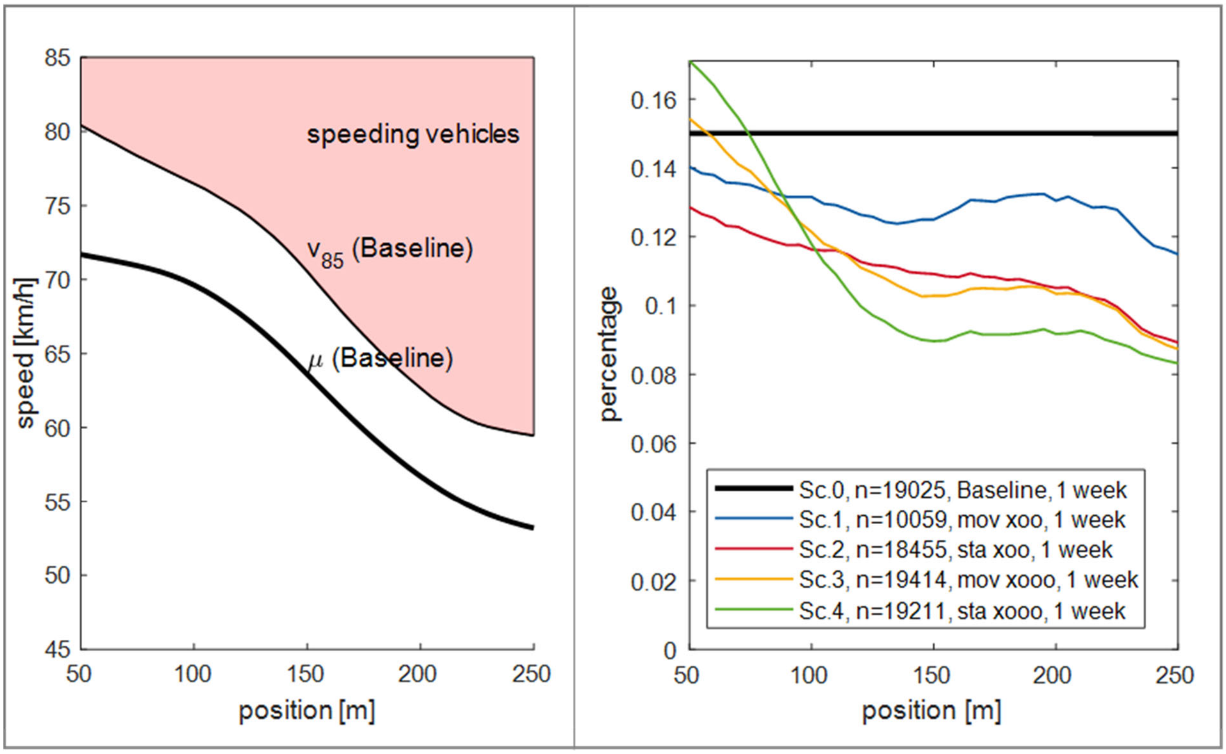

Figure 9-8: On the left: (example figure) a vehicle is defined as a "speeding vehicle" if it is faster than the 85% quantile of speed (V85) of the baseline scenario. On the right: ratio of speeding vehicles in each scenario.

Driver behaviour cannot only be described by speed but also by acceleration. Since drivers are supposed to react to the nudge by pressing the brake pedal, the acceleration (or deceleration) is a more direct indicator of driver behaviour. Figure 9-9 shows that drivers decelerated more between x = 50 and x = 150 in the nudging scenarios compared to the baseline scenario. It also shows that drivers reached their maximum deceleration slightly earlier than in the baseline scenario.

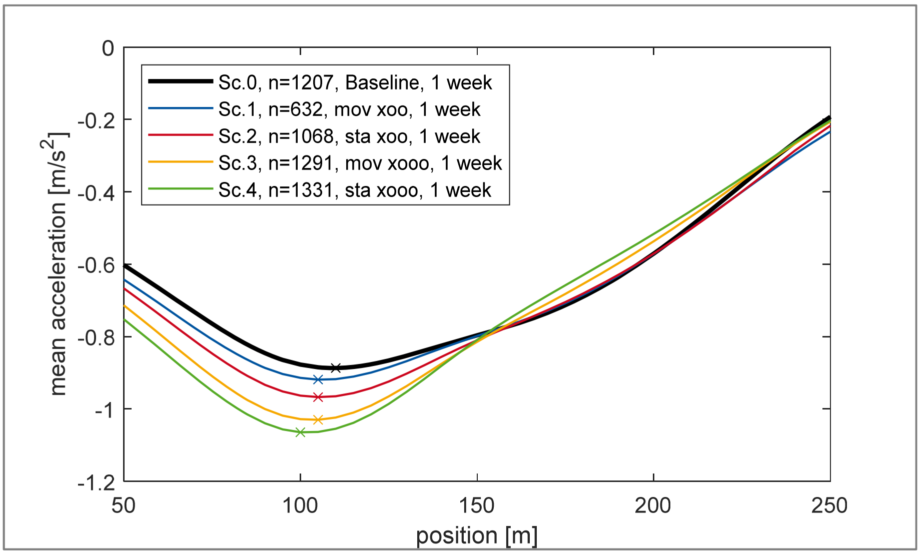

Figure 9-9: Mean acceleration of vehicles with an initial speed (at x = 50) between 80 and 85 km/h and a headway larger than 90 m throughout the exit. The figure shows testing phase 1. Each scenario (between-subjects) was tested for about one week.

Despite having a reduced brightness at night-time, the lights are inherently more visible at night. This might imply that the effect of the nudge was higher at night. Therefore, we analysed the differences between day and night conditions for the exemplary conditions baseline scenario 0 and scenario 2 (see Figure 9-10). Even in the baseline scenario, there was a difference between day and night. At night, drivers began their deceleration later and decelerated stronger, i.e. the maximum deceleration was larger, and the maximum was reached at a later position.

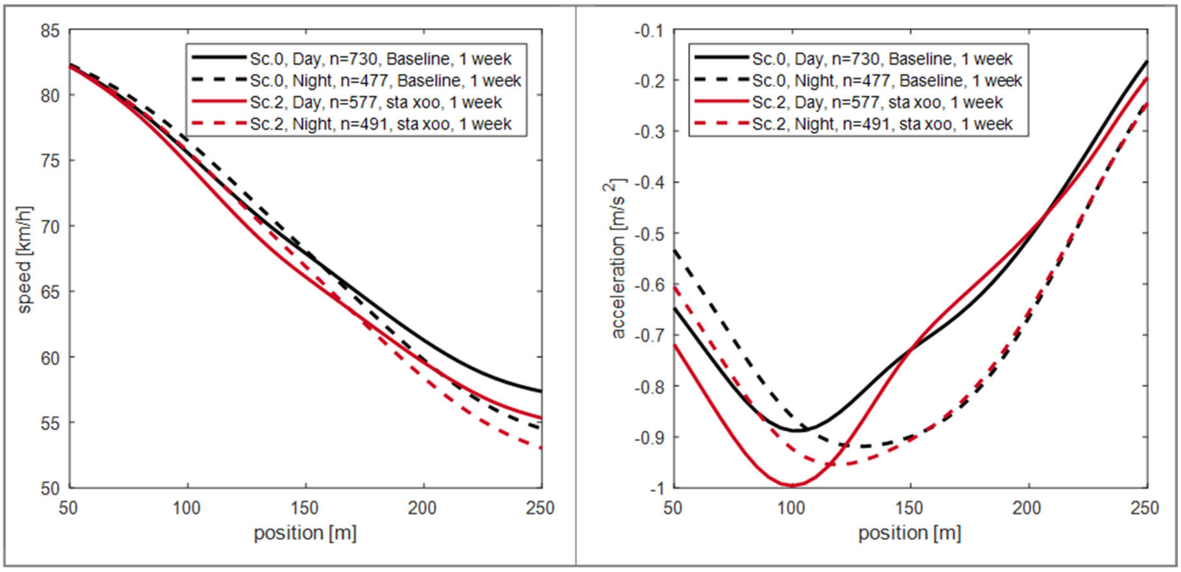

Figure 9-10: Differences in driver behaviour between day and night, comparison of scenarios 0 and 2. Each scenario (between-subjects) was tested for about one week. Only vehicles with initial speed between 80 and 85 km/h are included. On the left: speed, on the right: acceleration.

The overall results of the **testing phases 2 and 3** are shown in Figure 9-11. All nudging scenarios had a smaller ratio of speeding vehicles (x ≥ 115) and a smaller mean speed than the baseline scenario. However, scenario 8, which was an intermediate baseline scenario without nudging, had a lower speed and ratio of speeding vehicles than scenario 0, although the scenarios were identical.

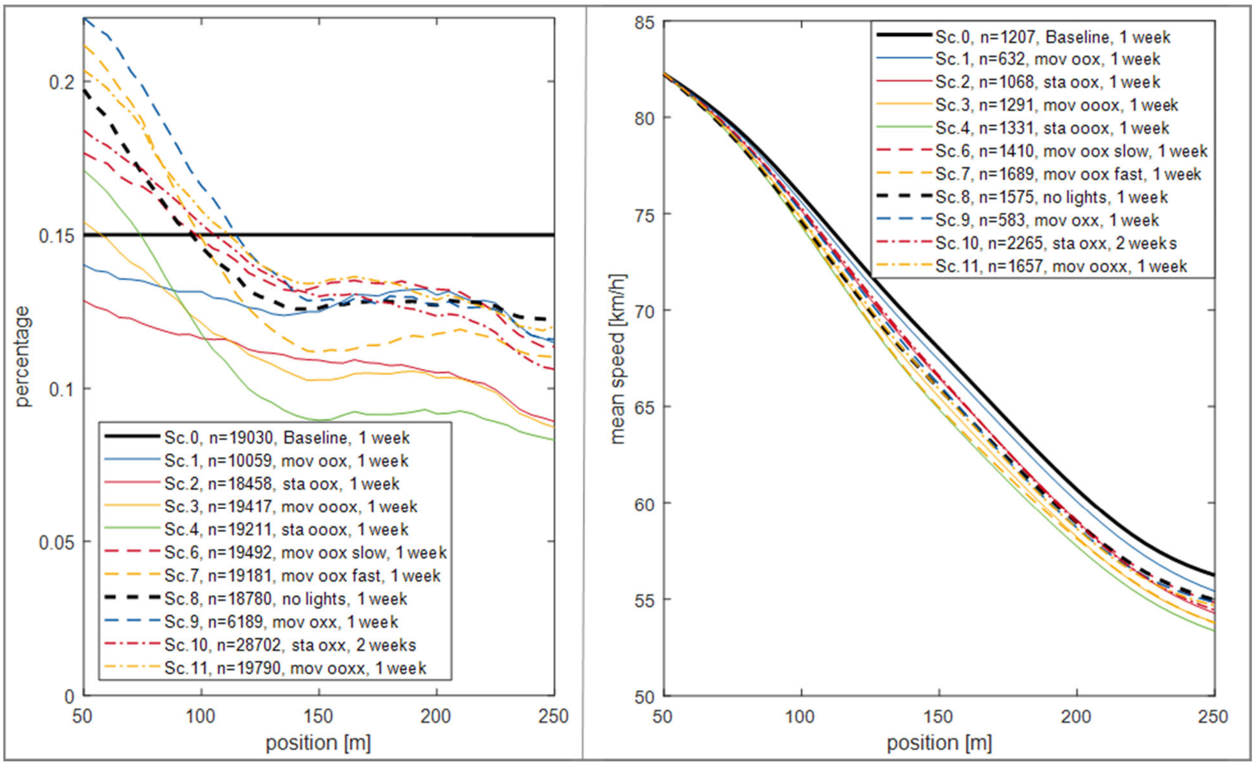

Figure 9-11: On the left: ratio of fast vehicles, On the right: mean speed of vehicles with initial speed between 80 and 85 km/h. The figure shows testing phases 1, 2, and 3. Each scenario (between-subjects) was tested for about one week.

In order to compare the infrastructure nudge with established speed reduction measures, we installed a Speed Indicator Device next to the road at x ≈ 195 (scenario 13, **testing phase 4**). Since the device records only one speed value per vehicle, the trajectory data from the thermal cameras were used to analyse the effect of the Speed Indicator Device depending on the position. While nudging reduced the mean speed at the beginning of the curve by up to 2.1 km/h (exemplary scenario 4) compared to the baseline scenario, the mean speed in scenario 13 was 3.8 km/h lower than in the baseline scenario. The results for vehicles with initial speed between 80 and 85 km/h were similar. For x ≤ 155, the percentage of speeding vehicles in scenario 4 was lower than in scenario 13, and vice versa for x > 155. The position at which the maximum deceleration occurs was x = 100 in scenario 4 and x = 110 in scenario 13 and in the baseline scenario.

When a vehicle drives in a curve, radial forces occur, which have to be compensated by friction forces between the tyres and the road surface. The difference between the actual and the required friction coefficient is called the margin of safety. The margin of safety can be increased either by decreasing the longitudinal acceleration or the radial acceleration. As mentioned above, there is a slight decrease in the mean longitudinal acceleration for some scenarios. To analyse the radial (or lateral) acceleration ($a_r = v^2/r$), the radius r of the curve must be known. Since the radius does not change between the scenarios, a rough estimation of the radius from satellite images is sufficient (see Figure 9-12).

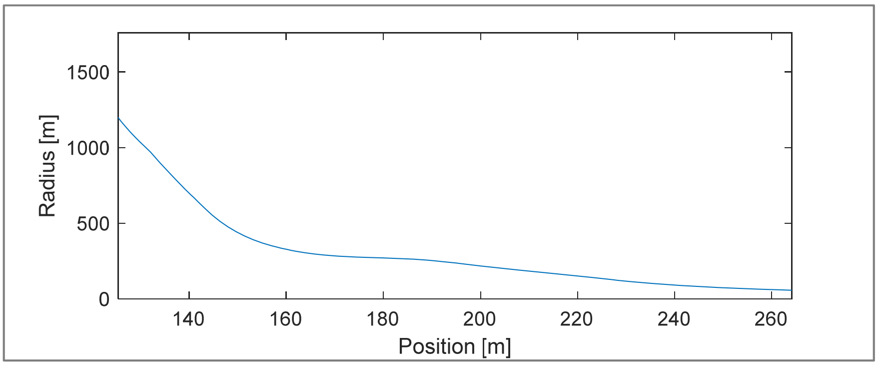

Figure 9-12: Estimated curve radius of the motorway exit

Due to the large radii at the beginning of the exit, the radial acceleration is analysed only at positions x > 150. Figure 9-13 shows the mean radial accelerations of all vehicles in each scenario. While the mean speed decreases in this section (see Figure 9-5), the radial acceleration increases due to the decreasing radius. Since the radius is approximately constant from x ≈ 260 on, the radial acceleration is expected to reach its maximum at this position. In each scenario, the mean radial acceleration is lower than in the baseline scenario. The mean radial acceleration can be reduced by up to 0.2 m/s^2 (7.5 %; scenario 4, x = 250). The distribution of y-positions in the curve has been analysed descriptively as well, but no differences between the scenarios could be found.

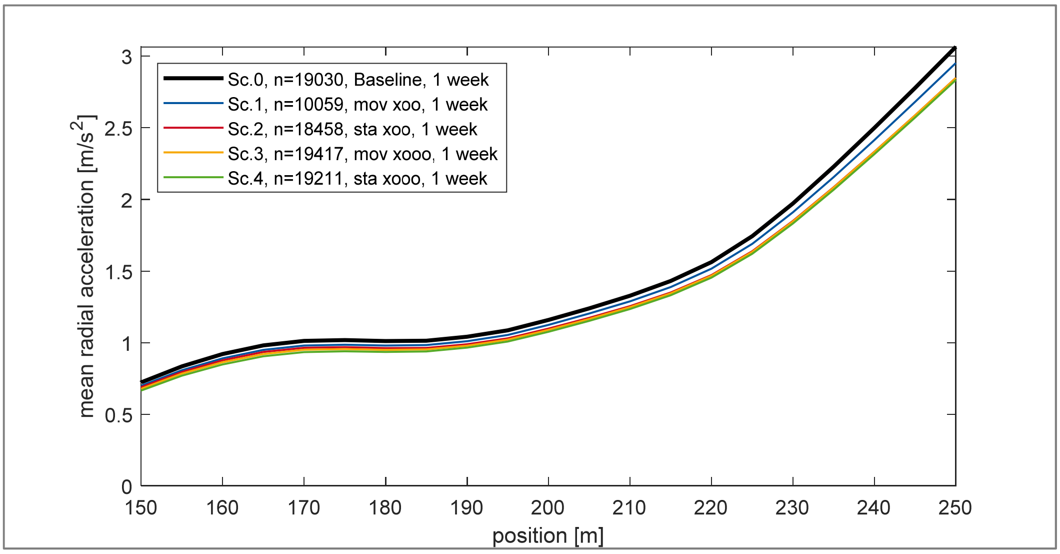

Figure 9-13: mean radial acceleration of all vehicles in testing phase 1 taking the motorway exit. Each scenario (between-subjects) was tested for about one week.

9.3.3 Discussion

The results presented above show that the nudge had a positive impact on traffic safety as it reduced the speed and the ratio of speeding vehicles in the exit and the radial acceleration in the curve. However, a descriptive analysis does not allow conclusions on the differences between the scenarios or the reasons behind these differences. This aspect will be further analysed and discussed in chapter 9.4. Furthermore, the differences in initial speed (x = 50) between the scenarios can only be explained by external factors. Traffic and weather conditions have been taken into consideration, but the data did not reveal an influence on the initial speed. Other factors such as time of day or day of the week are evenly distributed in every scenario and are therefore not expected to affect the results. However, the external factors can be controlled by comparing only vehicles with similar initial speed. Despite the differences in initial speed (x = 50), the mean speed in the nudging scenarios is below the mean speed in the baseline at later positions (x > 115).This also indicates that the external factors do not confound the results in such a way that the effect of the nudge is overestimated. This also applies to the ratio of speeding vehicles, which decreases in every nudging scenario between x = 50 and x = 150, although it differs at x = 50, similarly to the mean speed.

While the speed at x = 50 is assumed to be uninfluenced by the nudge, the differences in the mean acceleration at x = 50 (Figure 9-9) can be attributed to the nudge since this figure only includes vehicles with similar initial speed. This is because the lights have been in the drivers' expected FOV for up to 10 m (≈0.5 s at 20 m/s = 72 km/h) at x = 50, so their reaction to the nudge can be visible in the acceleration data.

The order of the scenarios is another aspect that might affect the results. The differences between scenarios 0 and 8 (both without nudging) indicate that drivers who use the motorway exit frequently might have become accustomed to the nudge and learned safer behaviour. With the available data, it is not possible to investigate the duration of this learning effect.

The reason for the speed and acceleration differences between day and night might be that drivers recognise the curve and its small radius later when driving at night. The mean speed in the curve is also lower at night, possibly because drivers feel less safe due to the reduced visibility. In the nudging scenario, this difference between day and night persists. However, the mean speed is lower in scenario 2 both in day and night conditions. Hence, the nudge is likely to be effective both, during the day and at night.

Although the results of testing phase 4 might be biased by the previous testing phases due to the test design and a potential learning effect, the results indicate that the Speed Indicator Device can reduce the speed at x = 200 more than the nudge. However, a direct statistical comparison of our system and the Speed Indicator Device displaying an emoticon is not possible due to the following reasons: (1) The nudging system is applied over a much longer stretch of the road and aims for a reduced speed long before the curve, not along the curve itself. The lights are displayed from the beginning of the exit on (scenarios 1-7 and 9-12), while the Speed Indicator Device (scenario 13) is only shown in front of the curve with no lights preceding the Speed Indicator Device. The lights already displayed at the beginning of the exit give drivers more time to have already adopted a safer speed when they reach the position of the Speed Indicator Device in the curve and is one of the benefits of MeBeSafe: drivers will already have adopted a safe speed before the situation becomes critical. (2) Further, the speed threshold of the Speed Indicator Device (when the emoticon turns from negative to positive) does not change in response to the position of vehicle, while the speed threshold of the lights decreases from 80 km/h at the beginning of the exit to 55 km/h in the curve, corresponding to the normal driving behaviour in an exit. Consequently, not only the position where drivers are influenced is a different one, the intensity and exposure time differs. (3) Furthermore, the Speed Indicator Device is a well-known means to give drivers feedback about their driving speed. As the nudging system of the Infrastructure Driver Nudge is new, the level of familiarity can be relevant. This can be especially true since a study by Gold, Lin, Ashcroft, and Osman (2020) found that the effectiveness of a measure could be determined by the desire to change, meaning that people are more likely to follow a nudge if they understand the way it works and which positive impact it can have. This is in line with another reason: (4) Speed indicator devices are sometimes used in combination with a speed camera. This uncertainty can also be a reason for a lower speed. Thus, implementing a Speed Indicator Device at the field trial location can give valuable insights into how people would behave with a commonly known measure on site.

A comparison of the trajectory data and the data from the Speed Indicator Device shows that the Speed Indicator Device also influenced vehicles that did not use the exit, which is undesirable as these vehicles are allowed to drive faster. Those drivers probably understand that the Speed Indicator Device is not relevant for them, but they still might be confused or distracted at first. Since the nudge is located on the right and on the left of the exit lane, it is clearer that it only applies to vehicles on this lane. Further, it is located within the drivers' usual field of vision, whereas the Speed

Indicator Device is located next to the road and is therefore potentially more distracting. The nudging measure is applicable to longer stretches of road with varying speed limits, whereas the Speed Indicator Device is effective only in a limited section.

Since the nudge reduced the speed in the curve, it automatically reduced the radial acceleration as well. Thus, the margin of safety increases and the vehicle trajectories become safer. The analysis of accidents in motorway exits based on GIDAS data has shown that accidents mostly occur at large radial accelerations (see Deliverable 3.2). Therefore, a reduction of the mean radial acceleration can be a valuable contribution to a safe trajectory.

The speed threshold that was used to decide which vehicles were nudged does not follow the actual speed profile since the threshold was defined before the first data were collected. As a result, a large proportion of vehicles were nudged only in the middle of the exit ($x \approx 150$) although they are below the speed threshold at the beginning of the exit. To limit the number of variables during this research the speed profile is kept constant for all scenarios. For future applications of the nudging measure, the speed threshold should be determined based on average driver behaviour or an "optimal" speed profile, based on a baseline measurement and adjusting over time. Traffic and weather conditions could also be considered to determine the speed threshold.

Since the trajectory data have been gathered automatically in real-time, their accuracy cannot be validated. It remains uncertain whether extreme speed or acceleration values or y-positions close to the road edges are errors in the data or actual unsafe driving behaviour. Small errors in the x-position could lead to larger errors in the speed and acceleration calculation. This leads to some vehicles being falsely nudged (or not nudged) although their speed is slightly below (or above) the speed threshold. The accuracy of the camera calibration also affects the accuracy of the trajectory data. For the analysis, these error sources can partly be compensated by smoothing and removing implausible data. Due to the large number of vehicles, we do not expect the results to be biased.

Despite the external influences on the speed, the test design and the data accuracy, the nudge clearly reduces the speed of fast drivers and the ratio of speeding vehicles. It therefore contributes to a safer speed and safer trajectory. It is also more suitable than Speed Indicator Devices for complex situations like motorway exits, where the safe speed varies along the road and differs from the speed limits.

9.4 Driver Behaviour

Subsequent to the overall traffic analysis as described in chapter 9.3, we analysed the behaviour of especially fast drivers according to the derived hypotheses (see chapter 9.1.1) by means of inferential statistical analyses. Within this chapter, the methods are stated along with sample, approach of the analysis, and design. After this, the results are stated separately for the respective testing phases. The chapter concludes with the discussion of the behavioural results according to the previously stated hypotheses.

9.4.1 Methods

9.4.1.1 Sample

The effect of the nudging measure on driving speed is estimated by evaluating the speed reduction between the light onset at x = 50 until the start of the curve of the exit at x = 205, which is also the position of the 50 km/h-sign. As we collected the data in a field trial and did not record any personal information of the drivers, further sample characteristics are not available. Drivers were not aware that they were participating in a field trial. However, we informed citizens of Eindhoven via local communication channels that a field trial on the test site at Kennedylaan was conducted within the scope of the MeBeSafe project.

As the nudging system targets mainly fast drivers, we narrowed the sample for the behavioural analysis. For this, we included only those drivers, whose driving speed was two standard deviations ($SD_{all\ drivers}$ = 8.68 km/h) above the mean speed of the baseline ($M_{all\ drivers}$ = 71.71 km/h). Therefore, all drivers in the sample for the analysis of **fast drivers** exceeded 89.07 km/h at light onset at x = 50.

In a next step, we narrowed the sample down further for analysing the driving behaviour of the very fastest drivers. This allows to analyse potential differences between a sample that includes drivers who exceeded the speed limit slightly and only those drivers who greatly exceeded the speed limit. For this, we included only those drivers whose driving speed was greater than 1 standard deviation from the sample of fast drivers ($SD_{sample\ +2SD}$ = 5.76 km/h) above the mean of the fast drivers ($M_{sample\ +2SD}$ = 94.36 km/h), thus creating a sample of the fastest drivers. Therefore, all drivers in the sample for the analysis of **fastest drivers** exceeded 100.12 km/h at light onset x = 50.

Table 9-3 shows the sample size for **fast** and **fastest drivers** of testing phases 1, 2, and 3. As stated in chapter 9.1.1.4, inferential statistical analyses are not calculated for the Speed Indicator Device. Therefore, the sample characteristics of scenario 13 are not displayed in this table.

Testing Phase	No.	Scenario			Number of fast drivers (faster than 89.07 km/h at x = 50)	Number of fastest drivers (faster than 100.12 km/h at x = 50)
		Colour	Movement	Spacing between lights		
	0	No nudge – baseline			*N* = 333	*N* = 40
1	1	red	Moving towards the driver at 50 km/h		*N* = 171	*N* = 14
	2	red	Static lights		*N* = 337	*N* = 23
	3	red	Moving towards the driver at 50 km/h		*N* = 258	*N* = 33
	4	red	Static lights		*N* = 371	*N* = 40
2	6	red	Moving towards the driver at 20km/h		*N* = 462	*N* = 64
	7	red	Moving towards the driver at 80km/h		*N* = 513	*N* = 62
	8	No lights (intermediate 'baseline')			*N* = 432	*N* = 49
3	9	red	Moving towards the driver at 50 km/h		*N* = 186	*N* = 20
	10	red	Static lights		*N* = 669	*N* = 90
	11	red	Moving towards the driver at 50 km/h		*N* = 472	*N* = 42

Table 9-3: Sample sizes for fast drivers (all drivers faster than 89.07 km/h at x = 50) and fastest drivers (all drivers faster than 100.12 km/h at x =50) for scenarios 0 to 11. Each scenario (between-subjects) was tested for about one week.

9.4.1.2 Stimuli

The stimuli description for the analysis on driver behaviour is according to the scenarios described in chapter 9.2 and table 9.2 (chapter 9.4.1.1).

9.4.1.3 Procedure/Approach of Analysis

Since the nudging measure is supposed to slow down drivers that are exceeding the speed limit, vehicles that are travelling substantially faster than the average are especially of interest. As a result, analysis of the data was conducted for two different groups of vehicles, depending on their entry speed at x = 50. This is described in the sample description in chapter 9.4.1.1.

The effect of the nudging measure on driving speed is estimated by evaluating the speed reduction between the light onset at x = 50 until the start of the curve of the exit at the 50 km/h-sign at x = 205. Information on driving speed at these two locations already yield enough insight to test the presented hypotheses (see chapter 9.1.1).

In order to be able to interpret the results properly, the entry speed at x = 50 was compared by calculating a univariate ANOVA with all scenarios of the respective testing phase. Entry speed should not differ between nudging measures as they all do not turn on prior to x = 50. Only if the driving speed does not vary at x = 50 between the different (nudging) scenarios, subsequent speed differences between scenarios can be attributed to the specific (nudging) measure.

9.4.1.4 Design

The test design in testing phase 1 was a mixed design with repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) and the between-subjects factor (nudging) *scenario*. The factor *scenario* had five levels, being either a) baseline (scenario 0), b) lights moving towards the driver with a narrow spacing between active lights (oox, scenario 1), c) static lights with a narrow spacing between active lights (oox, scenario 2), d) lights moving towards the driver with a wide spacing between active lights (ooox, scenario 3), or e) static lights with a wide spacing between active lights (ooox, scenario 4). The dependant variable was the driving speed in km/h. Each analysis was conducted for fast and fastest drivers, respectively (see chapter 9.4.1.1) to answer the hypotheses stated in chapter 9.1.1. An overview over the hypotheses for testing phase 1 is given in Table 9-4.

Hypothesis No.	Speed of drivers in scenario …	… is expected to be…	… than speed of drivers in scenario …
H1.1	Static lights (scenarios 2 & 4)	<	Baseline (scenario 0)
H1.2	Lights moving towards the driver (scenarios 1 & 3)	<	Baseline (scenario 0)
H1.3	Lights moving towards the driver (scenarios 1 & 3)	<	Static lights (scenarios 2 & 4)
H1.4	Static lights with narrow spacing (oox, scenario 2)	=	Static lights with wider spacing (ooox, scenario 4)
H1.5	Lights moving towards the driver with narrow spacing (oox, scenario 1)	=	Lights moving towards the driver with wider spacing (ooox, scenario 3)

Table 9-4: Overview of tested hypotheses on testing phase 1.

The test design in testing phase 2 was a mixed design with repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) and the between-subjects factor (nudging) *scenario*. The factor *scenario* had three levels, being either a) lights moving towards the driver at 20 km/h (scenario 6), b) lights moving towards the driver at

50 km/h (scenario 1), or c) lights moving towards the driver at 80 km/h (scenario 7). The dependant variable was the driving speed in km/h. Each analysis was conducted for fast and fastest drivers, respectively (see chapter 9.4.1.1) to answer the hypotheses stated in chapter 9.1.1. An overview over the hypotheses for testing phase 2 is given in Table 9-5.

Hypothesis No.	Speed of drivers in scenario …	… is expected to be …	… than speed of drivers in scenario …
H2.1	Lights moving towards the driver at 80 km/ (scenario 7)	<	Lights moving towards the driver at 50 km/ (scenario 1)
H2.2	Lights moving towards the driver at 50 km/h (scenario 1)	<	lights moving towards the driver at 20 km/h (scenario 6)
H2.3	Lights moving towards the driver at 80 km/h (scenario 7)	<	lights moving towards the driver at 20 km/h (scenario 6)

Table 9-5: Overview of tested hypotheses on testing phase 2.

The test design in testing phase 3 was a mixed design with repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) and the between-subjects factor (nudging) *scenario*. The factor *scenario* had three levels, being either a) lights moving towards the driver with narrow spacing between an activated set of two lights (oox, scenario 9), b) static lights with narrow spacing between an activated set of two lights (oox, scenario 10), or c) lights moving towards the driver with wider spacing between an activated set of two lights (oox, scenario 11). Scenario 12 could not be tested as intended (see chapter 9.2). The dependent variable was the driving speed in km/h. Each analysis was conducted for fast and fastest drivers, respectively (see chapter

9.4.1.1) to answer the hypotheses stated in chapter 9.1.1. An overview over the hypotheses for testing phase 3 is given in Table 9-6.

Hypothesis No.	Speed of drivers in scenario …	… is expected to be …	… than speed of drivers in scenario …
H3.1	red static lights with a set of two activated lights (scenarios 10 and 12)	<	Baseline (scenario 0)
H3.2	lights in a set of two move towards the driver (scenarios 9 and 11)	<	Baseline (scenario 0)
H3.3	lights moving towards the driver with a set of two activated lights (scenarios 9/11, respectively)	<	static lights with activated lights in a set of two (scenarios 10/12, respectively)
H3.4	static lights with a narrow spacing of lights with activated lights in a set of two (oxx, scenario 10)	=	static lights with a wider spacing between an activated set of two lights (ooxx, scenario 12)
H3.5	lights moving towards the driver with a narrow spacing between an activated set of two lights (oxx, scenario 9)	=	lights moving towards the driver with a wider spacing between an activated set of two lights with a wide spacing (ooxx, scenario 11)

H3.6	single activated lights moving towards the driver (oox, scenario 1)	=	sets of two activated lights moving towards the driver (oxx, scenario 9)
H3.7	single lights moving towards the driver with a spacing ooox (scenario 3)	=	a set of two activated lights moving towards the driver (ooxx, scenario 11)

Table 9-6: Overview of tested hypotheses on testing phase 3.

9.4.2 Results

This chapter displays the results of inferential statistical analyses. We conducted the analyses with IBM SPSS Statistics 23.

The results in this chapter are stated according to the testing phases and as a comparison between two positions: with light onset (x = 50) at the beginning of the exit lane and at the beginning of the curve (x = 205), where the 50 km/h-sign is located. ANOVAs with 32 positions (one position every 5 m between x = 50 and x = 205) revealed similar results and are therefore not reported. Within each testing phase, results for the entire sample of fast drivers are stated first followed by results for the fastest drivers within each testing phase.

9.4.2.1 Results of Testing Phase 1: *movement of lights* and *spacing between active lights*

This chapter displays the quantitative results for testing phase 1. All calculations reported in the following were carried out for both, the sample of fast drivers (drivers faster than 89.07 km/h at x = 50) and the sample of fastest drivers (drivers faster than 100.12 km/h at x = 50) as described in chapter 9.4.1.1.

9.4.2.1.1 Testing Phase 1: Fast Drivers

The results in this chapter are regarding the fast drivers (drivers faster than 89.07 km/h at x = 50) only.

In order to check if the entry speed at light onset is comparable among the different scenarios, we calculated a univariate ANOVA with the between-subjects factor *scenario* for the position x = 50. The entry speed did not differ significantly ($F[4, 1465] = 1.76$, $p = .134$, $\eta_p{}^2 = .005$).

We conducted a mixed ANOVA with the between-subjects factor *scenario* (5; baseline, static_oox, static_ooox, towards_oox, and towards_ooox) and repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) for the fast drivers (all drivers faster than 89.07 km/h at x = 50). Figure 9-14 illustrates the results.

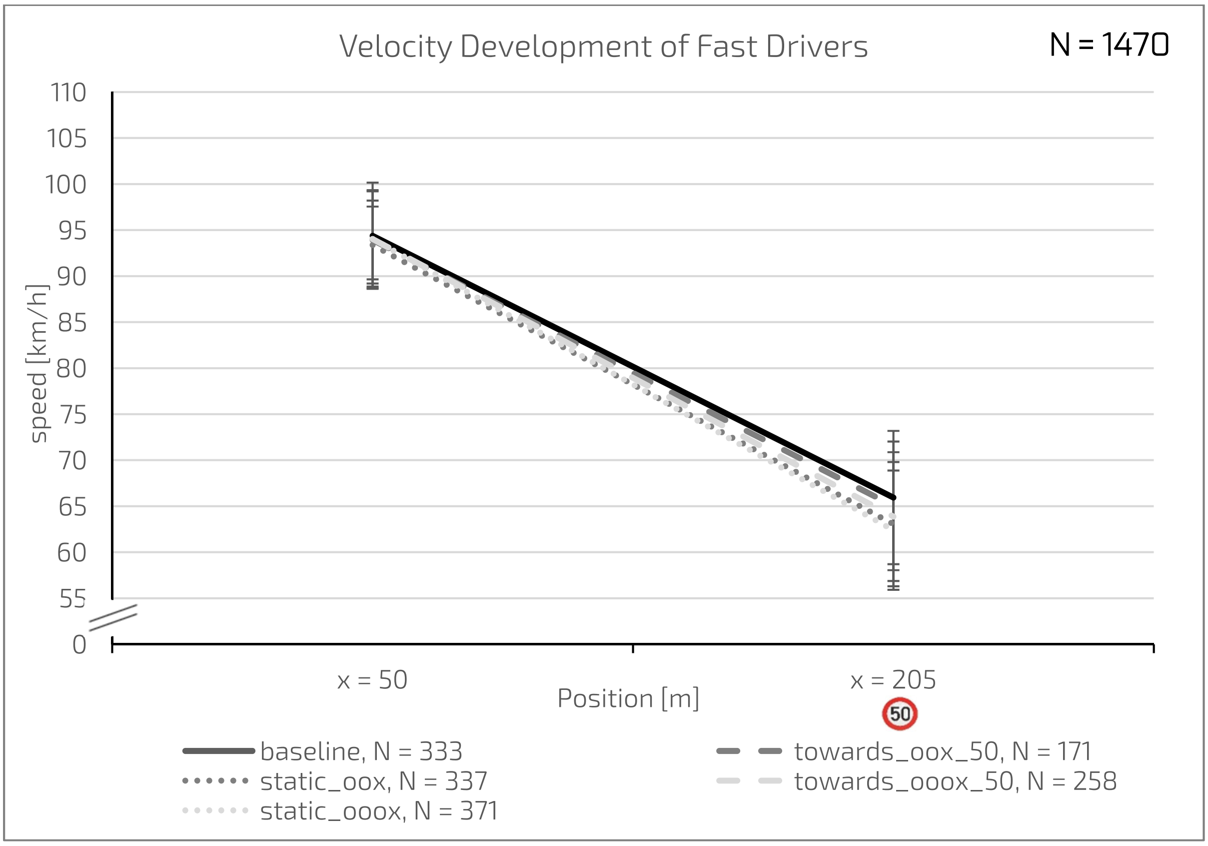

Figure 9-14: Results for the velocity development of fast drivers (drivers faster than 89.07 km/h at x = 50) of testing phase 1. Each scenario (between-subjects) was tested for about one week. The x-axis shows the within-factor position*, the y-axis shows the velocity in km/h, and the lines represent the different* scenarios *(between-subjects factor) of testing phase 1. Error bars depict standard deviations.*

The ANOVA revealed a significant main effect for *position* (F[1, 1465] = 25812.28, $p < .001$, $_p^2 = .95$) and a significant main effect for *scenario* (F[4, 1465] = 9.37 $p < .001$, $_p^2 = .03$). In addition, the results showed a significant interaction between the factors *position* (2) and *scenario* (5) (F[4, 1465] = 10.95, $p < .001$, $_p^2 = .03$).

To gain deeper insight into the interaction between the different scenarios, we conducted eight post-hoc mixed ANOVAs with the between-subjects factor *scenario* (different combinations of baseline, static_oox, static_ooox, towards_oox, and towards_ooox) and repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) for the fast drivers (all drivers faster than 89.07 km/h at x = 50). We furthermore conducted post-hoc t-tests at the positions x = 50 and x = 205. Table 9-7 shows the results of post-hoc comparisons between distinct scenarios. Other comparisons calculated in addition to the ones reported in this table did not show significance ($p > .05$).

Source	Univariate Tests	Significant post-hoc t-tests
Mixed ANOVA: baseline (scenario 0) – static (oox, scenario 2)		
Position	$F(1, 589) = 9654.48$, $p < .001$, $\eta_p^2 = .94$	x = 205: $T(589) = 3.49$, $p = .001$
Scenario	$F(1, 589) = 7.57$, $p = .003$, $\eta_p^2 = .01$	
Position * Scenario	$F(1, 589) = 8.28$, $p = .002$, $\eta_p^2 = .01$	
Mixed ANOVA: baseline (scenario 0) – static (ooox, scenario 4)		
Position	$F(1, 702) = 14057.92$, $p < .001$, $\eta_p^2 = .95$	x = 205: $T(670.29) = 6.82$, $p < .001$
Scenario	$F(1, 702) = 24.46$, $p < .001$, $\eta_p^2 = .03$	
Position * Scenario	$F(1, 702) = 39.96$, $p < .001$, $\eta_p^2 = .05$	

Mixed ANOVA: baseline (scenario 0) – moving towards (oox, scenario 1)		
Position	$F(1, 502) = 7459.29$, $p < .001$, $\eta_p{}^2 = .94$	
Mixed ANOVA: baseline (scenario 0) – moving towards (ooox, scenario 3)		
Position	$F(1, 668) = 12204.95$, $p < .001$, $\eta_p{}^2 = .95$	x = 50:
Scenario	$F(1, 668) = 25.14$, $p < .001$, $\eta_p{}^2 = .04$	$T(604.47) = 2.59$, $p = .005$
Position * Scenario	$F(1, 668) = 12.49$, $p < .001$, $\eta_p{}^2 = .02$	x = 205: $T(668) = 5.34$, $p < .001$
Mixed ANOVA: static (oox, scenario 2) – static (ooox, scenario 4)		
Position	$F(1, 627) = 12614.02$, $p < .001$, $\eta_p{}^2 = .95$	x = 205:
Position * Scenario	$F(1, 627) = 7.30$, $p = .007$, $\eta_p{}^2 = .01$	$T(627) = -2.72$, $p = .007$
Mixed ANOVA: towards (oox, scenario 1) – towards (ooox, scenario 3)		
Position	$F(1, 506) = 8583.09$, $p < .001$, $\eta_p{}^2 = .94$	x = 205:
Scenario	$F(1, 506) = 8.83$, $p = .003$, ${}_p{}^2 = .02$	$T(506) = 3.09$, $p = .002$
Position * Scenario	$F(1, 506) = 5.00$, $p = .026$, $\eta_p{}^2 = .01$	
Mixed ANOVA: static (oox, scenario 2) – towards (oox, scenario 1)		
Position	$F(1, 427) = 6882.53$, $p < .001$, $\eta_p{}^2 = .94$	
Mixed ANOVA: static (ooox, scenario 4) – towards (ooox, scenario 3)		
Position	$F(1, 706) = 15908.38$, $p < .001$, $\eta_p{}^2 = .96$	
Position * Scenario	$F(1, 706) = 7.26$, $p = .007$ $\eta_p{}^2 = .01$	

Table 9-7: Results of post-hoc comparisons of fast drivers (all drivers faster than 89.07 km/h at x = 50) in testing phase 1 at two positions (within-subjects factor) between distinct combinations of two scenarios (between-subjects factor). $\eta_p{}^2$ *is reported as effect size.*

9.4.2.1.2 Testing Phase 1: Fastest Drivers

The results in this chapter are regarding the fastest drivers (drivers faster than 100.12 km/h at x = 50) only.

Similar to the fast drivers, a univariate ANOVA with the between-subjects factor *scenario* for the position x = 50 was calculated to check if the entry speed at light onset is comparable among the different scenarios. The entry speed did not differ significantly ($F[4, 145] = 1.12$, $p = .352$, $_p{}^2 = .03$).

We conducted a mixed ANOVA with the between-subjects factor *scenario* (5; baseline, static_oox, static_ooox, towards_oox, and towards_ooox) and repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) for the fastest drivers (all drivers faster than 100.12 km/h at x = 50).

Figure *9-15* illustrates the results.

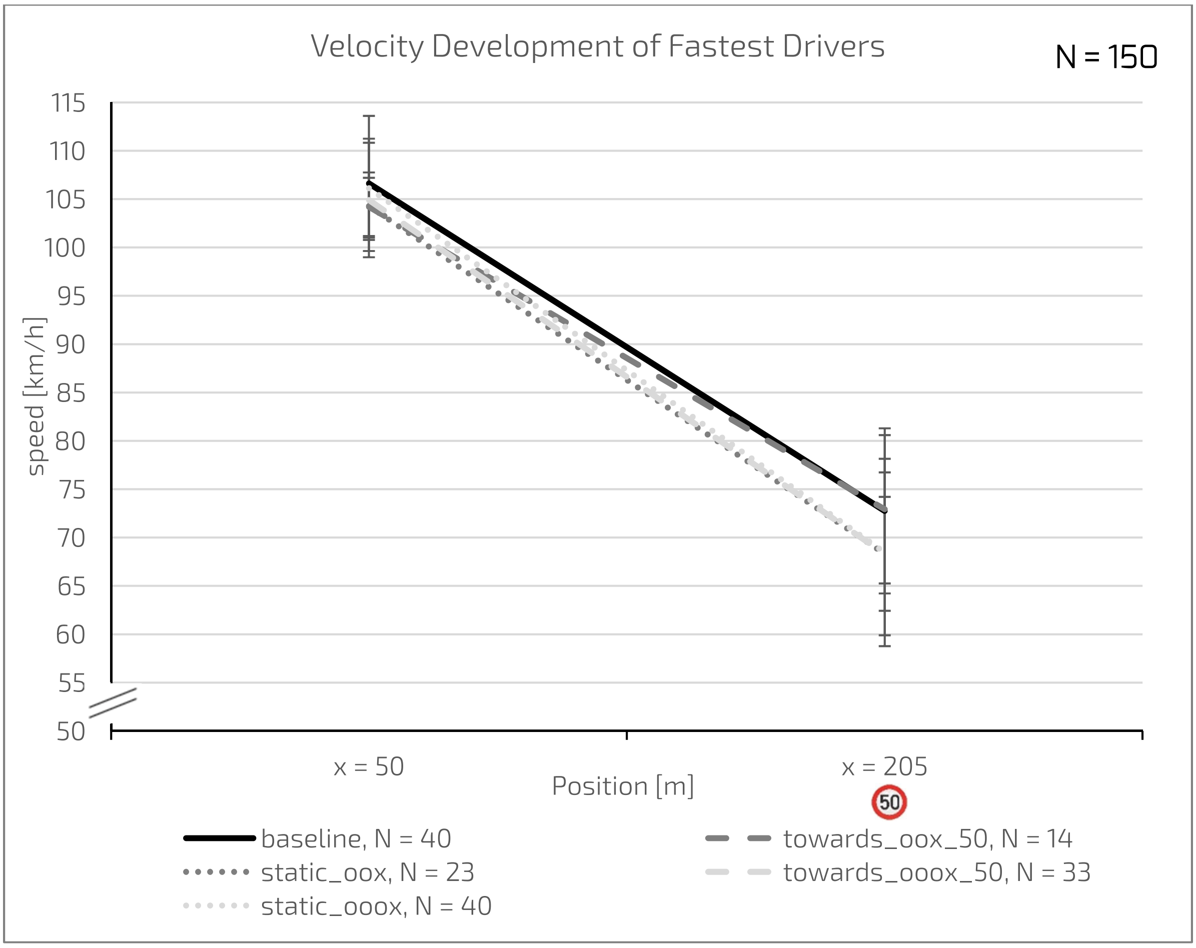

Figure 9-15: Results for the velocity development of fastest drivers (all drivers faster than 100.12 km/h at x = 50) of testing phase 1. Each scenario (between-subjects) was tested for about one week. The x-axis shows the within-factor position*, the y-axis shows the velocity in km/h, and the lines represent the different* scenarios *(between-subjects factor) of testing phase 1. Error bars depict standard deviations.*

We found a significant main effect for *position* (F[1, 145] = 2356.54, $p < .001$, $_{p}^{2} = .94$). Furthermore, the results showed a tendency towards a significant interaction between the factors *position* (2) and *scenario* (5) (F[4, 145] = 2.21, $p = .071$, $_{p}^{2} = .06$, reported two-tailed). Further effects were not significant ($p > .05$).

To gain deeper insight into the interaction between the different scenarios, eight post-hoc mixed ANOVAs with the between-subjects factor *scenario* (different combinations of baseline, static_oox, static_ooox, towards_oox, and towards_ooox) and repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) were conducted for the fastest drivers (all drivers faster than 100.12 km/h at x = 50). We furthermore conducted post-hoc t-tests at the positions x = 50 and x = 205. Table 9-8 shows the results of post-hoc comparisons between distinct scenarios. Other comparisons calculated in addition to the ones reported in this table did not show significance ($p > .05$).

Source	Univariate Tests	Significant post-hoc t-tests
Mixed ANOVA: baseline (scenario 0) – static (oox, scenario 2)		
Position	$F(1, 71) = 1306.00$, $p < .001$, $\eta_p^2 = .95$	x = 205: $T(71) = 2.23$, $p = .015$
Scenario	$F(1, 71) = 4.27$, $p = .021$, $\eta_p^2 = .06$	
Position * Scenario	$F(1, 71) = 1.96$, $p = .083$, $\eta_p^2 = .03$ (tendency)	
Mixed ANOVA: baseline (scenario 0) – static (ooox, scenario 4)		
Position	$F(1, 78) = 1256.80$, $p < .001$, $\eta_p^2 = .94$	x = 205: $T(78) = 2.11$, $p = .019$
Scenario	$F(1, 78) = 2.86$, $p = .048$, $\eta_p^2 = .04$	
Position * Scenario	$F(1, 78) = 3.57$, $p = .032$, $_{p}^{2} = .04$	
Mixed ANOVA: baseline (scenario 0) – moving towards (oox, scenario 1)		
Position	$F(1, 52) = 542.21$, $p < .001$, $\eta_p^2 = .91$	

Mixed ANOVA: baseline (scenario 0) – moving towards (ooox, scenario 3)		
Position	$F(1, 61) = 1180.19, p < .001, \eta_p^2 = .95$	x = 205: $T(61) = 2.21, p = .016$
Scenario	$F(1, 61) = 5.22, p = .013, \eta_p^2 = .08$	
Mixed ANOVA: static (oox, scenario 2) – static (ooox, scenario 4)		
Position	$F[1, 71] = 1433.46, p < .001, \eta_p^2 = .95$	
Mixed ANOVA: towards (oox, scenario 1) – towards (ooox, scenario 3)		
Position	$F[1, 35] = 856.96, p < .001, \eta_p^2 = .96$	x = 205: $T(35) = 2.06, p = .047$
Position * Scenario	$F(1, 35) = 4.16, p = .049, \eta_p^2 = .11$	
Mixed ANOVA: static (oox, scenario 2) – towards (oox, scenario 1)		
Position	$F[1, 45] = 725.78, p < .001, \eta_p^2 = .94$	
Position * Scenario	$F[1, 45] = 4.46, p = .04, \eta_p^2 = .09$	
Mixed ANOVA: static (ooox, scenario 4) – towards (ooox, scenario 3)		
Position	$F[1, 61] = 1291.44, p < .001, \eta_p^2 = .96$	x = 50: $T(59.09) = 1.71, p = .046$

Table 9-8: Results of post-hoc comparisons of fastest drivers (all drivers faster than 100.12 km/h at x = 50) in testing phase 2 at two positions (within-subjects factor) between distinct combinations of two scenarios (between-subjects factor). η_p^2 is reported as effect size.

9.4.2.2 Results Testing Phase 2: Effects of light movement speed

This chapter displays the quantitative results for testing phase 2. All calculations reported in the following were carried out for both, the sample of fast drivers (drivers faster than 89.07 km/h at x = 50) and the sample of fastest drivers (drivers faster than 100.12 km/h at x = 50) as described in chapter 9.4.1.1.

9.4.2.2.1 Testing Phase 2: Fast Drivers

The results in this chapter are regarding the fast drivers (drivers faster than 89.07 km/h at x = 50) only.

As in testing phase 1, a univariate ANOVA with the between-subjects factor *scenario* for the position x = 50 was calculated to check if the entry speed at light onset is comparable among the different scenarios. The entry speed did not differ significantly (*F*[2, 1143] = .587, *p* = .556, $_p^2$ = .001).

We conducted a mixed ANOVA with the between-subjects factor *scenario* (3; towards_oox at 20 km/h, towards_oox at 50 km/h, and towards_oox at 80 km/h) and repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) for the fast drivers (all drivers faster than 89.07 km/h at x = 50). Figure 9-16 illustrates speed in km/h over the first and last position of all drivers depending on different light scenarios with varied light movement speed.

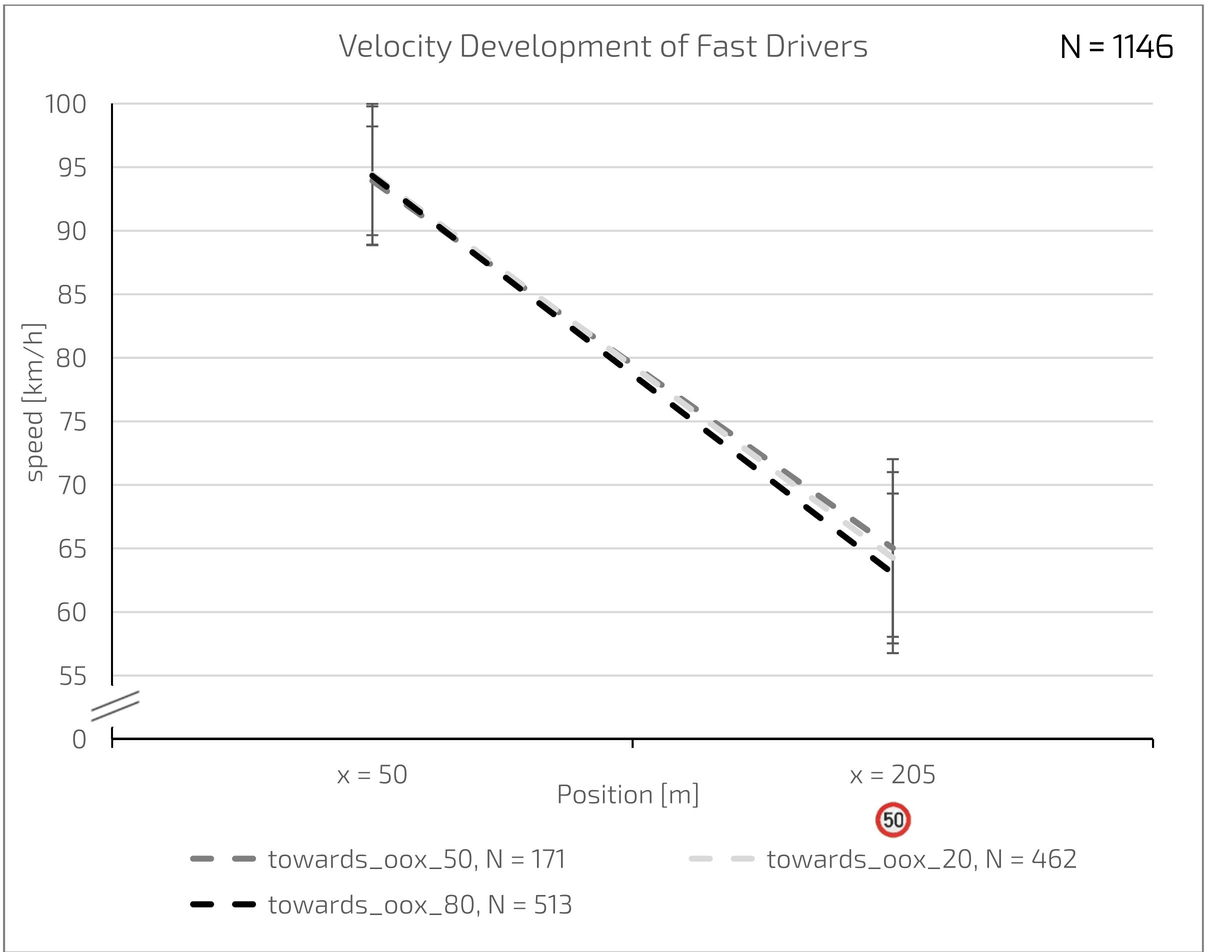

Figure 9-16: Results for the velocity development of fast drivers (all drivers faster than 89.07 km/h at x = 50) of testing phase 2. Each scenario (between-subjects) was tested for about one week. The x-axis shows the within-factor position*, the y-axis shows the velocity in km/h, and the lines represent the different* scenarios *(between-subjects factor) of testing phase 2. Error bars depict standard deviations.*

The results revealed a significant main effect for *position* (F[1, 1143] = 17817.13, $p < .001$, $_p{}^2 = .94$) and a tendency towards a significant main effect for *scenario* (F[2, 1143] = 2.96, $p = .052$, $_p{}^2 = .01$) as well. A significant interaction between the factors *position* (2) and *scenario* (3) (F[2, 1143] = 8.72, $p < .001$, $_p{}^2 = .02$) was observed.

To gain deeper insight into the interaction between the different scenarios, three post-hoc mixed ANOVAs with the between-subjects factor *scenario* (different combinations of towards_oox at 20 km/h, towards_oox at 50 km/h, and towards_oox at 80 km/h) and repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) were conducted for the fast drivers (all drivers faster than 89.07 km/h at x = 50). We furthermore conducted post-hoc t-tests at the positions x = 50 and x = 205. The following Table 9-9 illustrates the results. Other comparisons calculated in addition to the ones reported in this table did not show significance ($p > .05$).

Source	Univariate Tests	Significant post-hoc t-tests
Mixed ANOVA: moving towards (oox_50, scenario 1) – moving towards (oox_20, scenario 6)		
Position	F[1, 631] = 9458.20, $p < .001$, $\eta_p{}^2 = .94$	
Position * Scenario	F[1, 631] = 4.46, $p < .035$, $\eta_p{}^2 = .01$	
Mixed ANOVA: moving towards (oox_50, scenario 1) – moving towards (oox_80, scenario 7)		
Position	F[1, 682] = 9924.75, $p < .001$, $\eta_p{}^2 = .94$	x = 205: T(682) = 3.49, $p = .001$
Scenario	F[1, 682) = 3.62, $p = .029$, $\eta_p{}^2 = .01$	
Position * Scenario	F[1, 682] = 15.62, $p < .001$, $\eta_p{}^2 = .02$	

Mixed ANOVA: moving towards (oox_20, , scenario 6) – moving towards (oox_80, scenario 7)		
Position	$F[1, 973]$ =20222.49, $p < .001$, $\eta_p{}^2 = .95$	x = 205: $T(973) = 2.94$, $p = .002$
Scenario	$F[1, 973] = 4.44$, $p = .018$, $_p{}^2 = .01$	
Position * Scenario	$F[1, 973] = 6.53$, $p = .006$, $_p{}^2 = .01$	

Table 9-9: Results of post-hoc comparisons of fast drivers (all drivers faster than 89.07 km/h at x = 50) in testing phase 2 at two positions (within-subjects factor) between distinct combinations of two scenarios (between-subjects factor). ηp^2 *is reported as effect size.*

9.4.2.2.2 Testing Phase 2: Fastest drivers

The results in this chapter are regarding the fastest drivers (drivers faster than 100.12 km/h at x = 50) only.

As for the fast drivers in testing phase 2, a univariate ANOVA with the between-subjects factor *scenario* for the position x = 50 was calculated to check if the entry speed at light onset is comparable among the different scenarios. The entry speed did not differ significantly ($F[2, 137] = .72$, $p = .487$, $\eta_p{}^2 = .01$).

We conducted a mixed ANOVA with the between-subjects factor *scenario* (3; towards_oox at 20 km/h, towards_oox at 50 km/h, and towards_oox at 80 km/h) and repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) for the fast drivers (all drivers faster than 100.12 km/h at x = 50). Figure 9-17 illustrates speed in km/h over the first and last position of fastest drivers depending on different scenarios with varied light movement speed.

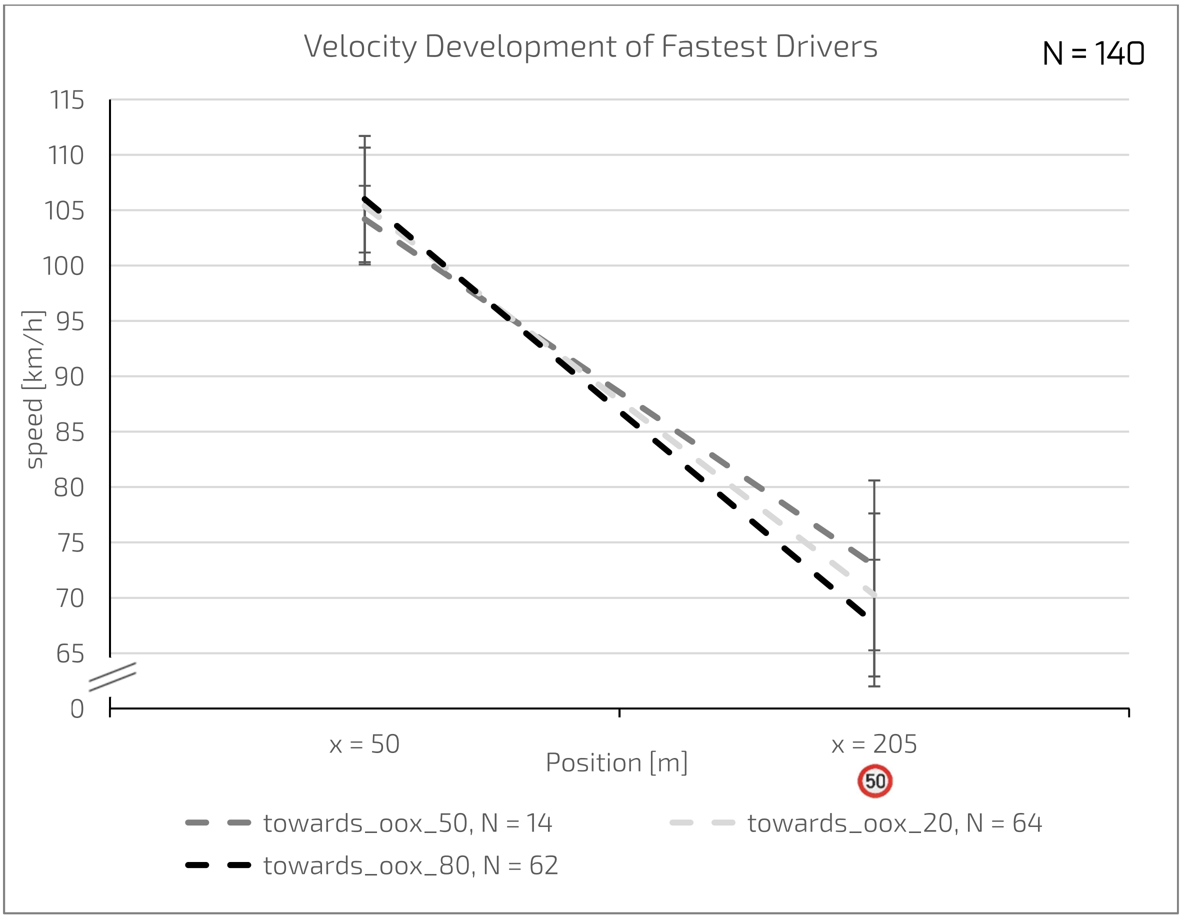

Figure 9-17: Results for the velocity development of fastest drivers (all drivers faster than 100.12 km/h at x = 50) of testing phase 2. Each scenario (between-subjects) was tested for about one week. The x-axis shows the within-factor position, *the y-axis shows the velocity in km/h, and the lines represent the different* scenarios *(between-subjects factor) of testing phase 2. Error bars depict standard deviations.*

The mixed ANOVA revealed a significant main effect for *position* (F[1, 137] = 1660.24, p < .001, $_{p}^{2}$ = .93) and a significant interaction between *position* (2) and *scenario* (3) (F[2, 137] = 5.36, p = .003, $_{p}^{2}$ = .07). Further effects were not significant (p > .05).

To gain deeper insight into the interaction between the different scenarios, three post-hoc mixed ANOVAs with the between-subjects factor *scenario* (different combinations of towards_oox at 20 km/h, towards_oox at 50 km/h, and towards_oox at 80 km/h) and repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) were conducted for the fastest drivers (all drivers faster than 100.12 km/h at x = 50). We furthermore conducted post-hoc t-tests at the positions x = 50 and x = 205. The following Table 9-10 illustrates the results. Other comparisons calculated in addition to the ones reported in this table did not show significance ($p > .05$).

Source	Univariate Tests	Significant post-hoc t-tests
Mixed ANOVA: moving towards (oox_50, scenario 1) – moving towards (oox_20, scenario 6)		
Position	F(1, 76) = 647.12, $p < .001$, $\eta_p{}^2 = .90$	
Mixed ANOVA: moving towards (oox_50, scenario 1) – moving towards (oox_80, scenario 7)		
Position	F(1, 74) = 1051.14, $p < .001$, $\eta_p{}^2 = .93$	x = 205: T(74) = 2.88, $p = .003$
Scenario	F(1, 74) = 1.67, $p = .100$, $\eta_p{}^2 = .02$ (tendency)	
Position * Scenario	F(1, 74) = 10.71, $p = .001$, $_p{}^2 = .13$	
Mixed ANOVA: moving towards (oox_20, scenario 6) – moving towards (oox_80, scenario 7)		
Position	F(1, 124) = 2736.58, $p < .001$, $\eta_p{}^2 = .96$	x = 205: T(124) = 2.16, $p = .017$
Position * Scenario	F(1, 124) = 5.11 $p = .013$, $\eta_p{}^2 = .04$	

Table 9-10: Results of post-hoc comparisons of fastest drivers (all drivers faster than 100.12 km/h at x = 50) in testing phase 2 at two positions (within-subjects factor) between distinct combinations of two scenarios (between-subjects factor). $\eta_p{}^2$ is reported as effect size.

9.4.2.3 Testing Phase 3: Effects of movement of lights and spacing between an activated set of two lights

This chapter displays the quantitative results for testing phase 3. All calculations reported in the following were carried out for both, the sample of fast drivers (drivers faster than 89.07 km/h at x = 50) and the sample of fastest drivers (drivers faster than 100.12 km/h at x = 50) as described in chapter 9.4.1.1.

9.4.2.3.1 Testing Phase 3: Fast Drivers

The results in this chapter are regarding the fast drivers (drivers faster than 89.07 km/h at x = 50) only.

As in testing phases 1 and 2, a univariate ANOVA with the between-subjects factor *scenario* for the position x = 50 was calculated to check if the entry speed at light onset is comparable among the different scenarios Baseline (scenario 0) and the three scenarios of testing phase 3. The entry speed did not differ significantly (F[3, 1656] = 1.03, p = .380, $_{p}^{2} < .01$).

We conducted a mixed ANOVA with the between-subjects factor *scenario* (4; towards_oxx at 50 km/h, static_oxx at 50 km/h, towards_ooxx at 50 km/h and a baseline) and repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) for the fast drivers (all drivers faster than 89.07 km/h at x = 50). Figure 9-18 illustrates speed in km/h over the first and last position of all drivers depending on different scenarios with varied light movement speed.

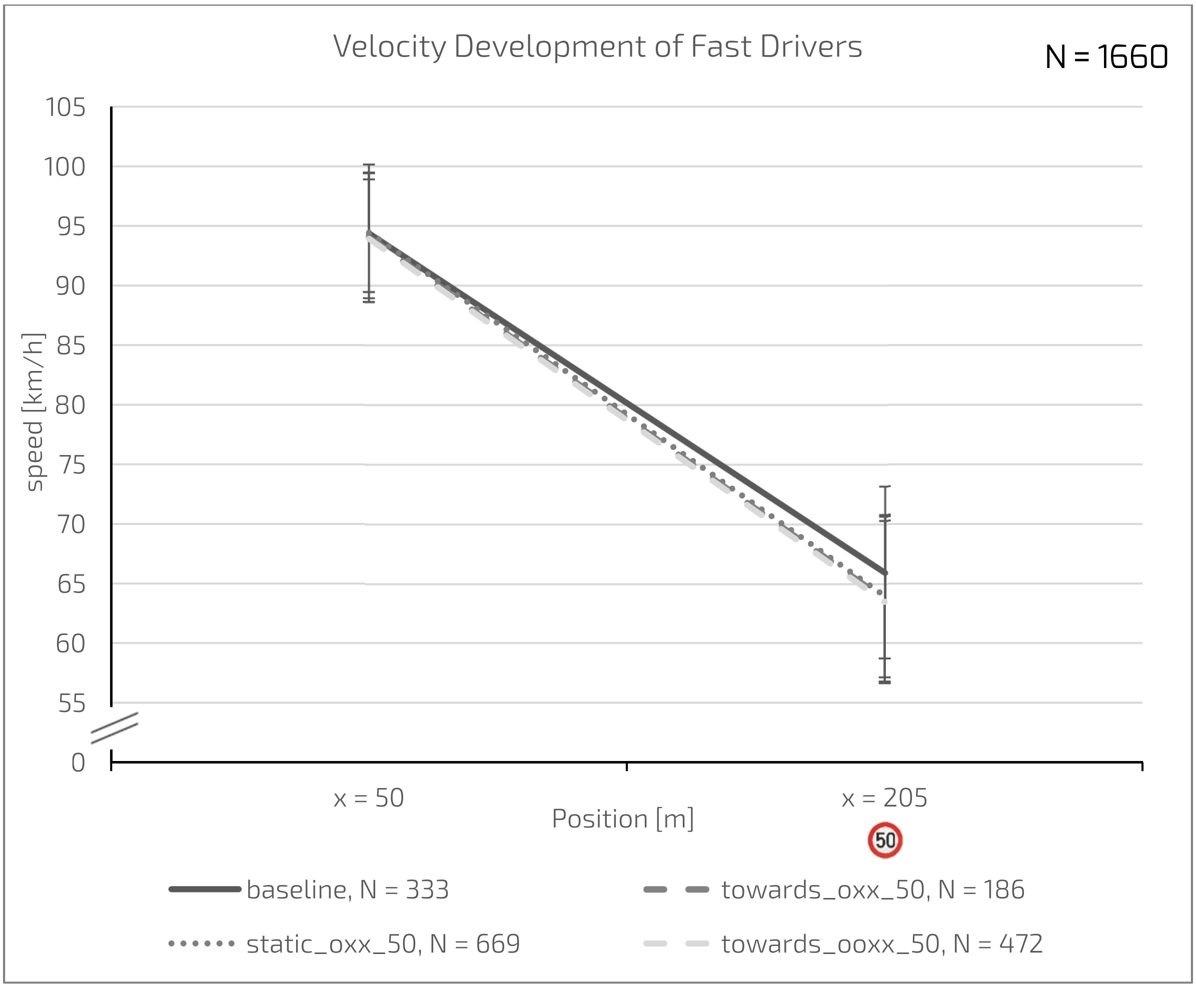

Figure 9-18: Results for the velocity development of fast drivers (all drivers faster than 89.07 km/h at x = 50) of testing phase 3. Each scenario (between-subjects was tested for about one week).The x-axis shows the within-factor position*, the y-axis shows the velocity in km/h, and the lines represent the different* scenarios *(between-subjects factor) of testing phase 3. Error bars depict standard deviations.*

The results revealed a significant main effect for *position* (F[1, 1656] 24248.37, $p < .001$, $_{p}^{2} = .94$), a significant main effect for the factor *scenario* (F[3, 1656] = 5.66, $p = .001$, $_{p}^{2} = .01$) and a significant interaction between the factors *position* (2) and *scenario* (4) (F[3, 1656] = 7.34, $p < .001$, $_{p}^{2} = .01$).

To gain deeper insight into the interaction of the different scenarios, seven post-hoc mixed ANOVAs with the between-subjects factor *scenario* (different combinations of baseline, towards_oox, towards_ooox, towards_oxx with 50 km/h, static_oxx with 50 km/h, and towards_ooxx with 50 km/h) and repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) were conducted for the fast drivers (all drivers faster than 89.07 km/h at x = 50). We furthermore conducted post-hoc t-tests at the positions x = 50 and x = 205. The following Table 9-11 illustrates the results. Other comparisons calculated in addition to the ones reported in this table did not show significance (p > .05).

Source	Univariate Tests	Significant post-hoc t-tests
Mixed ANOVA: baseline (scenario 0) – static (oxx, scenario 10)		
Position	$F(1, 1000) = 14926.11, p < .001, \eta_p{}^2 = .94$	x = 205: $T(1000) = 4.20, p < .001$
Scenario	$F(1, 1000) = 7.55, p = .003, \eta_p{}^2 = .01$	
Position * Scenario	$F(1, 1000) = 17.93, p = .053, \eta_p{}^2 < .02$	
Mixed ANOVA baseline (scenario 0) – towards (oxx, scenario 9)		
Position	$F(1, 517) = 7935.58, p < .001, \eta_p{}^2 = .94$	x = 205: $T(517) = 3.36, p = .001$
Scenario	$F(1, 517) = 6.93, p = .005, \eta_p{}^2 = .01$	
Position * Scenario	$F(1, 517) = 8.31, p = .002, \eta_p{}^2 = .02$	
Mixed ANOVA baseline (scenario 0) – towards (ooxx, scenario 11)		
Position	$F(1, 803) = 15007.65, p < .001, \eta_p{}^2 = .95$	x = 205: $T(803) = 4.95, p < .001$
Scenario	$F(1, 803) = 15.36, p < .001, \eta_p{}^2 = .02$	
Position * Scenario	$F(1, 803) = 17.72, p < .001, \eta_p{}^2 = .02$	
Mixed ANOVA towards (oxx, scenario 9) – towards (ooxx, scenario 11)		
Position	$F(1, 656) = 10817.53, p < .001, \eta_p{}^2 = .94$	
Mixed ANOVA towards (oxx, scenario 9) – static (oxx, scenario 10)		
Position	$F(1, 853) = 10120.15, p < .001, \eta_p{}^2 = .92$	

Mixed ANOVA towards (oox, scenario 1) – towards (oxx, scenario 9)		
Position	$F(1, 355) = 5947.01$, $p < .001$, $\eta_p^2 = .94$	
Mixed ANOVA towards (ooox, scenario 3) – towards (ooxx, scenario 11)		
Position	$F(1, 807) = 16893.27$, $p < .001$, $\eta_p^2 = .95$	

Table 9-11: Results of post-hoc comparisons of fast drivers (all drivers faster than 89.07 km/h) in testing phase 3 at two positions (within-subjects factor) between distinct scenarios (between-subjects factor). η_p^2 is reported as effect size.

9.4.2.3.2 Testing Phase 3: Fastest Drivers

The results in this chapter are regarding the fastest drivers (drivers faster than 100.12 km/h at x = 50) only.

As in testing phases 1 and 2, a univariate ANOVA with the between-subjects factor *scenario* for the position x = 50 was calculated to check if the entry speed at light onset is comparable among the different scenarios. The entry speed did not differ significantly ($F[3, 188] = .65$, $p = .582$, $_p^2 = .01$).

We conducted a mixed ANOVA with the between-subjects factor *scenario* ((4; towards_oxx at 50 km/h, static_oxx at 50 km/h, towards_ooxx at 50 km/h and a baseline) and repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) for the fastest drivers (all drivers faster than 100.12 km/h at x = 50). Figure 9-19 illustrates speed in km/h at the first and last position of the fastest drivers depending on the different scenarios.

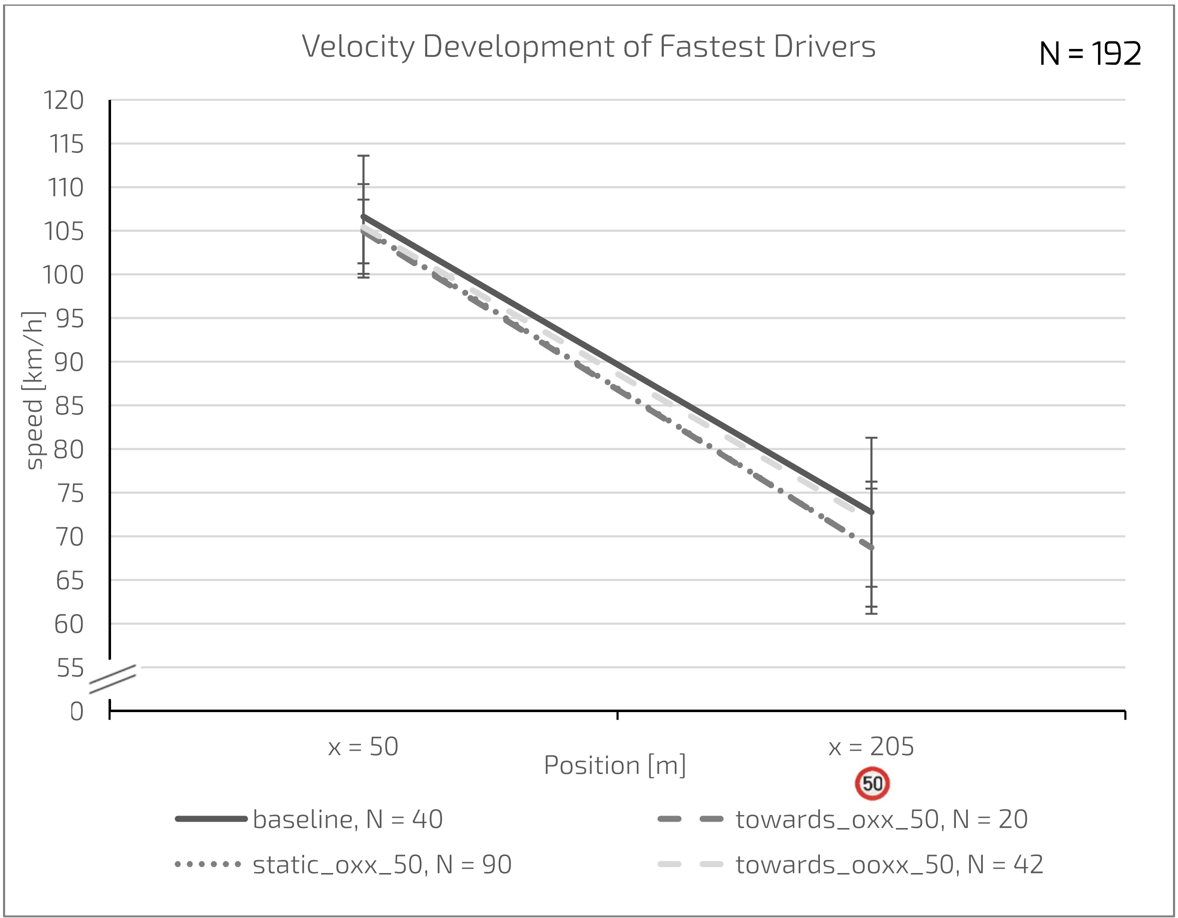

Figure 9-19: Results for the velocity development of fastest drivers (all drivers faster than 100.12 km/h at x = 50) of testing phase 3. Eeach scenario (between-subjects) was tested for about one week. The x-axis shows the within-factor position, *the y-axis shows the velocity in km/h, and the lines represent the different* scenarios *(between-subjects factor) of testing phase 3. Error bars depict standard deviations.*

The results revealed a significant main effect for *position* (F[1, 188] = 2722.61, p < .001, $_p^2$ = .94) and a significant main effect for *scenario* (F[3, 188] = 2.94, p = .034, $_p^2$ = .05). Further effects were not significant (p > .05).

To gain deeper insight into the interaction between the different scenarios, seven post-hoc mixed ANOVAs with the between-subjects factor *scenario* (different combinations of baseline, static_oox, towards_oox, static_ooox, towards_ooox, towards_oxx at 50 km/h, static_oxx at 50 km/h, and towards_ooxx at 50 km/h) and repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) were conducted for the fastest drivers (all drivers faster than 100.12 km/h at x = 50). We furthermore conducted post-hoc t-tests at the positions x = 50 and x = 205. The following Table 9-12 illustrates the results. Other comparisons calculated in addition to the ones reported in this table did not show significance ($p > .05$).

Source	Univariate Tests	Significant post-hoc t-tests
Mixed ANOVA: baseline (scenario 0) – static (oxx, scenario 10)		
Position	$F(1, 128) = 1916.20, p < .001, \eta_p^2 = .94$	x = 205: $T(128) = 2.71, p = .004$
Scenario	$F(1, 128) = 6.96, p = .005, \eta_p^2 = .05$	
Position * Scenario	$F(1, 128) = 2.73, p = .05, \eta_p^2 = .02$ (tendency)	
Mixed ANOVA baseline (scenario 0) – towards (oxx, scenario 9)		
Position	$F(1, 58) = 919.42, p < .001, \eta_p^2 = .94$	x = 205: $T(58) = 1.85, p = .035$
Scenario	$F(1, 58) = 3.37, p = .036, \eta_p^2 = .06$	
Mixed ANOVA baseline (scenario 0) – towards (ooxx, scenario 11)		
Position	$F(1, 80) = 1395.48, p < .001, \eta_p^2 = .95$	
Mixed ANOVA towards (oxx, scenario 9) – towards (ooxx, scenario 11)		
Position	$F(1, 60) = 1244.55, p < .001, \eta_p^2 = .95$	
Mixed ANOVA towards (oxx, scenario 9) – static (oxx, scenario 10)		
Position	$F(1, 108) = 1335.33, p < .001, \eta_p^2 = .93$	
Mixed ANOVA towards (oox, scenario 1) – towards (oxx, scenario 9)		
Position	$F(1,32) = 583.17, p < .001, \eta_p^2 = .95$	
Position * Scenario	$F(1,32) = 3.13, p < .086, \eta_p^2 = .09$ (tendency)	x = 205: $T(32) = 1.70, p = .100$ (tendency)
Mixed ANOVA towards (ooox, scenario 3) – towards (ooxx, scenario 11)		
Position	$F(1, 63) = 1657.99, p < .001, \eta_p^2 = .96$	x = 205:

Scenario	*F*(1, 63) = 3.04, *p* = .086, η_p^2 = .05 (tendency)	*T*(63) = -2.05, *p* = .045

Table 9-12: Results of post-hoc comparisons of fastest drivers (all drivers faster than 100.12 km/h) in testing phase 3 at two positions (within-subjects factor) between distinct scenarios (between-subjects factor). η_p^2 *is reported as effect size.*

9.4.2.4 Testing Phase 4: Effects of Movement of Lights and Interactive Speed Indicator Device

As stated in chapter 9.1.1.4, inferential statistical analyses were not calculated for the Speed Indicator Device. Descriptive results can be found in chapter 9.3.3.

9.4.2.5 Comparison of Baseline Scenarios

To evaluate whether the overall driving behaviour had changed over time, we conducted an interim baseline. This chapter illustrates the results.

9.4.2.5.1 Baseline Comparison: Fast Drivers

The results in this chapter are regarding the fast drivers (drivers faster than 89.07 km/h at x = 50) only.

We calculated a t-test for independent samples with the between-subjects factor *scenario* for the position x = 50 to check if the entry speed at light onset is comparable among the different scenarios. The entry speed did not differ significantly (*T*(763) = .74, *p* = .461).

We conducted a mixed ANOVA with the between-subjects factor *scenario* (2; first baseline and intermediate baseline) and repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) for the fast drivers (all drivers faster than 89.07 km/h at x = 50). Figure 9-20 illustrates speed in km/h over the first and last position of all fast drivers depending on different scenarios with varied light movement speed.

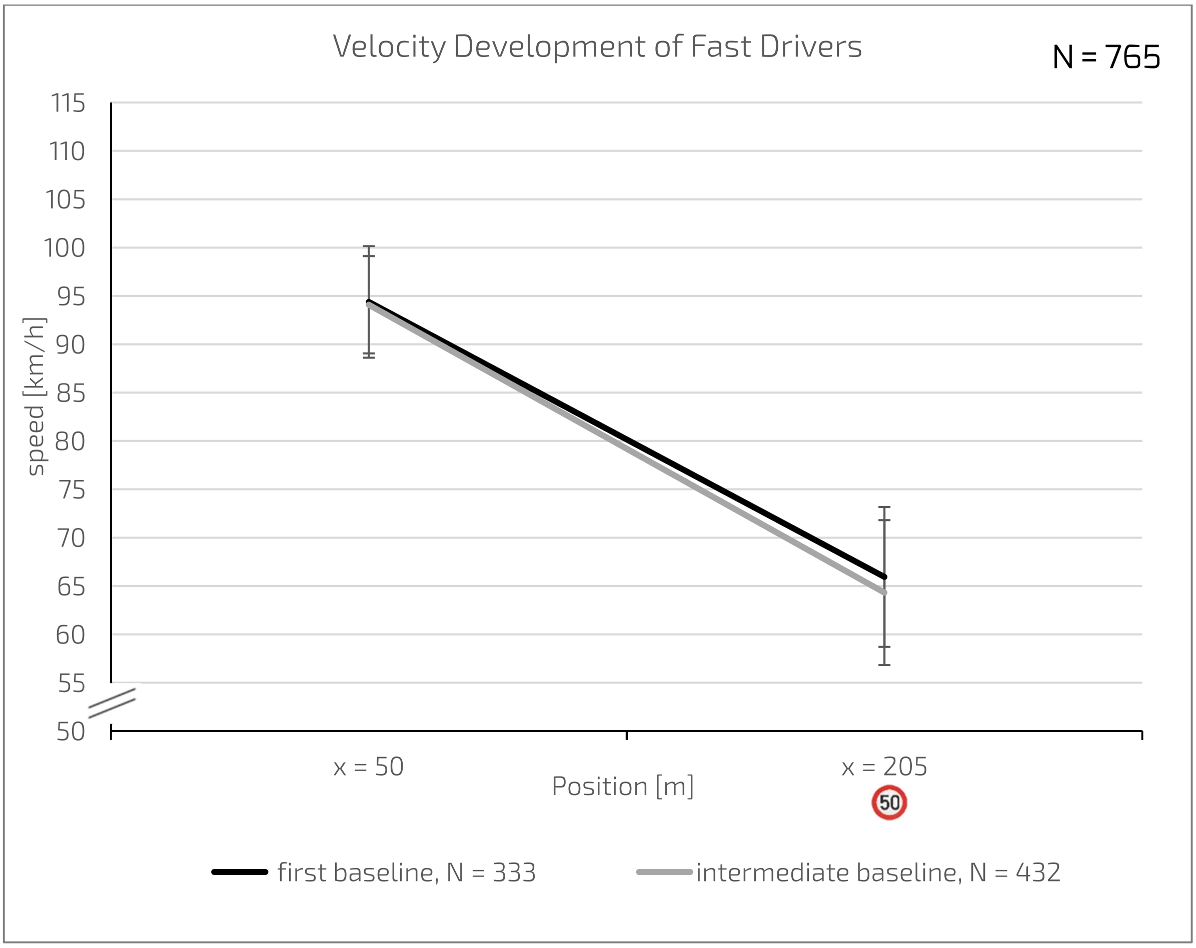

Figure 9-20: Results for the velocity development of fast drivers (all drivers faster than 89.07 km/h at x = 50) of both baseline conditions. Each scenario (between-subjects) was tested for about one week. The x-axis shows the within-factor position, *the y-axis shows the velocity in km/h, and the lines represent the two different baseline* scenarios *(between-subjects factor). Error bars depict standard deviations.*

The results revealed a significant main effect for *position* (F[1, 763] = 12735.32, p < .001, $_p{}^2$ = .94), a significant main effect for *scenario* (F[1, 763] = 5.88, p = .016, $_p{}^2$ = .01), and a significant interaction between *position* (2) and *scenario* (2), F(1, 763) = 6.65, p = .010, $_p{}^2$ = .01. Further, we calculated a post-hoc t-test for independent samples with the between-subject factor scenario for the position x = 205. Results show that driving speed at the position x = 205 for the first and intermediate baseline differed significantly (T(763) = 3.01, p = .003).

9.4.2.5.2 *Baseline Comparison: Fastest Drivers*

The results in this chapter are regarding the fastest drivers (drivers faster than 100.12 km/h at x = 50) only.

We calculated a t-test for independent samples with the between-subjects factor *scenario* for the position x = 50 to check if the entry speed at light onset is comparable among the different scenarios. The entry speed did not differ significantly ($T(87) = 1.06$, $p = .29$).

We conducted a mixed ANOVA with the between-subjects factor *scenario* (2; first baseline and intermediate baseline) and repeated measures on the within-subjects factor *position* (2; x = 50 and x = 205) for the fastest drivers (all drivers faster than 100.12 km/h at x = 50). Figure 9-21 illustrates speed in km/h over the first and last position of the fastest drivers depending on different scenarios with varied light movement speed.

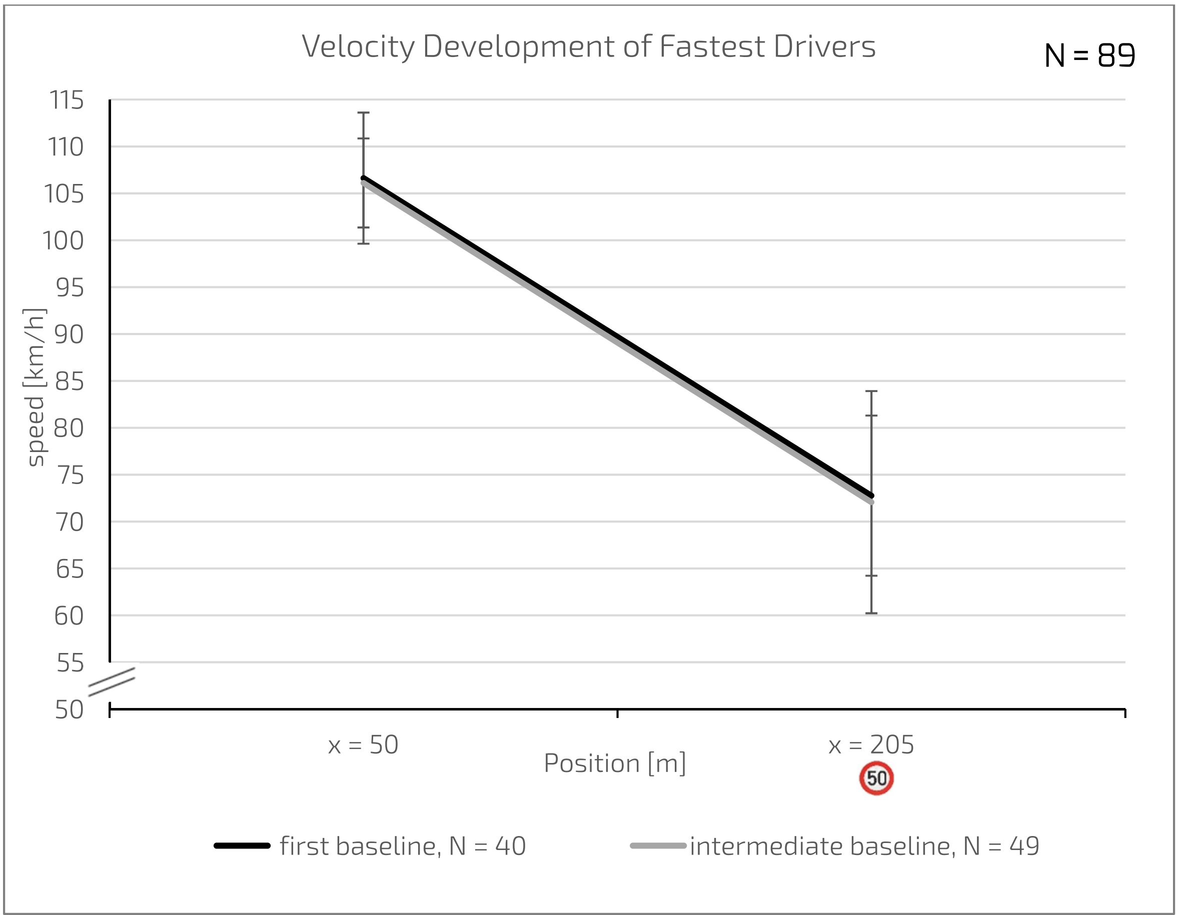

Figure 9-21: Results for the velocity development of fastest drivers (all drivers faster than 100.12 km/h at x = 50) of both baseline conditions. Each scenario (between-subjects) was tested for about one week. The x-axis shows the within-factor position, *the y-axis shows the velocity in km/h, and the lines represent the two different baseline* scenarios *(between-subjects factor). Error bars depict standard deviations.*

The results revealed a significant main effect for *position*, $F(1, 87) = 887.68$, $p < .001$, $_{p}^{2} = .91$. Further effects were not significant ($p > .05$).

9.4.3 Discussion of Hypotheses

Within the overall chapter 9.4 on driver behaviour, we reported our analyses on vehicle's driving speed per testing phase regarding the hypotheses as described in chapter 9.1.1. The following sub-chapter discusses the results stated in chapter 9.4.2 within each testing phase according to the hypotheses deduced in chapter 9.1.1.

Within the field trial of the Infrastructure Driver Nudge, we installed roadside markings in such a way that drivers who entered the exit lane at velocities above a predefined threshold could be exposed to various light patterns along the lane. Set-up and expected driver behaviour built directly on the results of WP3 – Driver Nudge (see deliverable D3.2). Nine different light scenarios were tested, including variations of light pattern, spacing between an activated set of two lights, brightness levels, and light movement speed. Further, one Speed Indicator Device-scenario and two baseline scenarios were tested for comparison reasons. The field trial was divided into four testing phases. Testing phase 1 compared a baseline with static lights and with lights moving towards the driver. Both nudging measures were tested in two different variations of spacing between an activated set of two lights, resulting in four nudging scenarios plus a baseline (see table 9.1). Within testing phase 2, we examined variations of movement speed of lights and within testing phase 3, we investigated scenarios with different numbers of lights activated as sets. Between testing phase 2 and testing phase 3, we conducted an intermediate baseline for control purposes. Testing phase 4 is not evaluated regarding driving behaviour (see chapter 9.1.1.4). The relevant results of the analysis regarding driver behaviour are discussed in the subsequent sub-chapters.

In all conducted comparisons, we found a significant main effect for *position*. This indicates that velocities significantly decrease from x = 50 to x = 205. In particular, results reveal that all drivers slowed down. This is likely moderated by the curve in the motorway exit causing drivers to slow down, and because drivers have likely learned that they need to slow down when leaving a motorway or comparable roads, thus forming a habit.

9.4.3.1 Discussion of Testing Phase 1

As described above, testing phase 1 compared four different nudging scenarios regarding **movement of lights** as well as **spacing between the lights** and tested them against a baseline with no lights. For the fast drivers' sample (drivers faster than 89.07 km/h at x = 50) and for the fastest drivers (drivers faster than 100.12 km/h at x = 50), results revealed no significant main effect for *scenario* (5 levels; baseline, static_oox, static_ooox, towards_oox, and towards_ooox) at x = 50 indicating that entry speed did not differ at light onset across nudging scenarios. Hence, subsequently reported significant effects for the fastest drivers' sample are likely to solely reflect the impact of the respective nudging scenario on driving speed.

In testing phase 1, we expected (**H1.1**) that drivers reduce their driving speed more in static light scenarios (scenarios 2 & 4) compared to a baseline (scenario 0). Due to the significant interactions (tendency towards a significant interaction for fastest drivers) between *position* and *scenario* for both, comparison between baseline and scenario 2 (oox) as well as baseline and scenario 4 (ooox), we can accept H1.1 for both, fast drivers and fastest drivers, respectively.

Further, we expected (**H1.2**) that lights moving towards the driver (scenarios 1 & 3) lead to a reduced driving speed compared to a baseline (scenario 0). Here, we have to distinguish between fast drivers and fastest drivers. For fast drivers, we have to reject H1.2 for lights moving towards the driver with a narrow spacing (oox, scenario 1). However, we can accept H1.2 for lights moving towards the driver with a wider spacing (ooox, scenario 3) as we found a significant interaction between *position* and *scenario* when comparing scenario 0 and scenario 3 for fast drivers. For the fastest drivers, we again found no effect for lights moving towards the driver with a narrow spacing (oox, scenario 1). However, we found a significant main effect for *scenario* for lights moving towards the driver with a wider spacing (ooox, scenario 3), but no significant interaction. Therefore, we do not have a clear result for fastest drivers and, hence, cannot accept H1.2. A potential confounding factor are external events such as traffic or weather conditions, which differed during the field test as stated in chapter 9.3.3. Follow-up research on lights moving towards the driver should take these confounding factors into consideration to better determine the influence of the movement component of the lights on drivers, drivers' speed perception, and drivers' speed choice.

Further, we expected (**H1.3**) that the driving speed in scenarios with lights moving towards the driver (scenarios 1 & 3) is even slower compared to static lights (scenarios 2 & 4). For fast drivers, we did find a significant interaction between *position* and *scenario* when comparing nudging scenarios with wider spacing (scenarios 3 & 4). Contrary to our expectation, post-hoc tests revealed that drivers in the static lights condition slowed down more than drivers in the condition with lights moving towards the driver when there was a wider spacing between active lights. We did not find a significant difference for scenarios with narrow spacing (scenarios 1 & 2). For fastest drivers, the other evaluated group of drivers, we did find a significant interaction between *position* and *scenario* when comparing scenarios with narrow spacing (scenarios 1 & 2), but, again, the results are contrary to our expectation, as drivers in the static lights condition drove more slowly than drivers in the condition with lights moving towards the driver with a narrow spacing between active lights. As a result of these analyses, H1.3 has to be rejected for all drivers.

Whenever we found a significant difference, this difference was in an unexpected direction. That is, scenarios with static light conditions lead to significantly lower speed under specific circumstances. This implies that lights moving towards the driver did not work better in slowing drivers down than static lights. The intended effect of drivers perceiving their own speed to be faster than in reality and therefore slowing down as a consequence of lights moving towards the driver could not be shown. Follow-up research should determine whether this effect is also true for speed perception in general: it is possible that drivers indeed perceived themselves as being faster when lights moved towards them, but that they did not consider it necessary to slow down.

Ongoing, we did not expect (**H1.4**) any significant difference in driving speed between the scenario with static lights with a narrow spacing (oox, scenario 2), and static lights with a wider spacing (ooox, scenario 4). We have to reject H1.4 for fast drivers, because we did find a significant interaction between *position* and *scenario*. However, we can accept H1.4 for the fastest drivers, as we did not find a significant interaction. Our results indicate that the salience due to spacing between active lights is only irrelevant for drivers encountering the static lights when driving much faster than allowed. A possible explanation could be that they were passing the lights so quickly that the difference in spacing could not be perceived, even subconsciously.

The spacing between activated lights seemed to have a moderating effect: fast drivers drove more slowly in static lights conditions when the spacing between two activated lights was wide. However, for the fastest drivers, such differences for different spacing between activated lights could not be found. Therefore, we could assume that when comparing static lights, fast drivers are receptive for spacing between active lights, but fastest drivers are not.

Concluding testing phase 1, we did not expect (**H1.5**) any significant difference in driving speed between the scenario with lights moving towards the driver with a narrow spacing (oox, scenario 1), and lights moving towards the driver with a wider spacing (ooox, scenario 3). For the fast drivers, we did find a significant main effect for *scenario*, as well as a significant interaction between *position* and *scenario*. Post-hoc t-tests showed a difference between the scenarios only at x = 205 but not as x = 50, indicating that differences in driving speed can be attributed to the different scenarios. H1.5 has to be rejected for fast drivers in our study because we did not find a clear evidence that differences regarding different spacing between activated lights do not have an influence on driving speed. This is in line with the unclear results of scenarios with lights moving towards the driver as discussed for H1.2. For fastest drivers, we found a significant interaction between *position* and *scenario*. Therefore, H1.5 has to be rejected for fastest drivers in our study as well. We can therefore say that the scenarios are likely to differ significantly, even though this effect should be evaluated further in subsequent research. Based on our analyses regarding H1.5, we can assume that when comparing lights moving towards the driver, lights' salience seems to play a role. Follow-up research should determine the operating principle of lights moving towards the driver further. Still, the results could be due to the sequence of scenarios (see chapter 9.4.3.5). Table 9-13 summarizes the results of testing phase 1.

Hypothesis No.	Speed of drivers in scenario …	… is expected to be…	… than speed of drivers in scenario …	Acceptance	
				fast	fastest
H1.1	Static lights (scenarios 2 & 4)	<	Baseline (scenario 0)	✓	✓
H1.2	Lights moving towards the driver (scenarios 1 & 3)	<	Baseline (scenario 0)	X (1) ✓ (3)	X - (3)
H1.3	Lights moving towards the driver (scenarios 1 & 3)	<	Static lights (scenarios 2 & 4)	X	X
H1.4	Static lights with narrow spacing (oox, scenario 2)	=	Static lights with wider spacing (ooox, scenario 4)	X	✓
H1.5	Lights moving towards the driver with narrow spacing (oox, scenario 1)	=	Lights moving towards the driver with wider spacing (ooox, scenario 3)	X	X

Table 9-13: Summary of results for testing phase 1.

Concluding testing phase 1, results for the fast drivers should be treated with caution as the scenarios already differed significantly at light onset at x = 50. Regardless of driver sample drivers in both static nudging scenarios (oox (scenario 2) and ooox (scenario 4) showed lower velocities than drivers in the baseline. However, static lights with a wider spacing seem to be most effective for fast drivers. Lights moving towards the driver were effective for the sample of fast drivers only when activated lights had a wider spacing. The reasons for this need to be elaborated further in future research. This difference was not found for fastest drivers. However, our study had limited applicability for fast drivers in testing phase 1 due to the difference at light onset, which is likely to have moderated the results. Lights moving towards the driver were not effective for fastest drivers. It is possible that they were not susceptible for the light movement because they had to focus their attention on the driving task and were not able to perceive the lights moving towards them as intended. Future research should determine this further.

9.4.3.2 Discussion of Testing Phase 2

As described above, testing phase 2 compared three different movement speed of lights. Entry speed did not differ at light onset ($x = 50$) for both driver groups. Therefore, subsequently discussed effects can be attributed to the nudging scenarios.

Due to the significant effects when comparing all three scenarios of testing phase 2, we conducted post-hoc ANOVAs to evaluate our hypotheses.

For **H2.1**, we expected the driving speed in scenarios with lights moving towards the driver at 80 km/h (scenario 7) to be lower compared to lights moving towards the driver at 50 km/h (scenario 1). The significant interactions between *position* and *scenario* for the comparison of scenario 7 (80 km/h) and scenario 1 (50 km/h), indicate that drivers who saw lights with light movement speed of 80 km/h slowed down more than drivers who saw lights moving at 50 km/h. Thus, we can accept H2.1 for both driver groups.

Regarding **H2.2**, we expected the driving speed in scenarios with lights moving towards the driver at 50 km/h (scenario 1) to be lower compared to lights moving towards the driver at 20 km/h (scenario 6). We did find a significant interaction between scenarios for fast drivers only, indicating that they were slightly slower when lights moved towards them at 20 km/h compared to lights moving towards. We did not find a significant difference for fastest drivers. Hence, H2.2 has to be rejected. It is possible that the difference in light movement speed could not be perceived by drivers.

For **H2.3**, we expected driving speed in scenarios with lights moving towards the driver at 80 km/h (scenario 7) to be lower compared to lights moving towards the driver at 20 km/h (scenario 6). Due to the significant interaction between *position* and *scenario* and the significant t-test at x = 205, we can conclude that there is a difference between lights moving towards the driver at 20 km/h and at 80 km/h. Furthermore, results show that drivers do indeed slow down more when lights move towards them at 80 km/h than when lights move towards them at a light movement speed of 20 km/h, which corresponds with our hypothesis. Therefore, H2.3 can be accepted for both groups, fast and fastest drivers. Table 9-14 summarizes the results of testing phase 2.

Hypothesis No.	**Speed of drivers in scenario …**	**… is expected to be…**	**… than speed of drivers in scenario …**	**Acceptance**	
				fast	**fastest**
H2.1	Lights moving towards the driver at 80 km/ (scenario 7)	<	Lights moving towards the driver at 50 km/h (scenario 1)	✓	✓
H2.2	Lights moving towards the driver	<	lights moving towards the driver at 20	X	X

	at 50 km/h (scenario 1)		km/h (scenario 6		
H2.3	Lights moving towards the driver at 80 km/h (scenario 7)	<	lights moving towards the driver at 20 km/h (scenario 6)	✓	✓

Table 9-14: Summary of results for testing phase 2

Concluding testing phase 2, lights moving towards the driver at 80 km/h (scenario 7) seem to be most effective considering only the overall velocity. However, results of the traffic analysis suggest that drivers at 80 km/h showed harsh braking (maximum deceleration in scenario 7 was the largest, see Figure 9-11). This was not observed between the scenarios of lights moving towards the driver at 20 km/h and 50 km/h, indicating that this difference in light movement speed did not lead to a different speed perception. Therefore, the reason why drivers slow down more when lights move towards them at 80 km/h is possibly not that drivers perceive their driving speed to be higher as intended by the measure, but that the rapidly blinking lights overwhelmed them. We saw that the light stimuli moving toward the driver indeed seem to have an influence on driving speed, but we suggest that future applications should carefully walk the line between influencing human speed perception to make them slow down and displaying stimuli that potentially diminish safety margins by confusing drivers. The latter could lead to potentially dangerous situations such as harsh braking events. Especially in the scenario with lights moving towards the driver at 80 km/h, drivers might have been just confused by the rapidly blinking lights. Colleagues passing the test site confirmed this possible explanation: drivers might have slowed down because of being too confused by this light movement speed.

9.4.3.3 Discussion of Testing Phase 3

As described above, testing phase 3 compared scenarios with different numbers of lights activated in sets and compared distinct scenarios to scenarios from testing phase 1. Entry speed did not differ at light onset (x = 50) for both driver groups. Therefore, subsequently discussed effects can be attributed to the nudging scenarios.

Due to the significant effects when comparing all three scenarios of testing phase 2, we conducted post-hoc ANOVAs to evaluate our hypotheses.

In **H3.1**, we expected that drivers slow down more when seeing red static lights with a set of two activated lights (scenarios 10 and 12) are displayed compared to a baseline (scenario 0). As scenario 12 could not be tested (see chapter 9.2), H3.1 can only be evaluated regarding scenario 10. For both driver groups, we did find a significant interaction between *position* and *scenario* and found the scenarios to differ significantly at x = 205. Therefore, H3.1 can be accepted.

For **H3.2**, we expected a reduced driving speed when lights in a set of two move towards the driver (scenarios 9 and 11) compared to baseline (scenario 0). When lights moved towards the driver in a set of two activated lights and a narrow spacing between an activated set of two lights (scenario 9) drivers slowed down more. We found a significant interaction between position and scenario and a significant difference between the scenarios at x = 205 for fast drivers as well as a significant main effect for scenario and a significant difference at x = 205 for fastest drivers. Therefore, H3.2 can be accepted for fast and fastest drivers for sets of two activated lights and a narrow spacing between an activated set of two lights. When a set of two activated lights moved towards the driver with a wider spacing between an activated set of two lights (scenario 11), the significant interaction for fast drivers leads to the acceptance of H3.2 for this group of drivers, but to the rejection of fastest drivers, as we did not find a significant difference for this driver group. For our group of fastest drivers, sets of lights moving towards the driver with a narrow spacing were effective, but not when the spacing was wider. This is contrary to testing phase 1, where we did not find a clear result for lights moving towards the driver. Reasons for this might be external factors such as weather conditions or potential sequence effects that have to be evaluated in follow-up research. Nevertheless, the present results indicate that lights moving towards the driver in sets of two activated lights and a narrow spacing indeed work better than just one activated light. Further, the results illustrate that lights moving towards the driver with a wider spacing seem to work for fast drivers, but not for fastest drivers. The reasons for this are not clear and should be evaluated in future research.

Regarding **H3.3**, we hypothesized that the driving speed in scenarios with lights moving towards the driver with a set of two activated lights (scenarios 9/11, respectively) is even slower compared to static lights with a set of two activated lights (scenarios 10/12, respectively). As scenario 12 could not be tested, H3.3 can only be evaluated regarding the comparison between scenario 9 and 10 (narrow spacing between two activated lights). We did not find a significant difference between the two scenarios; therefore, H3.3 has to be rejected. This is in line with the results of testing phase 1, indicating that static lights work better in slowing drivers down than lights moving towards the driver. As for H1.3, the intended effect of drivers perceiving their own speed to be faster than in reality and therefore slowing down as a consequence of lights moving towards the driver could not be shown.

For **H3.4**, we expected the driving speed in the scenario with static lights with a narrow spacing between a set of two activated lights (oxx, scenario 10), and static lights with a wider spacing between a set of two activated lights (ooxx, scenario 12) to not differ significantly. As scenario 12 could not be tested, this hypothesis could not be answered.

Consequently, in **H3.5**, we also expect that the lights moving towards the driver with a narrow spacing between a set of two activated lights (oxx, scenario 9) do not differ from a set of two activated lights with a wide spacing (ooxx, scenario 11) in driving speed. As we did not find a significant difference for both groups, fast and fastest drivers, we can accept H3.5. For moving lights in the tested conditions, stimulus salience did not play a role in our study. Similarly to H3.2, this is contrary to testing phase 1, where spacing between activated lights did have an influence (see H1.5 in chapter 9.4.3.1). Again, these results indicate that lights moving towards the driver in sets of two activated lights and a narrow spacing indeed work better than just one activated light.

Subsequently, we compared scenarios of testing phase 3 with scenarios from testing phase 1. In **H3.6**, we expected no difference in driving speed between the scenario with single activated lights moving towards the driver (oox, scenario 1) compared to sets of two activated lights moving towards the driver (oxx, scenario 9). As we did not find a significant difference for fast drivers, we can accept H3.6 for this group. However, we did find a significant interaction between scenario and position for fastest drivers as well as a tendency towards a significant t-test at x=205. This leads to the rejection of H3.6 for fastest drivers. However, scenario 1 did not differ significantly from the baseline (scenario 0), while scenario 9 did slightly. This should be a focus of follow-up research.

Furthermore, we expected no significant difference between single lights moving towards the driver with a spacing ooox (scenario 3) and a set of two activated lights moving towards the driver (ooxx, scenario 11) in **H3.7**. We did not find a difference between these two scenarios for fast drivers, which is why H3.7 can be accepted for this group of drivers. However, for fastest drivers, we did find a significant main effect for *scenario*, but no significant interaction. Scenarios differed significantly at x = 205. This indicates that the scenarios did only slightly differ significantly in our study but could differ more prominently in a replication. H3.7 can therefore not be clearly answered for fastest drivers. Table 9-15 summarizes the results of testing phase 3.

Hypothesis No.	Speed of drivers in scenario …	… is expected to be…	… than speed of drivers in scenario …	Acceptance	
				fast	fastest
H3.1	red static lights with a set of two activated lights (scenarios 10 and 12)	<	Baseline (scenario 0)	✓ (10) - (12)	✓ (10) - (12)
H3.2	lights in a set of two move towards the driver (scenarios 9 and 11)	<	Baseline (scenario 0)	✓ (9) ✓ (11)	✓ (9) X (11)
H3.3	lights moving towards the driver with a set of two activated lights (scenarios 9/11, respectively)	<	static lights with activated lights in a set of two (scenarios 10/12, respectively)	X (9) - (12)	X (9) - (12)
H3.4	static lights with a narrow spacing of lights with a set of two activated lights (oxx, scenario 10)	=	static lights with a wider spacing between an activated set of two lights (ooxx, scenario 12)	-	-

H3.5	lights moving towards the driver with a narrow spacing between an activated set of two lights (oxx, scenario 9)	=	lights moving towards the driver with a wider spacing between an activated set of two lights with a wide spacing (ooxx, scenario 11)	✓	✓
H3.6	single activated lights moving towards the driver (oox, scenario 1)	=	sets of two activated lights moving towards the driver (oxx, scenario 9)	✓	X
H3.7	single lights moving towards the driver with a spacing (ooox, scenario 3)	=	a set of two activated lights moving towards the driver (ooxx, scenario 11)	✓	-

Table 9-15: Summary of results for testing phase 3.

Concluding testing phase 3, the results found in testing phase 1 could be replicated for static lights. However, results for lights moving towards the driver showed that scenarios with lights moving towards the driver seem to work better when more than one light is activated. In testing phase 3, the spacing did not have an influence, as expected. The only exception are fastest drivers encountering a wide spacing of lights moving towards the driver. Here, results were inconclusive across testing phases.

9.4.3.4 Discussion of Baseline Comparisons

We conducted an interim baseline to evaluate whether the overall driving behaviour had changed. Entry speed did not differ at light onset (x = 50) for any driver group.

As this was an explorative comparison to gain further insights into whether driver behaviour would have changed over time when being exposed to nudging measures, no distinct hypotheses were deduced.

We found that the two baseline scenarios differed slightly but significantly for fast drivers but were not different for the fastest drivers. Changes in the nudging conditions for fast drivers can therefore not solely be attributed to the nudging conditions. Even though we followed a between-subjects design due to the specifications of the field trial, we cannot fully ignore potential sequence effects. A baseline, which is recorded sometime after the nudging system is deactivated, could give further insights into potential long-term effects. This had not been completed upon completion of this deliverable.

9.4.3.5 General Discussion of Behavioural Results

Taking everything into consideration, static light stimuli were most effective and showed the clearest results in our field trial. Testing phase 1 revealed that static lights with a wider spacing showed lower driving speed. Lights moving towards the driver did however not always show a clear result and seemed to work better when more than one light was activated in a set of two. Lights moving towards the driver with a wider spacing were indeed effective for fast drivers but did not show a clear result for the fastest drivers. Spacing between lights showed ambiguous results as well. The results of testing phase 3 indicate that spacing did not play a role when more than one light in a row was activated.

Further, we cannot rule out any potential sequence effects. Drivers at this field trial location pass the site regularly, as the exit leads to a residential area. Therefore, even though we can only assume a between-subjects design for the factor *scenario*, habituation could have taken place and affected our results. The results of the baseline comparison suggest that this is more relevant for the fast drivers and not for the small group of fastest drivers. A possible explanation could be that fastest drivers might have chosen to drive as fast as they did, while fast drivers might comprise a larger group of habitual speeders, who are the main target group for the Infrastructure Driver Nudge.

Further, the simulator studies as reported in D3.2 of the project suggest that one major advantage of the nudging measure is not simply the absolute decrease in speed, but rather in the shifting of driver attention to the traffic situation, thereby enlarging safety margins. This could also be an explanation for the differences between the scenarios at x = 50. People taking the exit on a daily basis likely know that they have to be attentive and therefore they slow down earlier. Replicating this finding in the field can however be challenging, as drivers would have to be made aware that they are tested, which is against the nature of the field test with oblivious drivers.

Future research should elaborate the findings of this field trial further and replicate them in order to support the current findings. Especially the principle of the lights moving towards the driver could not be clearly answered in all scenarios of the described field trial. As already stated in chapter 9.3.3, a study by Gold, Lin, Ashcroft, and Osman (2020) found that the effectiveness of a measure could be determined by the desire to change, meaning that people are more likely to follow a nudge if they understand the way it works and which positive impact it can have. If people are aware of the functioning of the nudging measure, it is possible that the effectiveness could be higher. For this, drivers need to be either explicitly educated on the functioning of the nudge or exposed to it more frequently and on more locations to implicitly learn about the principle of the intervention.

9.5 On-site Survey

We conducted an on-site survey with recruited drivers to examine how the light scenarios are perceived in a real-life testing environment. In order to get direct feedback right after the recruited drivers experienced the light scenarios in randomized order, we conducted a semi-structured on-site survey. In this chapter, the research questions are stated, followed by methods and results. The chapter concludes with a discussion of the results of the on-site survey.

9.5.1 Research Questions

The on-site survey was conducted to investigate the question on how drivers perceive the infrastructure nudge in a real-life environment and whether they would accept the measure in traffic. We expected participants to perceive both, the static lights and the lights moving towards the driver as a warning signal that creates awareness for the driving situation and influences driving behaviour. Further, we assumed that the lights moving towards the driver would be evaluated as most efficient for nudging drivers to reduce their speed. These expectations are based on the findings from the simulator studies that were reported in Deliverable 3.2.

9.5.2 Methods

The following chapter explains the method of the on-site survey conducted in October 2019 including the sample, questionnaire, procedure, design and outlines the results that are subsequently discussed. Drivers answered the questionnaire after the test drives to get direct feedback.

9.5.2.1 Sample

N = 20 participants participated in the on-site survey (56 % female). The mean age of the sample was *M* = 44 years (*SD* = 17 years, *range* = 20-76). 85 % of the participants had their place of residence in the Netherlands, 15 % in Germany. On average, the participants' mileage was 6640 km per year (*SD* = 6463 km, *range* = 240 km-15000 km). 60 % of the participants reported as driving a car daily, 20 % weekly, 5 % monthly and another 5 % stated that they drive a car less than once a month. When asked to rate their driving experience in comparison to other car drivers, 20 % rated themselves as much more experienced, 35 % as more experienced, 25 % as similar experienced and 10 % as less experienced. None of them rated themselves as much less experienced. 30 % of the participants took the exit J.F. Kennedylaan-Tempellaan the first time in the test drive.

9.5.2.1 Questionnaire

The study was conducted in October 2019 in Eindhoven and consisted of test drives with three experimental conditions: a baseline with no lights (scenario 0), static lights (scenario 2) and lights moving towards the driver (scenario 1). The static and the moving lights only differed in their luminescent behaviour but had the same positions on the roadside (see 9.1 for detailed information on the light stimuli). All participants were exposed to the three scenarios and they were randomly assigned the order in which they encountered the scenarios. Each scenario was driven twice in a row. After the test-drives, all participants participated in the semi-structured on-site survey, which included questions about the light stimuli and the demographic background of participants. First, participants were asked whether they noticed something inside or outside the vehicle. After that, they were questioned about their impression of the trials and if they had the feeling that the different light stimuli influenced their driving behaviour. Before questions regarding the perception and safety of the different light patterns were queried, all participants were debriefed with the following information:

"The subject of the study is the lights system on the exit. During your test-drive you took the exit six times. Each time you took the exit the light system looked different: one time there were no lights at all, one time there were static red lights and one time there were red lights moving towards you. The lights system aims to reduce the driving speed of the driver."

After the debriefing, the participants had to rate their experience and acceptance of the static and moving lights according to the Van der Laan Acceptance Scale (Van Der Laan et al., 1997). In order to be able to compare the lights to other infrastructure measures, the participants were additionally asked to evaluate the effectiveness of both scenarios compared to other measures, such as regular traffic signs indicating the allowed speed and speed cameras. In the last part of the survey, demographic data and information on driving experience was assessed. A simplified presentation of the questionnaire is displayed in the following in Table 9-16.

Question		Answer Format
Questions 1-3: General Impression of the Traffic Situation		
Q1	How often do you take the exit J.F. Kennedylaan – Tempellaan?	Open Questions
Q2	Did you notice something inside and/or outside of the vehicle during the previous rides?	
Q3	Did you see lights on the roadside? If yes, did you notice differences in the lights among the rides? If yes, in what did the lights differ (colour, intensity, shape)?	
Questions 4-9: General Impression of the Static and Moving Scenarios		
Q4/6/8	What do you think did the lights aim to achieve?	Open Questions
Q5/7/9	Do you think that the lights influenced your driving behaviour? If yes, in what way?	
Debriefing on Subject of the Study: Aim of the Lights to Reduce Speed		
Questions 10&12: Perception of speed reducing light intervention: static and moving		
I felt safe with the light system.		4-point Likert scale + "I don't know": 1: Not at all to 4: Absolutely
The light system supported my driving trajectory.		
The light system made me aware of a hazardous situation.		
The light system made me decrease my driving speed.		
The light system made me nervous.		

<table>
<tr><td colspan="5">The light system made me increase my driving speed.</td><td rowspan="7">+ I don't know</td></tr>
<tr><td colspan="5">The measure distracts me.</td></tr>
<tr><td colspan="5">The measure indicates clearly, which behaviour is demanded.</td></tr>
<tr><td colspan="5">I would accept this measure in traffic.</td></tr>
<tr><td colspan="5">The measure is stressful to me.</td></tr>
<tr><td colspan="5">The measure is suitable for drawing more attention to the course of the road.</td></tr>
<tr><td colspan="5">The measure supports safe driving behaviour in this traffic situation.</td></tr>
<tr><td colspan="6">Questions 11&13: Acceptance of static and moving light scenarios (+ recoded items)</td></tr>
<tr><td colspan="5">Useful vs. useless*</td><td rowspan="9">4-point Likert scale + "I don't know":
-2. Very Negative
-1. Negative
0. I don't know
1. Positive
2. Very Positive</td></tr>
<tr><td colspan="5">Pleasant vs. unpleasant*</td></tr>
<tr><td colspan="5">Bad vs. good</td></tr>
<tr><td colspan="5">Nice vs. annoying*</td></tr>
<tr><td colspan="5">Effective vs. superfluous*</td></tr>
<tr><td colspan="5">Irritating vs. likeable</td></tr>
<tr><td colspan="5">Assisting vs. Worthless*</td></tr>
<tr><td colspan="5">Undesirable vs. desirable</td></tr>
<tr><td colspan="5">Raising alertness vs. sleep-inducing*</td></tr>
<tr><td colspan="6">Questions 14-16: Evaluation of measures for speed reduction</td></tr>
<tr><td rowspan="4">Q14</td><td colspan="4">Traffic sign</td><td rowspan="4">Sorting items from most effective to less effective</td></tr>
<tr><td colspan="4">Traffic sign + Static light system</td></tr>
<tr><td colspan="4">Traffic sign + Moving light system</td></tr>
<tr><td colspan="4">Traffic sign + Speed camera</td></tr>
<tr><td>Q15</td><td colspan="4">Are there any measures you consider appropriate to reduce speed?</td><td rowspan="2">Open Questions</td></tr>
<tr><td>Q16</td><td colspan="4">Do you have anything else you wish to add?</td></tr>
<tr><td colspan="6">Questions 17-24: Demographic data</td></tr>
<tr><td>Age</td><td>Gender</td><td>Visual impairment</td><td>Driving frequency</td><td>Driver's license</td><td>Driving experience</td></tr>
</table>

Table 9-16: Questionnaire of the on-site survey.

9.5.2.2 Procedure/Approach of Analysis

Upon arrival, participants were welcomed at the entrance of Heijmans and were brought to the interviewing area. At the beginning, participants were asked to sign a declaration of data protection after having been informed that their data would be used in an anonymized manner. Subsequently, one participant and two testing investigators walked to the test vehicle, a Ford Kuga, and took a seat. All participants were instructed to drive as they usually do and they were informed about their right to withdraw from the experiment at any time and without having to face any consequences. One investigator sat in the front passenger seat next to the participant and one sat on the right rear seat. The investigator in front told the participant where to drive and the investigator in the back observed the rides. Each participant completed a warm-up ride while driving to the test site to get used to the test vehicle. Subsequently, two test drives for every scenario (baseline with no lights, static lights and lights moving towards the driver) were conducted in a randomized order, resulting in six drives in total. After finishing the test drives and returning to the starting point at the Heijmans office, the questionnaire and the demographic survey were conducted in the interviewing area. In a face-to-face setting, an investigator asked the participants the questions from the questionnaire and recorded their answers in writing. The questionnaire entailed the semi-structured interview and the additional demographic survey. After the experiment, the participants were thanked for their participation and received a monetary compensation of 25 € each (+25€ extra for participants from Germany for the travel time), or, in cases involving colleagues who were not involved in the project, they participated within their working hours.

9.5.2.3 Design

The study was based on a one-factorial design with the two-level inner-subject factor light scenario (static lights and moving lights) and a baseline. The order in which the three scenarios were presented varied randomly across participants. Due to technical issues with the light system, the scenario sequences were not fully balanced. The answers to the questionnaires serve as dependent variable when analysing the data.

9.5.3 Results

The qualitative and statistical analyses were carried out after the study. Responses to the open questions were analysed qualitatively and clustered according to their content. All quantitative data was transferred into IBM SPSS Statistics 23. Descriptive results were calculated for the general observations and impressions of the lights from the participant's perspective as well as for the demographic data. Inferential statistical analysis was performed for the analysis of the scales. The significance threshold was set to 0.05.

All participants stated that they saw the lights on the roadside **(Questions 2/3)**. *N* = 13 participants (65 %) stated that they noticed differences among the visual appearance of the lights without knowing the purpose of the study. *N* = 11 of these *N* = 13 participants stated that they recognized blinking lights **(Question 3)**. Table 9-17 shows all answers given by the *N* = 13 participants that noted differences among the lights.

Qualitative Results Q3: General Observations on Light Differences *Did you see lights on the roadside? If yes, in what way did the lights differ? (colour, intensity, shape)*	Quantity from *N* = 13 *(multiple answers possible)*	Percentage from *N* = 13
Different scenarios: blinking	11	84.62 %
Intensity and sequence of lighting	3	23.08 %
Moving lights	1	7.69 %

Number of lights	1	7.69 %

Table 9-17: General observations on light differences for both scenarios (Question 3).

As can be seen in Table 9-18, 4 of 19 participants thought that the static light scenarios aimed to reduce speed and served as a more intense regulation for speed reduction **(Questions 4/6/8)**. One participant did not answer this question and thus the following results are valid for *N* = 19 participants. The second most common thought was that the static lights served as a warning signal for high speed in the curve (3/19) **(Questions 4/6/8)**. The answer "warning signal" was the most common one for the lights moving towards the driver (4/19), followed by "attention to the sharpness of the curve" that was answered by 3 out of 19 participants **(Questions 4/6/8)**.

Qualitative Results Questions 4/6/8: Observations for the Static lights *Have you seen lights and if so, what do you think the lights aim to achieve?*	Quantity from *N* = 19 *(multiple answers possible)*	Percentage from *N* = 19
More intense regulation/reduction of speed	4	21,1 %
Warning signal for high speed in the curve	3	15,8 %
Caution	1	5,3 %
Show the traffic lane border	1	5,3 %
„Not seen, seemingly there was habituation"	1	5,3 %
"Seen it, turned the lights off, because I had driven in permitted speed?"	1	5,3 %
Qualitative Results Questions 4/6/8: Observations for the Moving lights *Have you seen lights and if so, what do you think the lights aim to achieve?*	**Quantity from *N* = 19** *(multiple answers possible)*	**Percentage from *N* = 19**
Warning signal for high speed in the curve	4	21,1 %
Attention to the sharpness of the curve	3	15,8 %
Reducing speed	2	10,5 %
Show the traffic line border	2	10,5 %

It is noticeable that one will leave the highway and will get into the traffic	1	5,3 %
Patterns seems to be more alarming	1	5,3 %

Table 9-18: Observations for the static and the moving lights for the question "Have you seen lights and if so, what do you think the lights aim to achieve?" (Questions 4/6/8).

As listed in Table 9-19 below, the most common answers to the question *"Do you think that the lights influenced your driving behaviour?"* were: "Increasing attention/alertness to the driving situation" (5/19), "attention to the speed limit" and "avoid a sudden slowing down" (3/19) **(Questions 5/7/9)**. For the scenarios in which lights were moving towards the driver, six participants thought that the lights influenced their speed, led to smoother braking and driving more cautious. Two participants felt that the lights moving towards them influenced their alertness and another two stated that they were surprised and that the moving lights distracted them at first sight **(Questions 5/7/9)**.

Qualitative Results Questions 5/7/9: Observations for the Static lights *Do you think that the lights influenced your driving behaviour?*	Quantity from *N* = 19 *(multiple answers possible)*	Percentage from *N* = 19
increasing attention/alertness to the driving situation	5	26.32 %
Attention to the speed limit, avoid a sudden slowing down/ smoother braking	3	15.79 %
Risk of habituation to lights	1	5.26 %
Preparing for the curve	1	5.26 %
Recognition of blinking lights when speed was too fast	1	5.26 %
Did not influence the speed	1	5.26 %
Qualitative Results Questions 5/7/9: Observations for the Moving lights ***Do you think that the lights influenced your driving behaviour?***	**Quantity from *N* = 19** *(multiple answers possible)*	**Percentage from *N* = 19**
Reducing speed/Smoother braking/Driving more cautious	6	31.58 %
Alertness/attention	2	10.53 %

Shocked/Surprised/Distracted with first sight	2	10.53 %
Not consciously perceived, but I think, I drove more cautiously	1	5.26 %
Curiosity	1	5.26 %
I don't think it influenced my driving behaviour	1	5.26 %
Less noticeable	1	5.26 %

Table 9-19: Observations for the static and the lights moving towards the driver for the question "Do you think that the lights influenced your driving behaviour?" (Question 5/7/9).

To measure the attitude of the participants towards both measures, the central tendencies of the static lights were compared to the values of the lights moving towards the driver for questions 10 and 12 (Figure 9-22 and Figure 9-23). Due to the non-parametric nature of the data for each item, a Wilcoxon signed-rank test was used to compare the light scenarios. Results revealed that the lights moving towards the driver were rated significantly higher than the static lights for the statement "*The light system made me decrease my driving speed*" ($Z = -2.25$, $p < .05$) **(Questions 10/12)**. For the statement "*The measure supports safe driving behaviour in this traffic situation*" **(Questions 10/12)**, the lights moving towards the driver were rated in tendency significantly higher than the static light ($Z = -1.78$, $p = .075$). The attitude towards the static lights and the lights moving towards the driver did not differ significantly for the other items of questions 10 and 12.

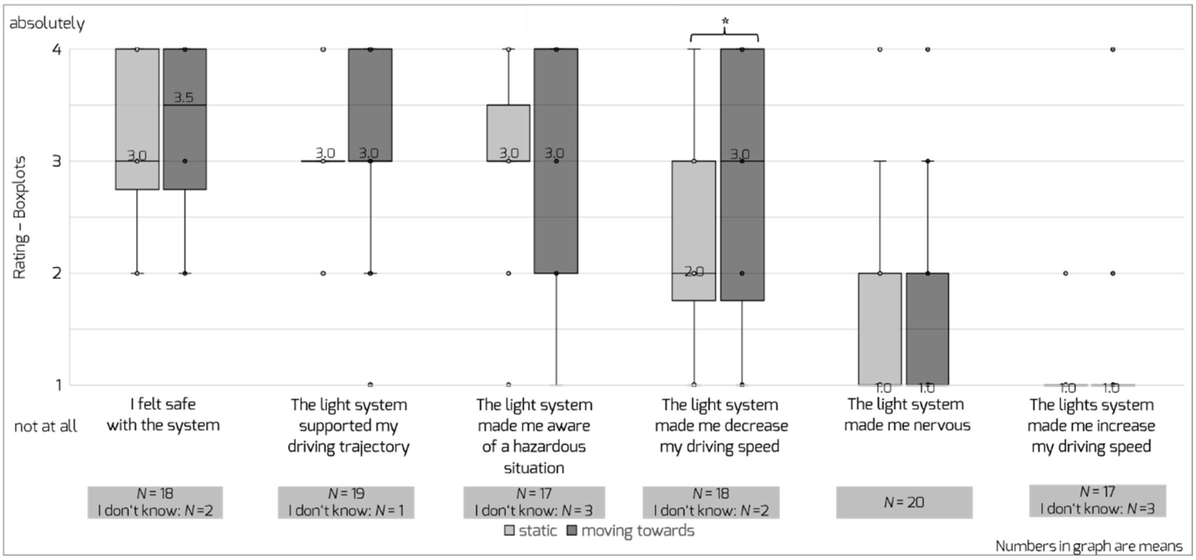

Figure 9-22: Boxplot ratings of qualitative results of the attitudes towards the static and lights moving towards the driver for items 1-6 (Questions 10/12).

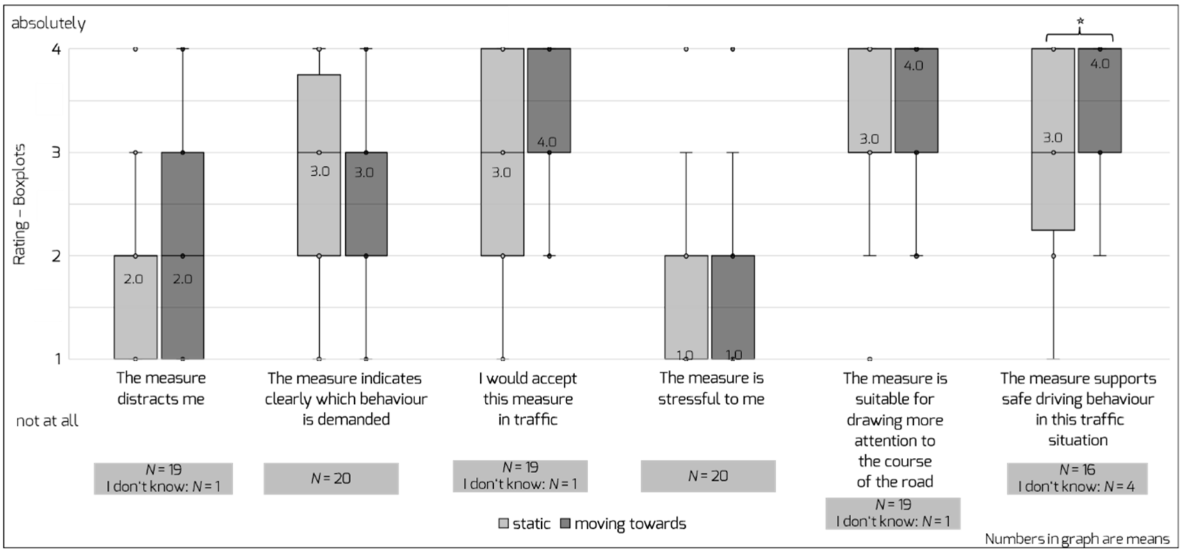

Figure 9-23: Boxplot ratings of qualitative results of the attitudes towards the static and lights moving towards the driver for items 7-12 (Questions 10/12).

As shown in Figure 9-24, a one-tailed Wilcoxon Test demonstrated that the participants regarded the lights moving towards the driver as significantly more useful ($Z = -2{,}89$, $p = .002$), nice ($Z = -2{,}60$, $p = .005$) and effective ($Z = -1{,}96$, $p = .025$) in comparison to the static lights **(Questions 11/13)**.

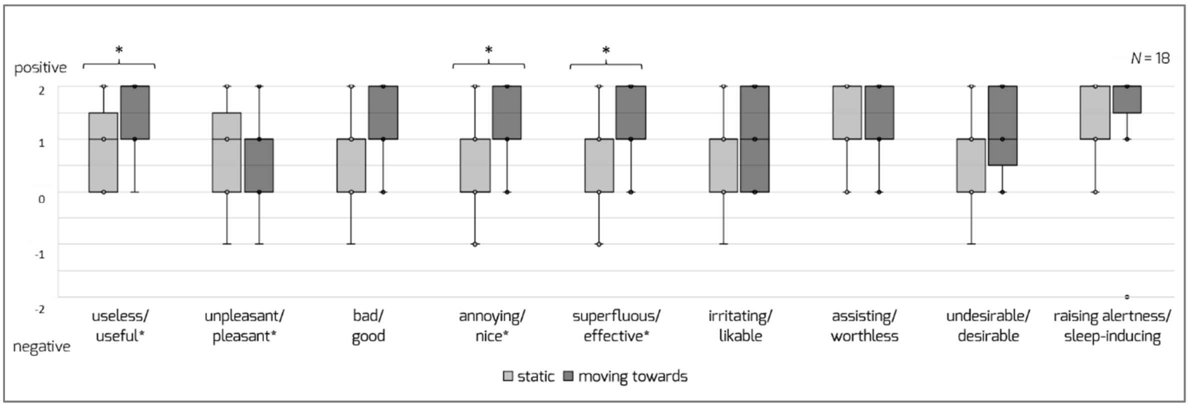

Figure 9-24: Results of the Van der Laan Acceptance Scale for the static and moving towards lights (Questions 11/13).

Further analysis focused on comparing the results of the Van der Laan-subscales. Since the subscales "satisfaction" and "usefulness" show high reliability with Cronbach's alpha above 0.7, the mean values of the two scores were compared for *N* = 18 participants (see Figure 9-25). One-tailed t-tests were conducted to compare the mean scores of the subscales for the static light condition with those in the moving lights condition and revealed significant differences for the usefulness subscale ($t(17) = 3.51$, $p = .015$) as well as the satisfaction subscale ($t(17) = 1.95$, $p = .034$). For both sub-scales, lights moving towards the driver were rated more positively.

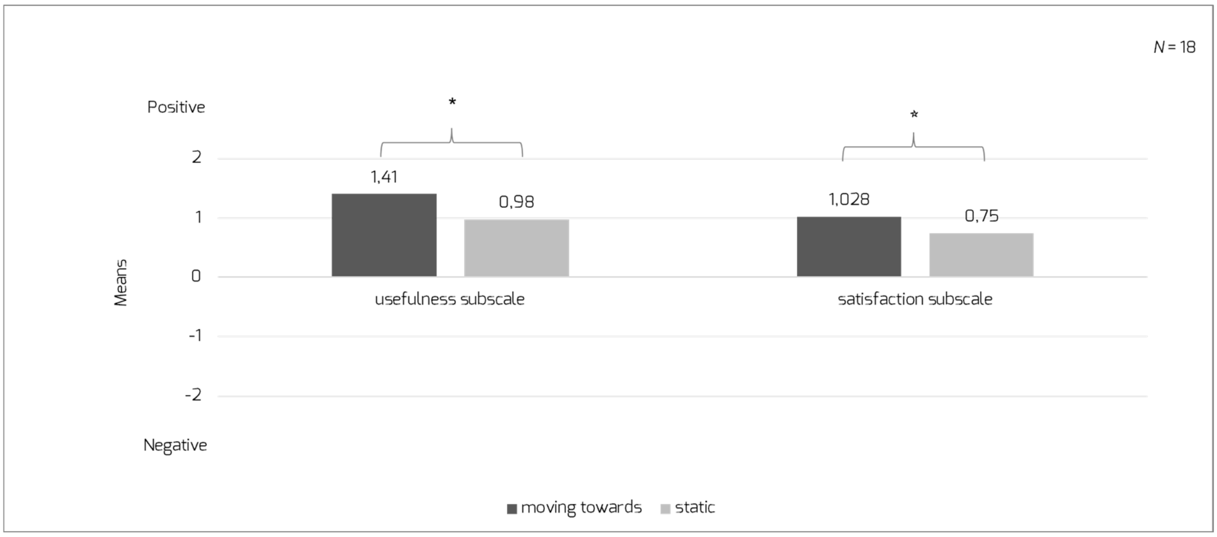

Figure 9-25: Overall results of the Van der Laan-subscales "usefulness" and "satisfaction" (Questions 11/13).

For *N* = 17 in question 14, a descriptive comparison of the rating of measures for speed reduction showed that 70.6 % of the participants rated the option "Traffic sign + light system with lights moving towards the driver" as most effective, 17.6 % as effective, 5.9 % as less effective and 0 % as least effective (see Figure 9-26). The static lights in combination with a traffic sign were rated as effective by 52.9 % of the participants. 41.2 % rated the option "Traffic sign + speed camera" as less effective. The option with a traffic sign only was rated as least effective by 70.6 % of the participants **(Question 14)**.

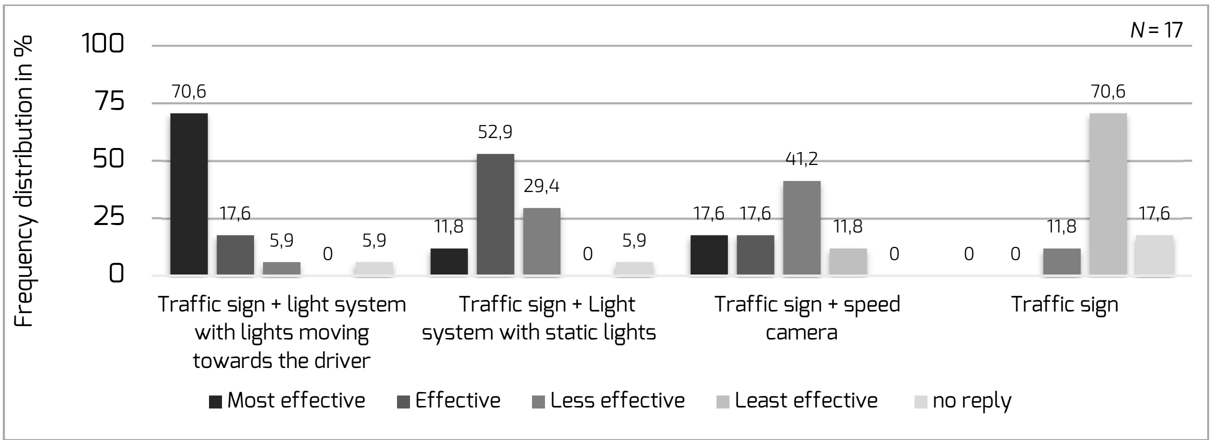

Figure 9-26: Rating of measures for speed reduction from most effective to least effective (Question 15).

9.5.4 Discussion

This study aimed to gain insights on the perception of the static and moving lights as well as the experience of their usefulness to reduce speed in a real-life testing situation. For this, a questionnaire with recruited drivers was conducted. *N* = 20 participants drove the following three scenarios from the field trial in a randomized order: static lights, moving towards lights and a baseline without lights.

Descriptive results of the open questions showed that both, the static and the moving scenarios were mostly perceived as a warning signal to reduce speed in the curve. Generally, participants felt that the lights influenced their driving behaviour, particularly the moving lights. Thus, results suggest that especially the lights moving towards the driver seem appropriate to nudge drivers. Since one participant stated that they had not seen the static lights, presumably due to learning, further investigations should clarify if and how potential learning effects influences the perception of the light scenarios.

Results of the questions regarding the different light patterns showed that the attitude towards the moving lights is on average more positive. Regarding the attitude towards both light scenarios, the lights moving towards the driver were generally perceived as being more supportive for safe driving behaviour than the static lights. Neither the static nor the moving lights were rated as stressful or irritating. The participants felt safe with both light scenarios, but perceived the lights moving towards the driver as more suitable to draw attention to the road and stated more often that they would accept this measure in traffic.

The positive attitude towards the moving lights can also be emphasized by evaluating how the participants experienced the measures. A comparison of the static and the moving lights regarding their rating on the Van der Laan Acceptance Scale revealed that the moving lights were perceived as more useful, nice and effective. Although the comparison of the other items did not differ significantly, both light scenarios received positive ratings. None of the light scenarios were rated as useless, unpleasant, annoying, or sleep inducing.

In comparison to speed signs, speed cameras and static lights, the moving light scenario was rated as most effective to reduce speed. The option with a traffic sign only was rated as least effective. Results show that there is demand and acceptance for further measures in traffic than those that already exist.

The on-site survey was designed to explore how the static and moving lights are perceived and rated in a real-life testing environment. For this purpose, a number of N = 20 participants is sufficient to get a first impression of potential user's perception, but the results have to be treated with care since they only have a limited validity due to the small number of participants. A resident survey with N = 287 valid questionnaires supplements the findings of this study (see chapter 9.6). Throughout the experiment, the participants had contact with German and Dutch speaking investigators due to organizational reasons. Different styles, languages and interviewers could have influenced the degree of detailedness of the answers given by the participants. In addition, the on-site survey was the last part of the experiment. Since it was conducted after the test-drives, spontaneous reactions to each trial could not be captured and information might have been lost, especially from the first drives. Another potential influential factor is that all participants were aware of the existing test situation. This might have caused participants to act different from their usual behaviour and their answers in the survey could be prone to social desirability bias. Further, due to technical issues with the light system, the sequence of scenarios was not fully balanced. Therefore, further investigations are needed to validate the findings from this study.

Concluding, it can be stated that the moving lights were usually perceived as more effective than either static lights or no lights for reducing speed in our study. Although the results are subject to methodological limitations, they give valuable insights into how the different light scenarios are perceived and rated regarding their usefulness in order to reduce speed.

9.6 Resident Survey (lead: Heijmans & ika/ RWTH Aachen)

We conducted an online resident survey to evaluate how people living in the neighbouring residential area and frequently taking the motorway exit perceive the infrastructure nudge. As participants could answer the survey anytime within a four-week timeframe between October 31, 2019, and December 1, 2019, we were not able to determine which scenario participants experienced. Therefore, we asked for their experience with the system as a whole. In the following chapter, the research questions are stated, followed by methods and results. The chapter concludes with a discussion of the results of the resident survey.

9.6.1 Research Questions

The main research question of the resident survey was how people perceive the infrastructure nudge. This research question was further specified in three sub research questions: (1) Are drivers aware of the infrastructure nudging system? (2) Do drivers accept the infrastructure nudging system? (3) Does the infrastructure nudge support the driving tasks in people's subjective perception?

9.6.2 Methods

The following chapter explains the method of the resident survey conducted in November 2019 including the sample, a description of the questionnaire and the procedure of the survey.

9.6.2.1Sample

The target group for the survey consisted of people who took the exit regularly, i.e. the testing location was part of their daily commuting route.

For the qualitative survey to be distributed among residential areas surrounding the test site, the Digi panel from the city of Eindhoven was used. This is a way to contact the citizens of Eindhoven to give feedback regarding relevant issues in the city. In addition, the communication channels of the participation project *JouwLichtop040* were used to distribute the survey. Target populations were selected based on postal codes. Furthermore, city area managers for the areas Tempel, Blixembosch, Heesterakker and Esp in Eindhoven were included in the recruitment strategy. Figure 9-27 illustrates the Digi panel areas used for the distribution of the survey. For details of the recruitment strategy, please see D5.1.

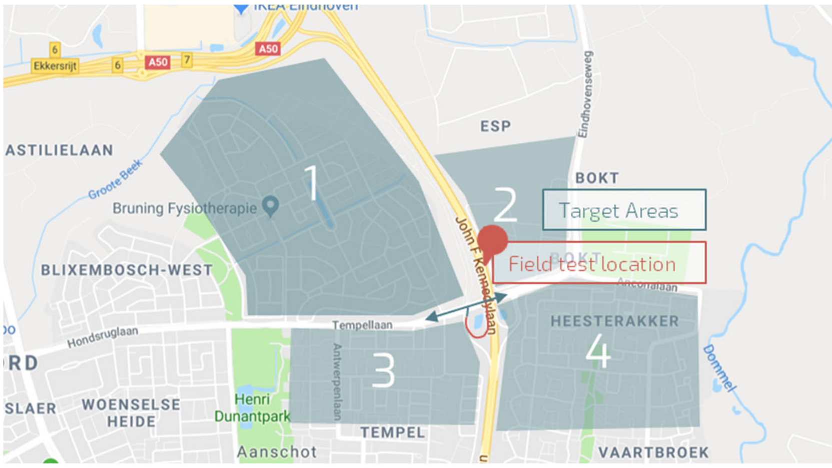

Figure 9-27: Digi Panel survey areas in Eindhoven around the test site.

A total of *N* = 346 participants answered the questionnaire. Participants (*N* = 31), who stated that they did not see the lights, were excluded from analysis as well as those who suffered from visual impairment like colour blindness (*N* = 4 participants) or a poor eyesight during the night (*N* = 24 participants). Detailed information about participants' visual impairment can be seen in Table 9-20.

Do you have a visual impairment?	Number of participants
Yes, that is why I wear glasses and lenses while driving.	*N* = 142
Yes, but I do not wear glasses and lenses while driving.	*N* = 3
Yes, I am colour-blind.	*N* = 4*
Yes, I see poorly during the night.	*N* = 24*
No.	*N* = 158

*Table 9-20: Overview of the participants' visual impairments. Multiple answers were possible. * Participants who had those visual impairments were excluded from further analysis.*

Therefore, the final sample size amounted for *N* = 287 valid questionnaires. The mean age of the sample was *M* = 48 years (*SD* = 14 years, *range* 18-85 years). One participant gave no age-related information. 49 % of the participants were female; one participant gave no gender-related information. The mean number of years of possessing a driver's license was *M* = 29 years (*SD* = 14 years). *N* = 15 participants gave no information about their driver's license.

9.6.2.2 Questionnaire

The questionnaire can be subdivided into five parts. The first six questions asked for general information about the frequency of participants using the exit J.F. Kennedylaan – Tempellaan. These questions were raised to get a better understanding of what the driving/traffic situation was, when the participant took the exit. However, they were not designed to answer any of the research questions. An overview of the exact questions and the answer possibilities is listed in Table 9-21.

Question	Answer Format
1. How often do you take the exit J.F. Kennedylaan – Tempellaan	4-point Likert scale: 1. Very often, every day 2. Often, every workday 3. Regularly, a few days per week 4. Sometimes, one day or less per week
2. When I took the exit, I was...	1. The driver of the car 2. A passenger and sat in front 3. A passenger and sat in back 4. A motorcycle driver
3. Do you remember when this moment was? Fill in the date (xx-xx-2019) or the week number (xx)	Free text field
4. Do you remember at what time of the day this was? I drove on the exit...	1. During dusk, sunrise 2. During daytime, it was light 3. During dusk, sunset 4. During the evening or night, it was dark
5. Did you find the traffic situation calm or busy at this moment?	5-point Likert scale: 1. Very calm, there was no other traffic 2. 3. 4. 5. Very busy, there was a traffic jam
6. Was there a queue at the traffic light at the end of the exit?	1. Yes, a queue of 1-3 cars 2. Yes, a queue of more than 3 cars 3. No, I was the first car.

Table 9-21: Overview of the questions on general information (Questions 1-6).

The next five questions targeted the first sub research question, asking whether the drivers were aware of the infrastructure nudging system. As described before, the question on whether the participant consciously perceived the stimulus (**Question 7**) was necessary to be included for further analysis. If participants stated that they did not see the lights, replies to further questions on their impression of the lights would not be valid and would suggest that they had in fact not encountered the light system. An overview of the exact questions and the answer possibilities are listed in Table 9-22.

Question	Answer Format
7. In the road surface of the exit a dynamic light system has been installed. The street lampposts are not part of the system. Were the lights in the road surface activated when you took the exit?	1. Yes, I saw that there were lights in the road surface 2. No, I did not see lights in the road surface
8. From your own experience, can you describe how the light system looked? (consider for example colour, movement, etc.)	Free text field
9. Was the light system different from previous weeks?	1. Yes, the light itself was different (for example: colour, number of lights) 2. Yes, the light was activated differently 3. No, the light was the same 4. I don't know
10. Can you explain in your own words the difference in light system / activation of the light system from previous weeks?	Free text field
11. Do you think that the light system influences your driving behaviour? Explain your answer.	Free text field

Table 9-22: Overview of the questions concerning awareness (Questions 7-11).

The next part of the questionnaire targeted the second sub research question regarding the acceptance of the infrastructure nudging system. In **question 12**, the participants were asked to evaluate their experience with the light system at the exit by rating statements on a 4-point Likert scale with the options "1 = Completely Agree", "2 = Agree", "3 = Disagree", "4 = Completely disagree" or "I don't know". An overview of all expressions is given in Table 9-23. The expressions were based on impressions of participants in previous studies.

Expression	Answer Format
The light system made me increase my speed.	4-point Likert scale + "I don't know": 1. Completely Agree 2. Agree 3. Disagree 4. Completely Disagree I don't know
The light system irritated me.	
The light system made me nervous.	
Because of the light, I decreased my driving speed.	
The light system made me aware of a hazardous situation.	
The light system guided my trajectory.	
I felt safe when the light system was on.	

Table 9-23: Overview of the expressions of scale (Question 12).

The participants were then asked to indicate on a 5-point Likert scale how accurately the given words of the Van der Laan Acceptance scale describe the light system at the exit (**Question 13**). The Van der Laan scale (Van der Laan et al., 1997) aims to assess the acceptance of advanced transport telematics using two sub-scales. The first scale denotes the usefulness of the system (e.g. items "useful", "good", "effective") and the second scale measures the satisfaction associated with the system (e.g. items "pleasant", "nice", "likeable"). An overview of the Van der Laan Scale can be seen in Table 9-24.

	5-point Likert Scale					
	-2	-1	0	1	2	
Useful*	O	O	O	O	O	Useless*
Pleasant*	O	O	O	O	O	Unpleasant*
Bad	O	O	O	O	O	Good
Nice*	O	O	O	O	O	Annoying*
Effective*	O	O	O	O	O	Superfluous*
Irritating	O	O	O	O	O	Likeable
Assisting*	O	O	O	O	O	Worthless*
Undesirable	O	O	O	O	O	Desirable
Raising Alertness*	O	O	O	O	O	Sleep-inducing*

Table 9-24: Van der Laan Acceptance Scale as used in this study. Stars (*) indicate recoded items (Question 13).

The questions 14 to 18 targeted the third sub research question regarding how the infrastructure nudge supported the driving task. A detailed description of the questions can be seen in Table 9-25.

Question	Answer Format
14. Which colour was the light system?	Free text field
15. Did you think the colour of the lights was suitable for this application?	1. Yes 2. No 3. I don't know
16. Which colour do you think is (also) suitable for this application? Explain your answer.	Free text field
17. If you could choose, which traffic measures would you use to reduce driving speed? Rank the measures below in order from 1 (most effective) to 3 (least effective).*	1. Speed limit sign 2. Speed limit sign + Light system 3. Speed limit sign + Speed camera
18. Can you explain your choice?	Free text field

*Table 9-25: Overview of the questions regarding the support of the infrastructure nudge. *For a better understanding, the participants were also shown pictures of the different measures (Questions 14-18).*

In the end, we asked the participant six demographic questions regarding their age (Question 19), gender (Question 20), driving license (Question 21) and potential visual impairment (Question 22 and Question 23) in order to contextually define the sample. In the last question (Question 24), the participants had the opportunity to state further comments in a free text field. A detailed description of the questions can be seen in Table 9-26.

Question	Answer
19. What is your age?	Free text field
20. What is your gender?	1. Male 2. Female
21. How long have you had your driver's license?	Free text field
22. Do you have a visual impairment?	1. No 2. Yes, I wear glasses/contact lenses while driving 3. Yes, I don't wear glasses/contact lenses while driving 4. Yes, I suffer from reduced vision in the dark*

	5. Yes, I am colour-blind* 6. Other
23. If you responded yes to Question 22, can you explain your visual impairment? (far-sighted, near-sighted, reading glasses, degree of night blindness, colour-blindness for red/green)	Free text field
24. Do you have any other comments you would like to share with us? Your feedback is welcome!	Free text field

*Table 9-26: Demographic questions. *If the participant gave this answer, they were excluded from further analysis (Questions 19-24).*

9.6.2.3 Procedure/Approach of Analysis

This chapter describes the results of the resident survey. The participants were contacted via email and could fill out the questionnaire as soon as they were contacted. At the beginning, they were informed that the questionnaire was about a new lighting system installed by RWTH Aachen University and Heijmans Infra in agreement with the Municipality of Eindhoven. Further, they were informed that they would be asked about their experience with and opinion on this lighting system. The questionnaire consisted of 18 substantive questions about the traffic situation and the lighting system plus six general questions at the end (see tables 9.7 - 9.12). Filling in the questionnaire typically took 15-20 minutes. The participants could withdraw from filling out the questionnaire any time and without stating a reason. The answers to the questionnaire were analysed anonymously and compliantly with the General Data Protection Regulation (GDPR). The answers could not be traced back to individual participants.

9.6.3 Results

The majority of the participants (37.98 %) stated that they used the exit J.F. Kennedylaan – Tempellaan only a few days a week, while 26.13 % used it every day and 14.98 % used it every working day, 13.59 % used it one day a week and 7.32 % used it less than one day a week **(Question 1)**. Most of the participants (90.97 %) were the drivers of the car, 8.36 % sat next to the driver and 0.7 % were motor cyclists

(Question 2). Nearly half of the participants (49.48 %) took the exit in the evening and at night, while 27.53 % took the exit during dusk, 5.23 % during dawn and 17.42 % by daylight **(Question 4)**. The participants rated the traffic situation on a 5-point Likert scale (1 "very calm, no other traffic" to 5 "very busy, there was a traffic jam") with regard to the time point they took the exit **(Question 5)**. A proportional distribution of question 5 can be seen in Figure 9-28.

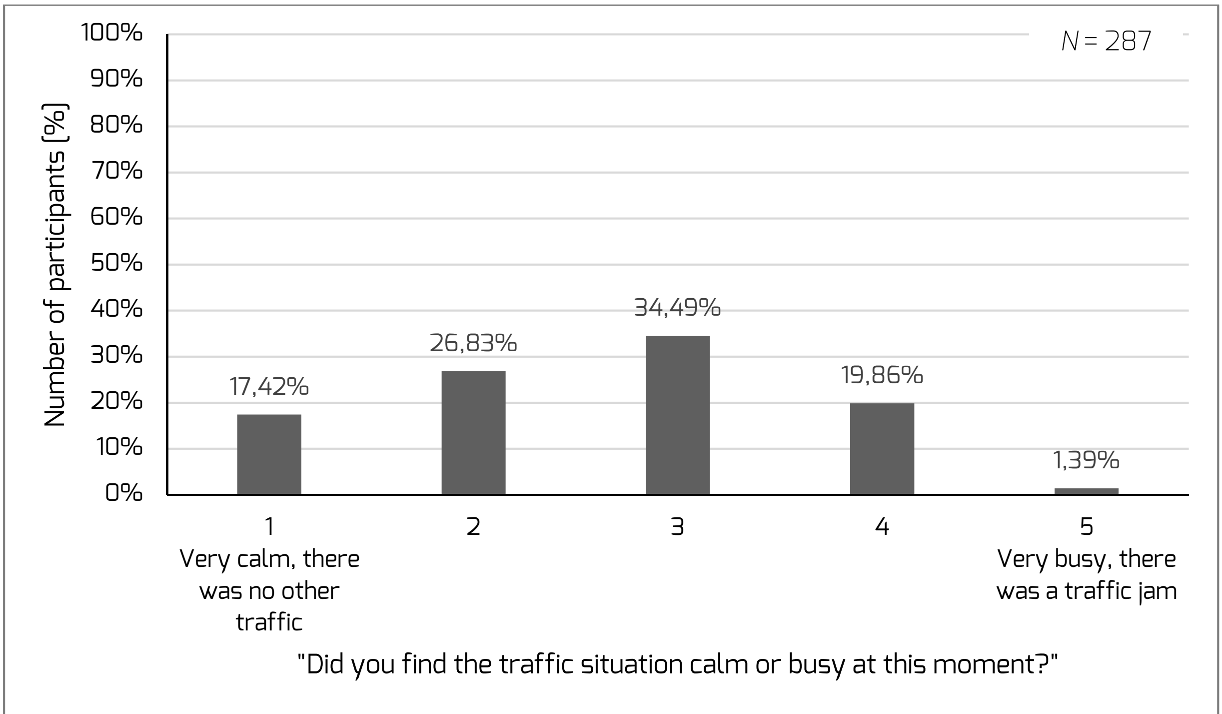

Figure 9-28: Rating of the amount of traffic on the day the participants took the exit J.F. Kennedylaan – Tempellaan (Question 5).

The participants rated the traffic situation on a 5-point Likert scale (1 = "very calm, no other traffic" to 5 = "very busy, there was a traffic jam") with regard to the time point they took the exit **(Question 5)**. 42.16 % of the participants stated that there was a queue of one to three cars at the traffic light at the end of the exit, while 23.69 % said there was a queue of more than 3 cars, and 34.15 % were the first car **(Question 6)**. **Questions 7 & 8** were control questions whether the participants had seen the system and were able to evaluate what they saw. Data sets were only used for analysis if replies to these two questions made sense.

When being asked if the light system was different in the previous weeks, 14.98 % of the participants stated that the light itself was different (e.g. colour, number of lights), 16.38 % said that the light was activated differently, 21.25 % said the lights were the same and a majority of 47.39 % did not recognize any change **(Question 9)**. In **question 10**, participants were asked to describe the difference of the light system in their own words. Those who had reported a difference before e.g. stated a difference in light movement ("lights moving towards the vehicle") or differences in colour (e.g. blue lights instead of red lights). To the question "Do you think that the light system influences your driving behaviour?" **(Question 11),** participants stated the lights created awareness for the sharpness of the curve, made the trajectory of the exit lane more visible and made them slow down. In total, 134 participants agreed that the lights influenced their behaviour, 114 participants disagreed, 30 participants were undecided and nine participants gave no answer. Regarding the general acceptance and experience of the lights **(Question 12)**, we found that 62.37 % of the participants did not feel that the light system made them increase their speed. The proportional distribution of all expressions can be seen in Figure 9-29.

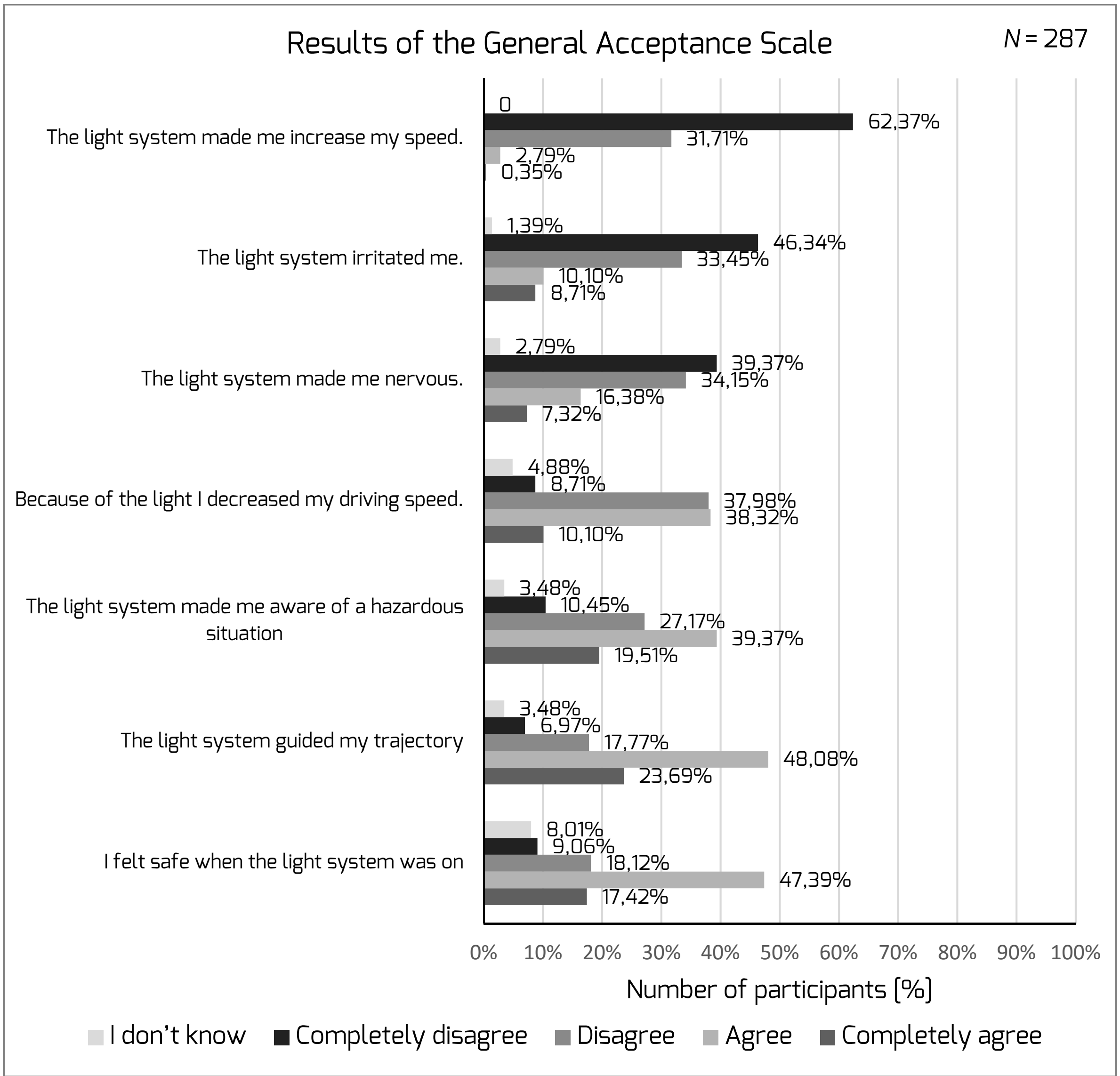

Figure 9-29: Proportional distribution of general acceptance and experience of light (Question 12).

The descriptive results of each item of the Van der Laan Acceptance Scale **(Question 13)** can be seen in Figure 9-30. We chose a histogram to illustrate the results more comprehensibly for this sample. Further analysis of the Van der Laan Acceptance subscales revealed a value of -0.45 for the usefulness subscale and a value of 0.03 for the satisfaction subscale on the rating scale ranging from -2 to +2 (see chapter 9.6.2.2).

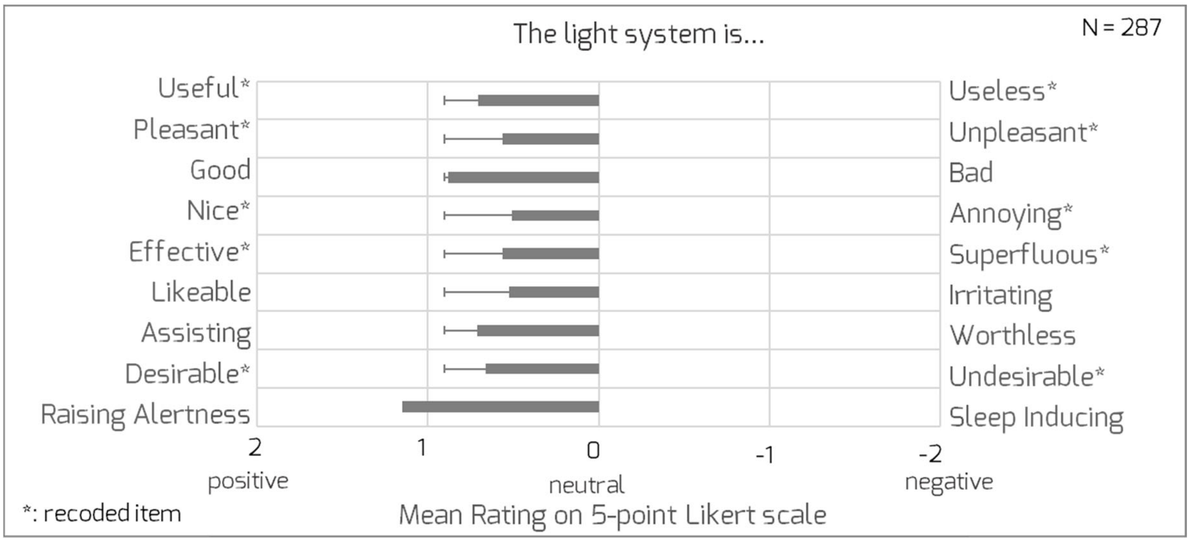

Figure 9-30: Results of the Van der Laan Scale asking how accurately the words describe the light system at the exit (Question 13).

As shown in Figure 9-31, 92.33 % of the participants perceived the installed lights in the colour red **(Question 14)**.

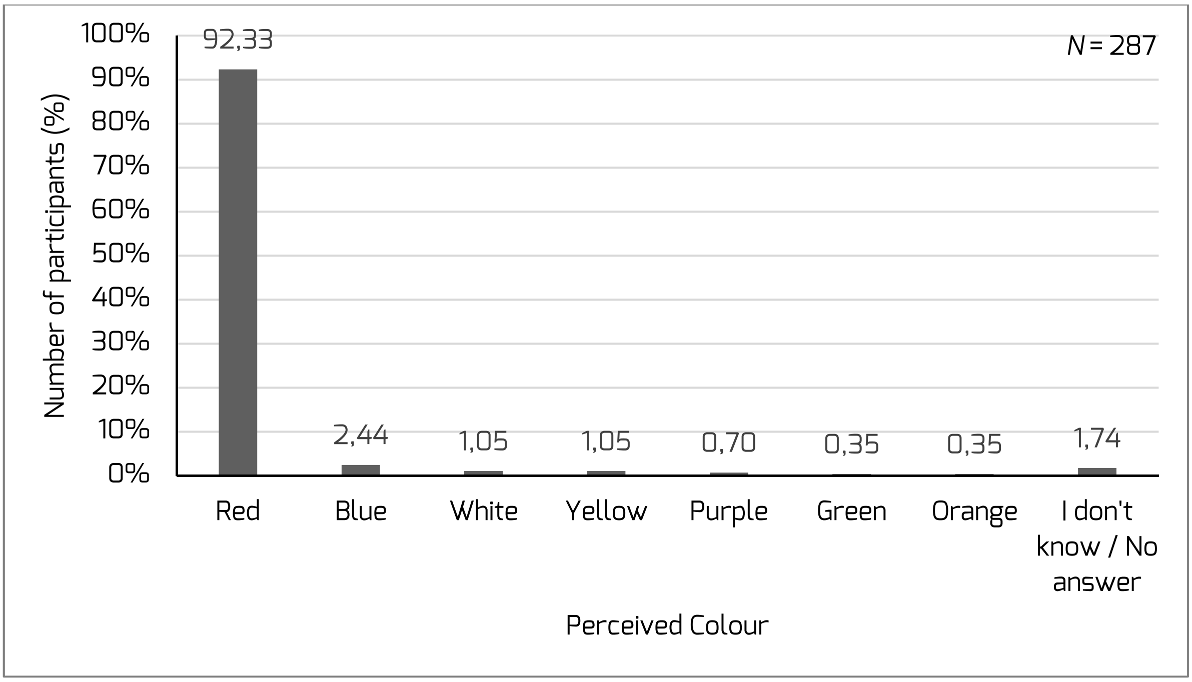

Figure 9-31: Perceived colour of the installed lights (Question 14).

The participants were also asked, which traffic measure they would use to reduce driving speed **(Question 17)**. Combinations of measures should be sorted in order of preference: "Traffic sign", "Traffic sign + light system" and "Traffic sign + speed camera". An overview of the proportional distribution of the answers can be seen in Figure 9-32.

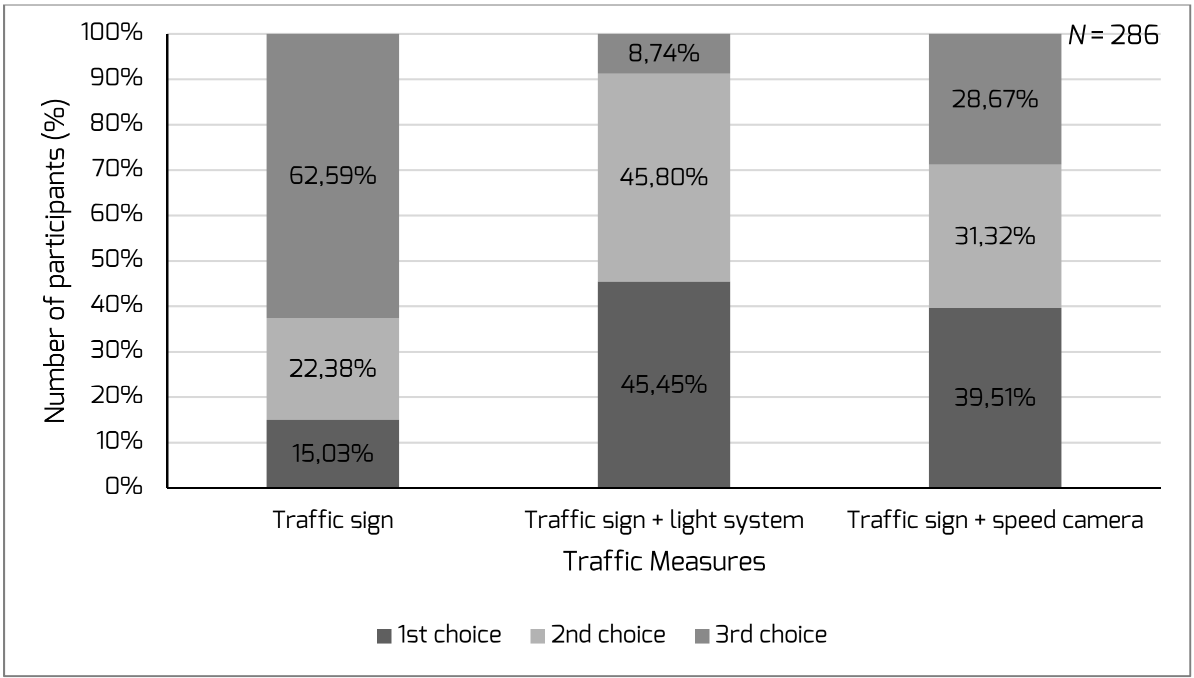

Figure 9-32: Ranking of traffic measures to reduce driving speed (Question 16).

9.6.4 Discussion

This study aimed to expand the insights on how people perceive the infrastructure nudge installed in Eindhoven. The resident survey was used to examine whether drivers who take the exit are aware of the infrastructure nudging system, whether they accept the system in traffic and whether they perceive the infrastructure nudge as supportive for their driving. For this, residents of the city of Eindhoven were contacted and *N* = 287 valid questionnaire replies were analysed within this survey.

The majority of the participants used the exit lane with the implemented infrastructure nudge frequently and mostly there was no traffic jam reported when taking the exit. Thus, it can be assumed for the analysis of the data obtained within the study that the perception of the lights was not disturbed by a busy traffic situation. Participants stated that the light system influenced their driving behaviour by making them slow down and raising attention to the sharpness of the curve. Those who claimed that they were not influenced by the light system were mostly used to the trajectory of the exit, nonetheless few of those admitted that in general the lights create awareness and are able to improve the visibility of the curve. This is especially beneficial for those taking the exit for the first time. Results show that the majority of the participants stated that their driving behaviour was influenced by the lights or reported seeing advantages to the light system, even if their driving behaviour was not influenced from their own perspective. This emphasizes that the light system is appropriate to nudge drivers towards reducing their speed.

Results show that most participants were not irritated by the light system and felt that the light system made them decrease their driving speed. In addition, the light system did not make the participants nervous. This emphasizes that the infrastructure nudging system did not distract participants of our study. Furthermore, the infrastructure nudge was perceived mostly positive, safe and appropriate to attract attention to the driving situation.

Descriptive results of the participants'' ratings on the Van der Laan Acceptance Scale show a strong tendency towards the centre, with all means of the items on the scale varying between -1.1 and 0.8. The analysis of the usefulness subscale as well as the satisfaction subscale confirm this finding.

Almost all participants perceived the lights in red colour, which conveys that the drivers were aware of the nudging system since the lights were, in fact, red.

When being asked what measure they would use to reduce driving speed, the option „Traffic sign + light system“ was preferred by almost half of the participants. The second preference was the option „Traffic sign + speed camera“ and the option traffic sign only was least chosen. This suggests that drivers recognize the need for further infrastructure measures in addition to already existing ones and underlines their positive attitude towards the light system.

As mentioned in chapter 9.6.2, the participants filled out the survey at different times and not directly after taking the exit. Due to this procedure, information might have gone lost and spontaneous reactions to the system could not be captured. Furthermore, the participants did not fill out the survey in a controlled environment and thus, a potential influence of external deflections cannot be ruled out completely. Furthermore, the results of this online resident survey do not distinguish between different scenarios. Therefore, the results can only give insights into an overall acceptance of the measure in general.

Considering all aspects, the results provide evidence that the infrastructure nudge in general was perceived as appropriate to decrease driving speed and that drivers were aware of the nudging system. The lights did not seem to distract the participants as most of them felt safe with the infrastructure nudge. Thus, the results give valuable insights into how people perceive the infrastructure nudge and emphasize that the infrastructure nudge is perceived positively by drivers. From the participants' subjective perception, the infrastructure nudge supports their driving tasks. However, quantitative results as stated in chapters 9.3 and 9.4 are needed to quantify the subjective results.

9.7 PTW Analysis

In addition to the field trial as described so far in chapter 9, the potential effectiveness of the system on PTWs is stated in the following. This was investigated independently from the nudging measure's potential influence on car drivers with different resources and approaches.

9.7.1 Technology for detection and tracking

ISAC provided video records of three days in October (from 8th to 11th) 2019 and three days in late June (from 21st to 23rd) 2020. In the first periods, two different groups were defined: 'baseline' and 'treatment'. The former includes *N* = 35 riders (65 %), who used the exit lane when the system was off; whereas the latter contains *N* = 19 riders (35 %), who were detected by the video cameras while the nudging system was active. In the latter group, *N* = 17 out of *N* = 19 riders activated the nudging system at least in one section. These PTW riders (*N* = 54) are the only ones (12 %) who took the exit lane out of a total of *N* = 470 riders detected in the video during the first period (October 2019). In the second period (June 2020), the light system was switched off. The detected PTW riders (*N* = 36) in the exit lane were considered as a whole 'post-treatment' group and the hypothesis of a residual effect of the nudging system was investigated. In the definition of the baseline, we assumed that there was no permanent effect on the riders from the preliminary tests of the nudging system. In fact, preliminary tests were run for approximately 4 weeks before the video recordings. This assumption was made since there were no velocity data before September 2019 (i.e. previous to the preliminary tests of the nudging system). In addition, since different light scenarios were used in early October (see chapter 9.5), and there is a limited number of PTWs in the videos, we did not distinguish each scenario, but we only considered the difference between baseline (light off) and treatment (light on).

Differently from the real-time detection system used so far for car drivers, an *a posteriori* detection was used for PTWs as the real-time system cannot distinguish between different vehicle categories. As in the previous sections, the vehicle velocities were measured processing videos from thermal cameras, but for PTWs the detection was performed exploiting image contrasts, generated by the different temperatures of moving objects on the background. After a few frames of observation, the algorithm learned to distinguish the foreground, with moving vehicles, from the background. A challenging aspect of this implementation was coping with the heavy differences in lights (and thus temperature) during night-time and daytime and in different seasons (Fall and Summer). In fact, with an overall cold background it's likely that acquisition refers to the hottest parts of the vehicle (i.e. tyres and muffler), whereas with a sunny and hot road, the coolest part (i.e. rider himself) was detected (Figure 9-33).

Figure 9-33: On the left side: CAM1 in October. On the right side: CAM2 in June.

A similar challenging problem involves shadows (Figure 9-34), which could interrupt detections prematurely. This problem causes different lengths for each tracking.

Figure 9-34: Shadows projected on road determines hot and cold spots. On the left image, the engine part (circled in red)and the body part (circled in blue), both hardly visible. On the right image, the whole rider better visible after a few frames.

When detecting different parts of each rider/PTW, we were introducing an error. In fact, the calibration matrices of the cameras (provided by ISAC) allowed a bijection between 'Camera reference' and 'World reference' for the road surface only and their use for out-of-road surface points introduced an error. In terms of velocity, this error was estimated in the range 0-10 km/h, depending whether either the upper half or the lower half of the rider/PTW system was detected. To overcome this issue, we chose to consider the lower part for each vehicle and a correction vector for the upper ones was applied. With this method, every PTW was detected and tracked along the camera view with a maximum error of about 1km/h. Between cameras no interpolation was performed, in order not to introduce additional uncertainties and errors.

The raw data used for the analyses in this chapter consist of:

- Vehicle ID
- Timestamp t (~30 Hz)
- Current position x, y (~30 Hz)

No additional frame reference was used. Every trajectory and velocity were obtained from the overall coordinates, which define the road map (Figure 9-1). The acquired data were processed with a Butterworth filter to remove high frequency peaks not feasible for the vehicle kinematics. As the framerate (i.e. the sampling frequency) was 30 Hz, a low pass filter with 1 Hz cut-off frequency was chosen. The filter settings were considered appropriate to avoid any aliasing effect (Nyquist's limit: 15 Hz) and to preserve the information associated to the velocity and trajectory time histories. In the following sections, the nudging effects on the velocity and rider trajectory will be evaluated.

9.7.2 Descriptive Analysis

In this section we give a descriptive analysis for the PTW dataset according to three different velocity parameters. Every graph has three points, one under each camera field of view, and three bars, representing the range of values. On the left side of Figure 9-35, the mean velocity for riders was plotted for baseline and treatment data. On the right side of the same figure, we plotted the peak velocities. A blank x-axis is used, since the peak velocity value occurs at a different position under each camera for each rider. The three selected points were located approximately at the beginning of each stretch for both graphs, since the velocity curve is generally monotonic and therefore its peaks were located there. In addition, also the mean values occurred at different positions, so they are reported on the same points for a better visual comparison. In Figure 9-35 on the left side, there is almost no difference between the two scenarios. This could mean that velocity differences could occur, but the mean criterion does not allow to perceive them. On the right side, there was an overall decrease of 1.5 km/h in the treatment group compared to the baseline for every stretch. The mean velocity is likely biased by different tracking lengths. Therefore, we assumed that the peak speed is a better parameter to investigate the nudging effect.

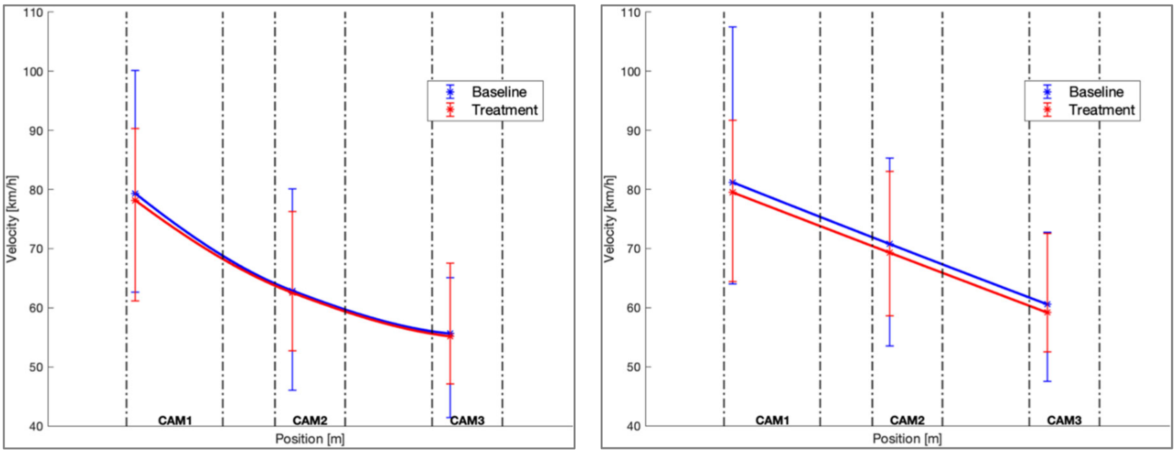

Figure 9-35: On the left side: mean velocity of all riders and range of mean velocity for each rider; on the right side: mean peak velocity of all riders and range of peak velocity for each rider.

Another possible parameter was the instant velocity at different sections along the road. The results of three sections (at x = [50, 140, 230]) are shown in Figure 9-36, whereas in 9.7.3 more sections will be analysed. The differences between baseline and treatment are 0.7 km/h at x = 50, 4.5 km/h at x = 140, and 1.3 km/h at x = 230. The values suggested that this parameter might also be a good candidate for the investigation of the nudging effect.

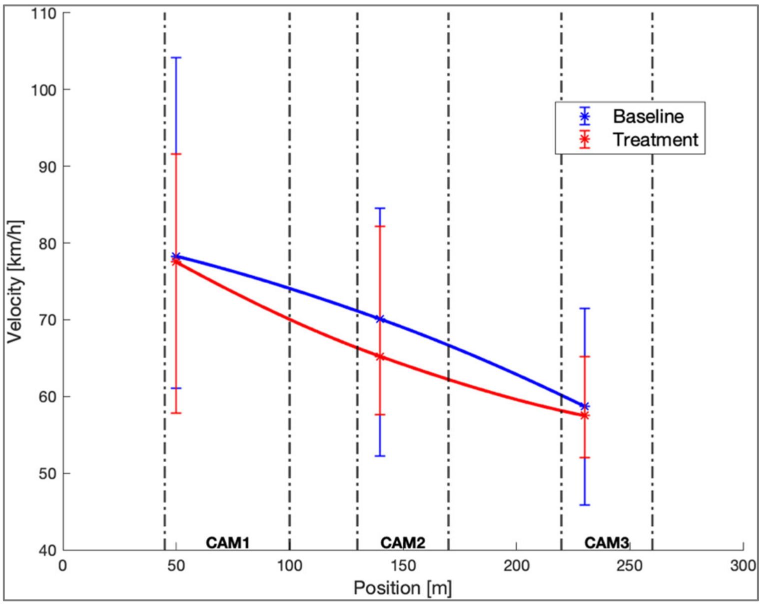

Figure 9-36: Mean velocity of all riders at x = [50, 140, 230] and distribution of rider velocities.

The same steps were applied to assess the overall effect for the post-treatment group compared to the baseline Figure 9-37, left and right).

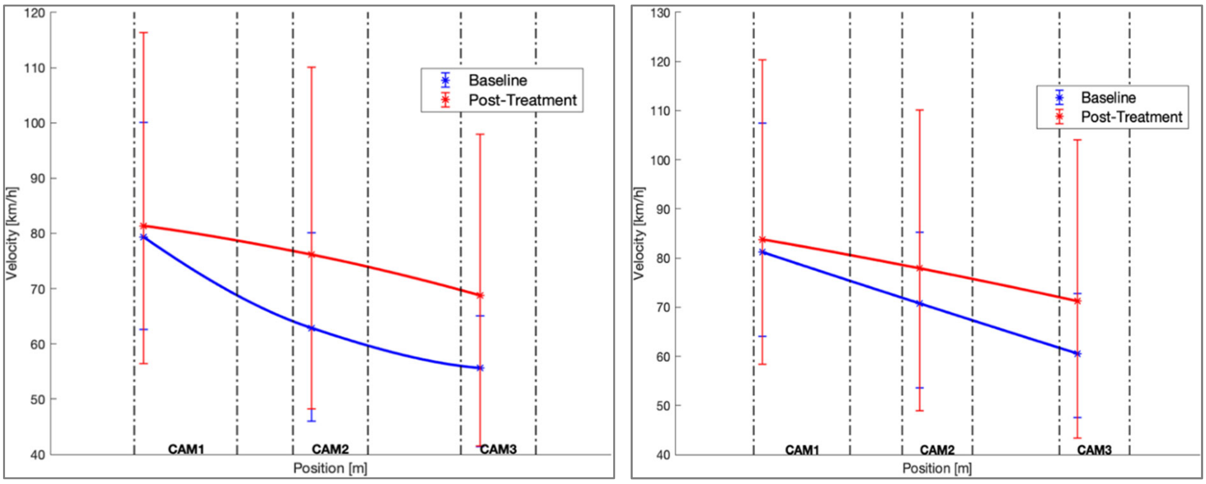

Figure 9-37: On the left side: mean velocity of all riders and range of mean velocity for each rider; on the right side: mean peak velocity of all riders and range of peak velocity for each rider.

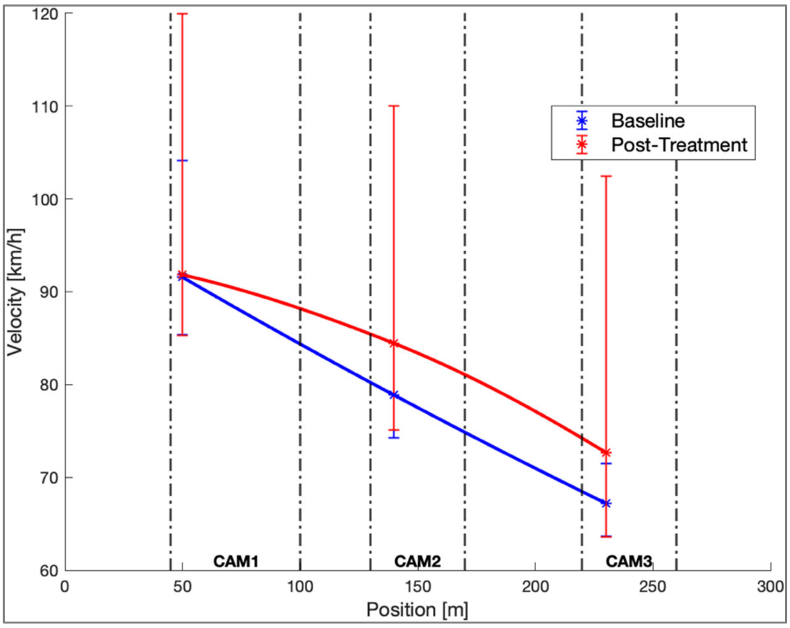

Figure 9-38: Mean velocity of all riders at x = [50, 140, 230] and distribution of rider velocities.

The post-treatment group has always had a velocity higher than the baseline. In 9.7.5, a more in-depth analysis will be reported, but the velocity gap can easily be detected with all velocity parameters.

9.7.3 Velocity Results

As the nudging system targets fast drivers, we started the analysis of the dataset excluding the 75 % of acquisitions, i.e. considering only the fastest riders, defined as the highest velocity quartile (Q3) for each camera. The 'V85' design criterion was not considered because it requires vehicles to travel in free-flowing conditions, i.e. when the preceding vehicle has at least 4 seconds headway, and only the fastest riders above the 85th percentile can be included. Because of the limited number of cases, the criterion was too restrictive and thus not appropriate for the analysis of this set of PTW data.

To evaluate the nudging effect, the best parameters among those identified in chapter 9.7.2 were used, thus excluding the mean velocity since it could blur the differences between the groups. The results for peak velocity (i.e. the maximum value of rider/PTW velocity within each stretch) are reported in figure 9-39: there was an initial offset of 3.0 km/h between the two sets of data, which reduces to 1.5 km/h in the last stretch. A blank x-axis was used, since the peak velocity value occurred at different positions under each camera for each rider. The three selected points were located approximately at the beginning of each stretch, since the velocity curve is generally monotonic and therefore its peaks were located there.

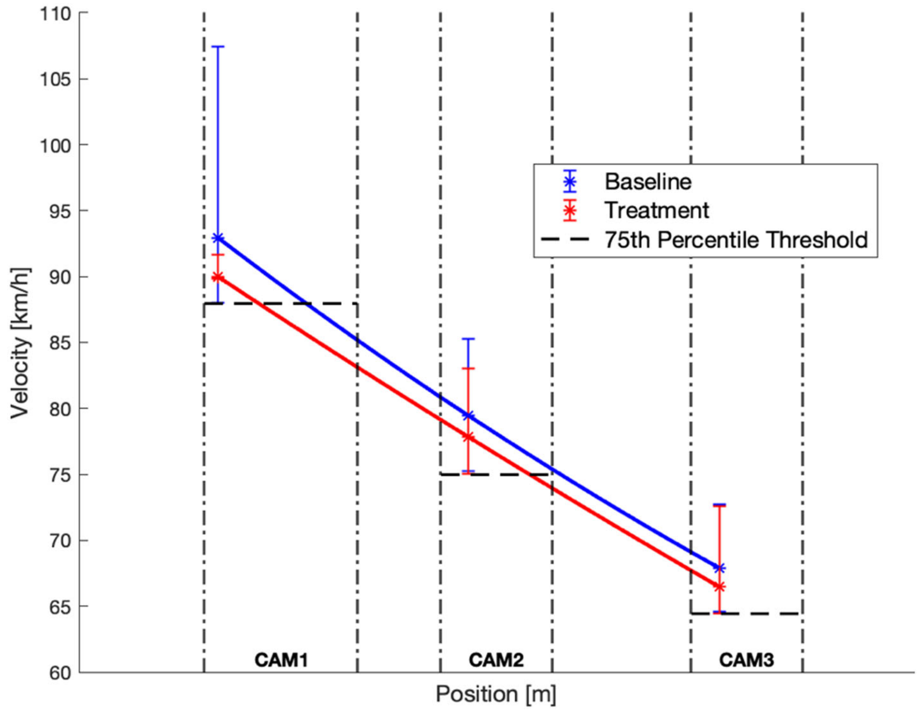

Figure 9-39: Peak velocity under each camera for every biker over Q3

To better investigate the nudging effect, a second parameter, the instant velocity, was considered in several sections along the road. As detected trajectories had different lengths, we optimized the position of the sections to include as maximum number of PTWs while having a fair number of sections to evaluate the riders' behaviour. We chose eight sections located at x = [50, 60, 75, 135, 165, 225, 240, 255]. That is three sections in the first stretch, two sections in the second one (close to the extremities of the field of view) and three sections for the last stretch. In the latter, one section was at the beginning of the camera field of view, whereas the other sections were, 5 and 25 metres after the last light, respectively.

The main differences cropped up after x = 135: the behaviour in the first 100 meters will be better explained in section 9.7.3. A velocity reduction of 1.7 km/h was measured between the baseline and treatment group at the end of the second stretch (at 165 meters). The main reduction of 2.5 km/h was within the last stretch, where the velocity was 62 km/h for the treatment group.

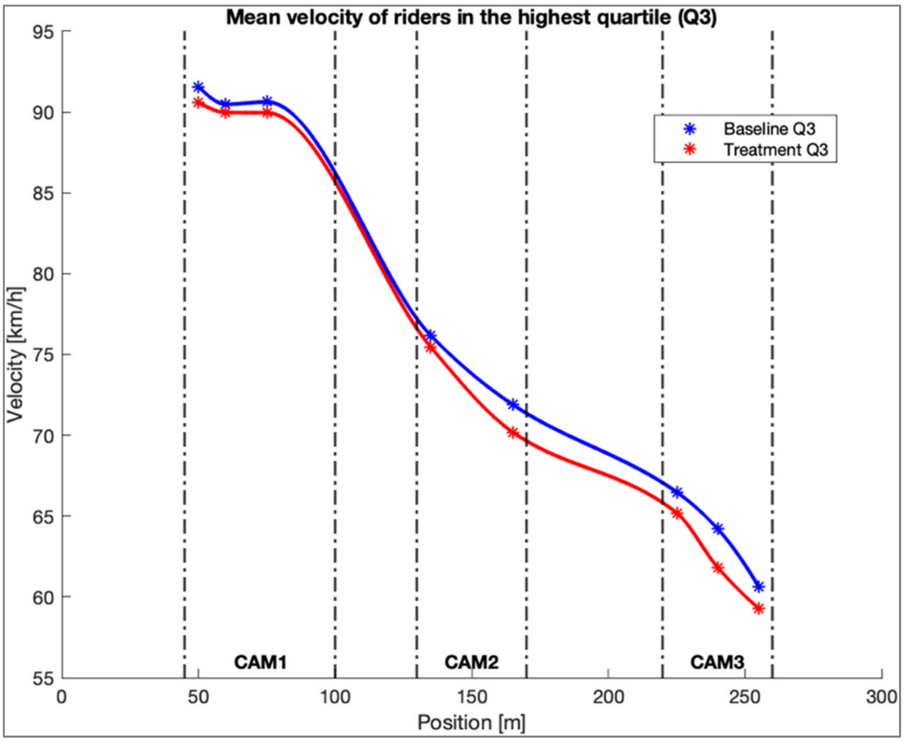

Figure 9-40: Instant mean velocity for drivers in Q3 quartile at x = [50, 60, 75, 135, 165, 225, 240, 255]. An interpolation with C1 continuity was made to better represent data.

A two-way ANOVA analysis was carried out to verify the significance of the above difference. The main effects of (1) *scenario* (i.e. baseline or treatment group) and (2) *position* on velocity were examined. Five replications (i.e. the sections) were used in this test, excluding the section of CAM1, since in the first stretch no PTW is into the exit lane (ref. to section 9.7.4 for data evidence). As only few PTWs were included in the 75th quartile, we extended the statistical basis also to the 50th and the 25th quartile for this test. Generally, there was no effect both for the interaction between the two main factors (i.e. the model is *additive*) and for the scenario itself, as the p-values were over its significatively values. Results are shown in Table 9-27 and Table 9-28.

Threshold	Criteria	P-values			Number of PTWs in the ANOVA test	
		Longitudinal Position	Scenario	Interaction	Baseline	Treatment
Q3	Velocity at X	< .001	0.508	0.958	N = 8	N = 3
	Peak Velocity	< .001	0.670	0.823	N = 9	N = 4
	Mean Velocity	< .001	0.490	0.9215	N = 9	N = 3
Q2	Velocity at X	< .001	0.499	0.944	N = 16	N = 9
	Peak Velocity	< .001	0.975	0.198	N = 17	N = 9
	Mean Velocity	< .001	0.371	0.729	N = 17	N = 8
Q1	Velocity at X	< .001	0.199	0.819	N = 31	N = 18
	Peak Velocity	< .001	0.486	0.370	N = 26	N = 13
	Mean Velocity	< .001	0.376	0.709	N = 26	N = 13

Table 9-27: ANOVA tests for PTWs above Q3 threshold with eight replications.

Factors	*Statistics*	*Q3*			*Q2*		
		Velocity at X	*Peak Velocity*	*Mean Velocity*	*Velocity at X*	*Peak Velocity*	*Mean Velocity*
Scenario	*F*	0.44	0.19	0.50	0.46	0	0.81
	d.f.	1	1	1	1	1	1
	d.f. Errors (within)	42	25	18	101	50	47
Longitudinal Position	*F*	23.86	69.25	39.45	42.16	106.65	93.73
	d.f.	4	2	1	4	1	1
	d.f. Errors (within)	42	25	18	101	50	47
Interaction	*F*	0.16	0.05	0.01	0.19	1.7	0.12
	d.f.	4	1	1	7	1	1
	d.f. Errors (within)	42	25	18	101	50	47

Factors	*Statistics*	*Q1*		
		Velocity at X	*Peak Velocity*	*Mean Velocity*
Scenario	*F*	1.66	0.49	0.79
	d.f.	1	1	1
	d.f. Errors (within)	165	81	80
Longitudinal Position	*F*	40.31	87.97	92.27
	d.f.	4	1	1
	d.f. Errors (within)	165	81	80
Interaction	*F*	0.39	0.81	0.14

	d.f.	4	1	1
	d.f. Errors (within)	165	81	80

Table 9-28: Overall statistics 'between' groups throughout five sections.

Figure 9-41 and Figure 9-43 show box-plots with the velocity variance over Q3 and over Q2 for the five sections used in the ANOVA and the two groups of riders. Sections are numbered progressively from the first at x = 135 and the last at x = 255, as the first stretch is excluded.

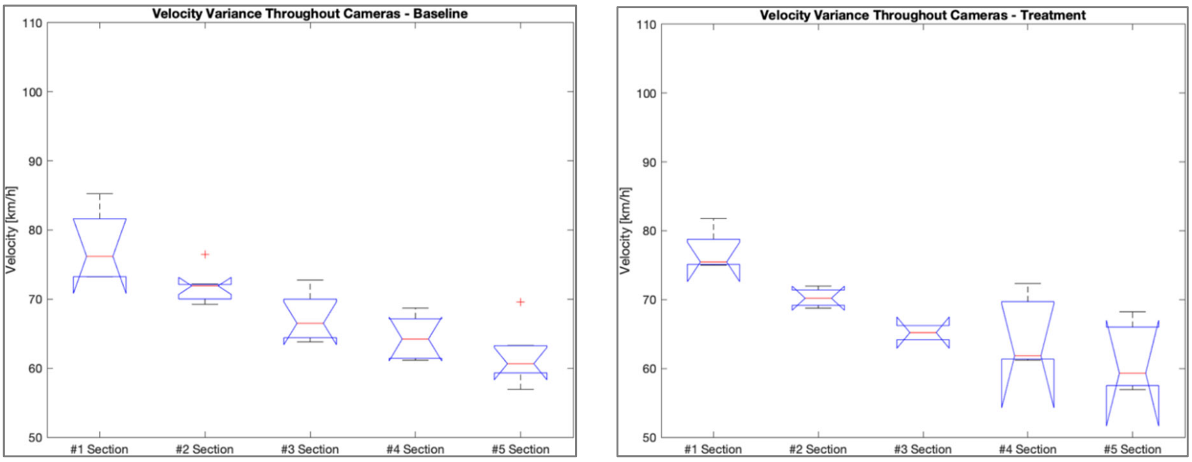

Figure 9-41: Velocity variance in Q3 along the road for every section.

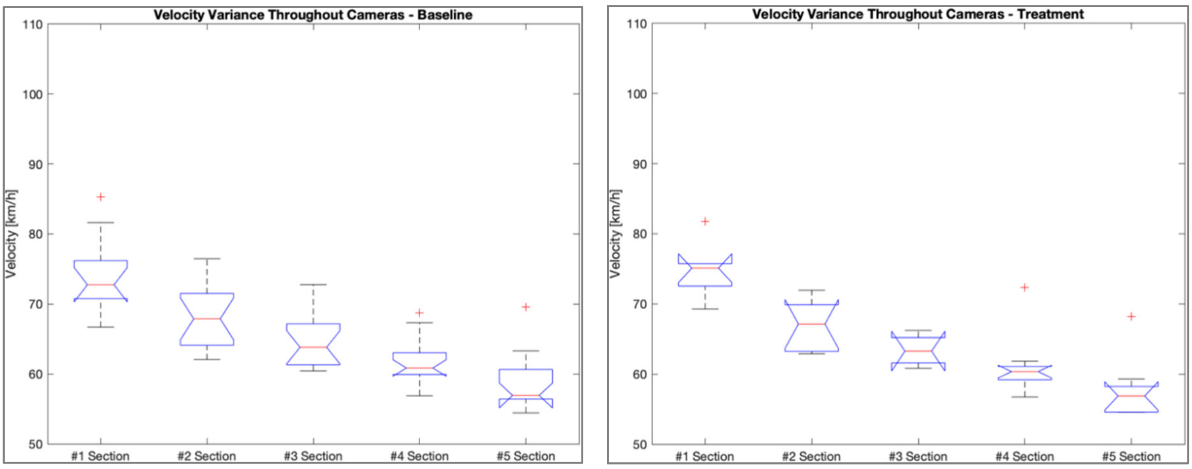

Figure 9-42: Velocity variance in Q2 along the road for every section

Some notched boxes are folded back on themselves. As the size of the notch is indicative of the uncertainty in the value of median, some boxes show big uncertainties and, thus, they are folded back. This might suggest that the size of the dataset is not always appropriate.

9.7.4 Trajectory Results

Trajectories were obtained in the reference system used to describe the exit lane. In Figure 9-43, our data set was superimposed on the road map to get an overview of the PTW's trajectory profiles. It's already visible that many PTWs in the first stretch were outside the exit-lane; anyway, this behaviour is better shown in the next figures.

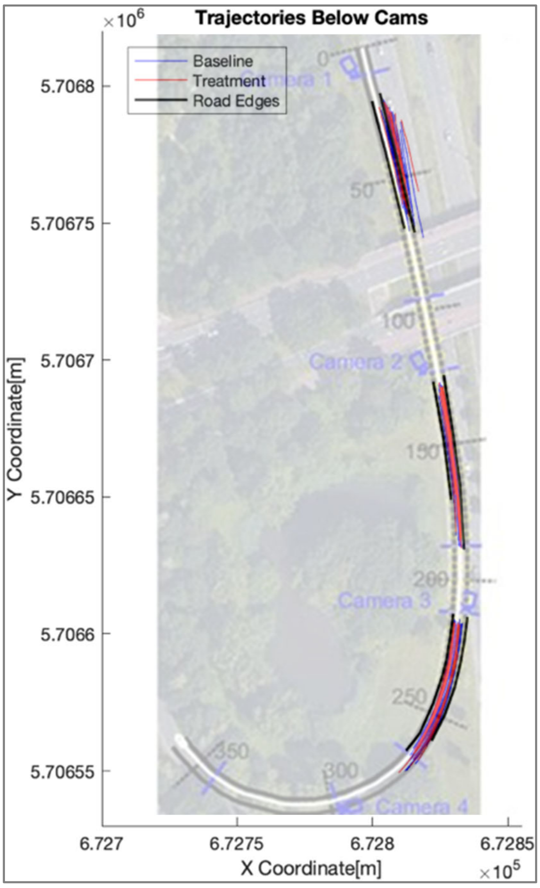

Figure 9-43: Trajectories under each camera, superimposed on real map.

We considered six sections along the road. Each stretch has two sections: they are at x = [50, 75, 135, 165, 225, 255]. The selection criterion for the dataset is analogous to the velocity processing and the Q3 threshold was used. Unlike velocities, the trajectories were not filtered, as they did not show artefacts from the processing.

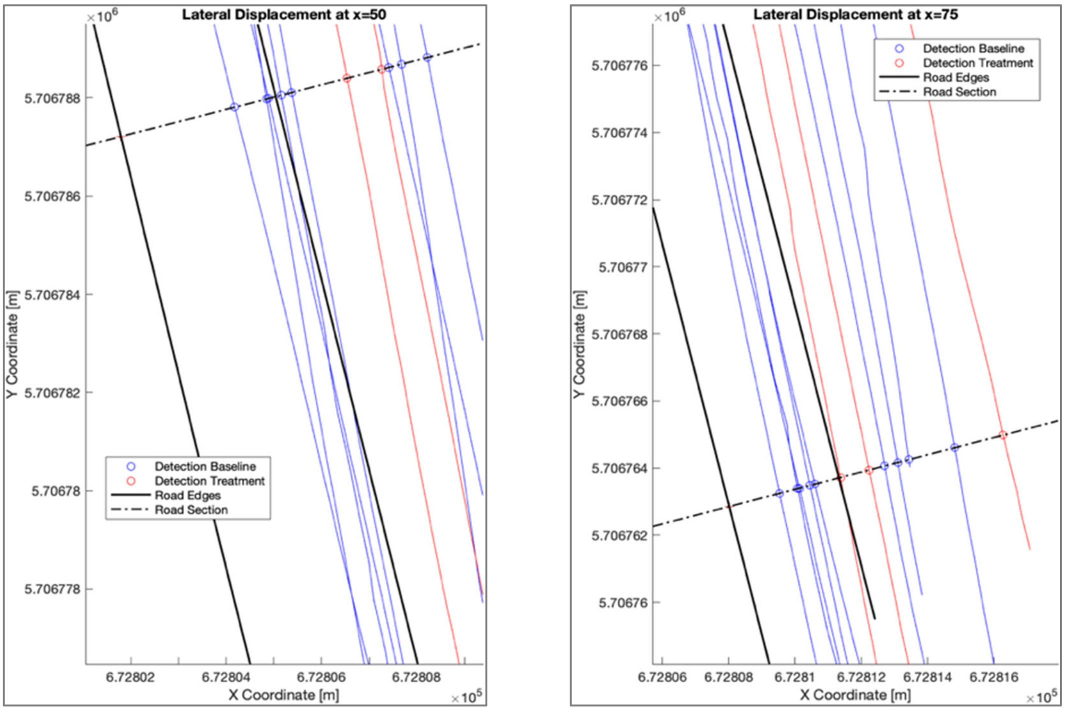

Figure 9-44: Comparison of rider lateral displacement above Q3 at x = 50 and x = 75.

Being outside the exit-lane is a behaviour which didn't belong just to riders in Q3, but it was common to all PTWs. In Figure 9-44, Figure 9-45, Figure 9-46 and Figure 9-47 lateral displacement was shown for CAM1 and CAM2 both for every rider and just those above Q3.

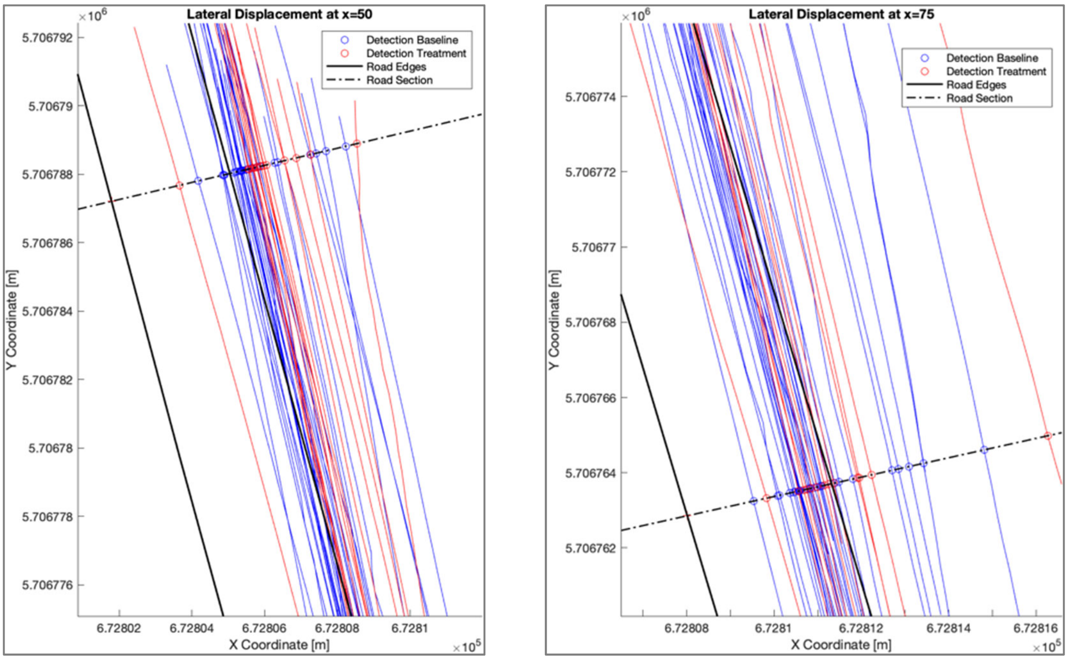

Figure 9-45: Comparison of rider lateral displacement for the whole dataset at x = 50 and x = 75.

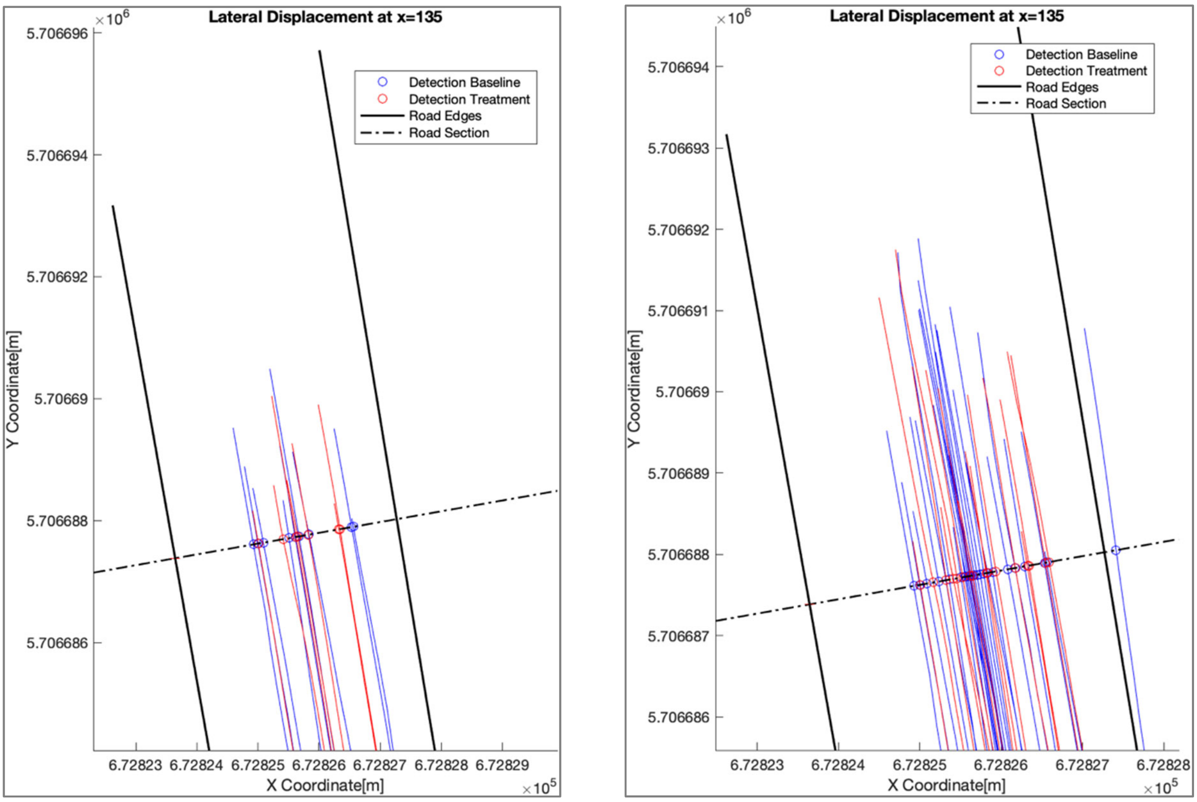

Figure 9-46: Comparison of rider lateral displacement at x = 135 for riders above Q3 (left side) and for the whole dataset (right side).

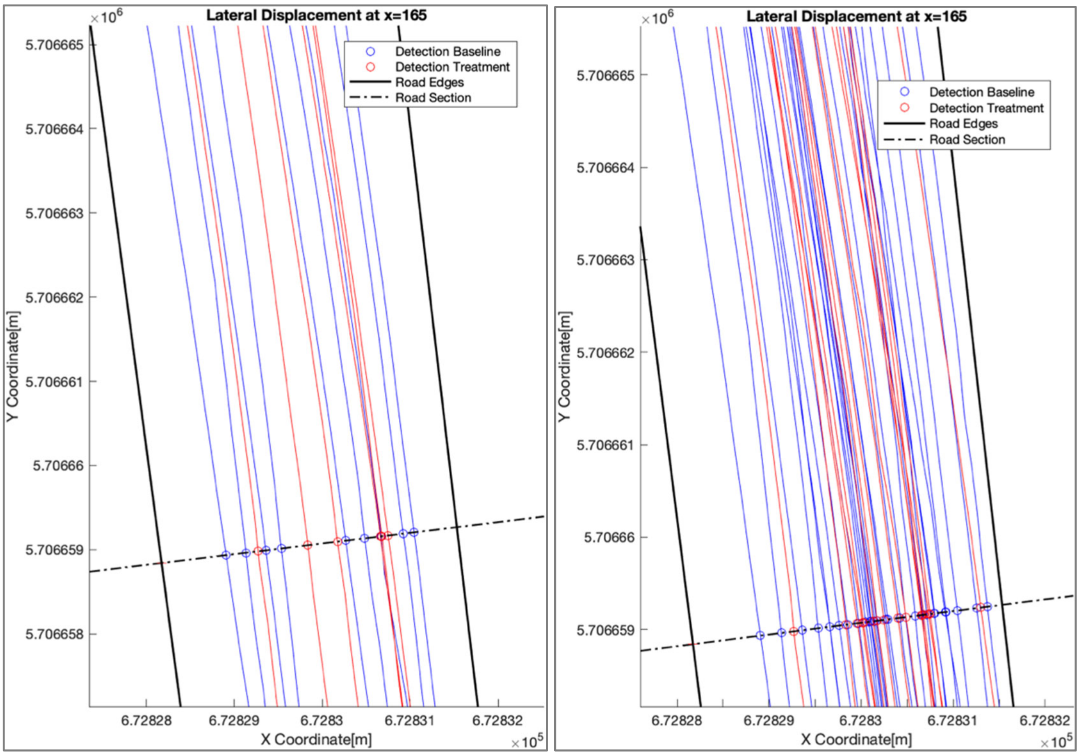

Figure 9-47: Comparison of rider lateral displacement at x = 165 for riders above Q3 (left side) and for the whole dataset (right side).

The velocity gap under CAM1 (Figure 9-40) was investigated in relation to the trajectories shown in Figure 9-44. The PTW position reveals that for the treatment group each rider above Q3 was outside the exit lane at x = 50 and was still outside at x = 75. Only under the second camera at x = 135, all PTWs were in the exit lane. For this reason, the initial velocity gap could not be an effect of nudging, but it might be the result of traffic conditions.

In Figure 9-48 the results of rider lateral displacement in six sections along the exit lane are reported. The initial velocity gap was bigger for bikers above the Q3. In general, who had a velocity above the 75th percentile threshold came from the second or the third lane within the first camera view. This might point out that who was less aware of the exit point held a higher velocity compared to the others (above the Q2), who seemed to have a lower velocity on average. After this initial velocity gap, PTWs had very similar trajectories with small differences into the last stretch. In Figure 9-49 and Figure 9-50, the trajectories below CAM3 are shown.

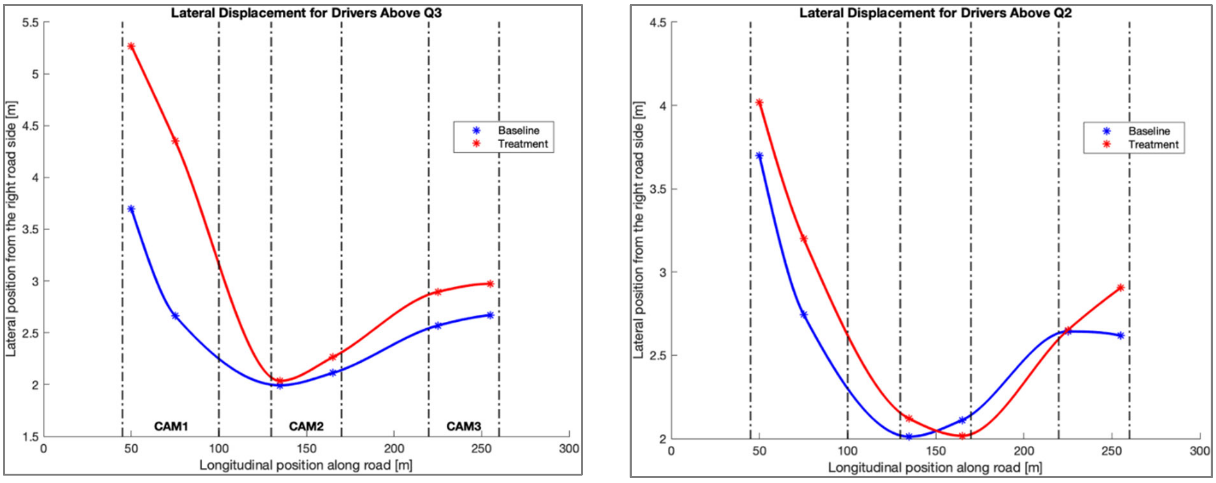

Figure 9-48: Lateral displacement along the exit-lane throughout six sections for riders over Q3 (left side) and riders over Q2 (right side).

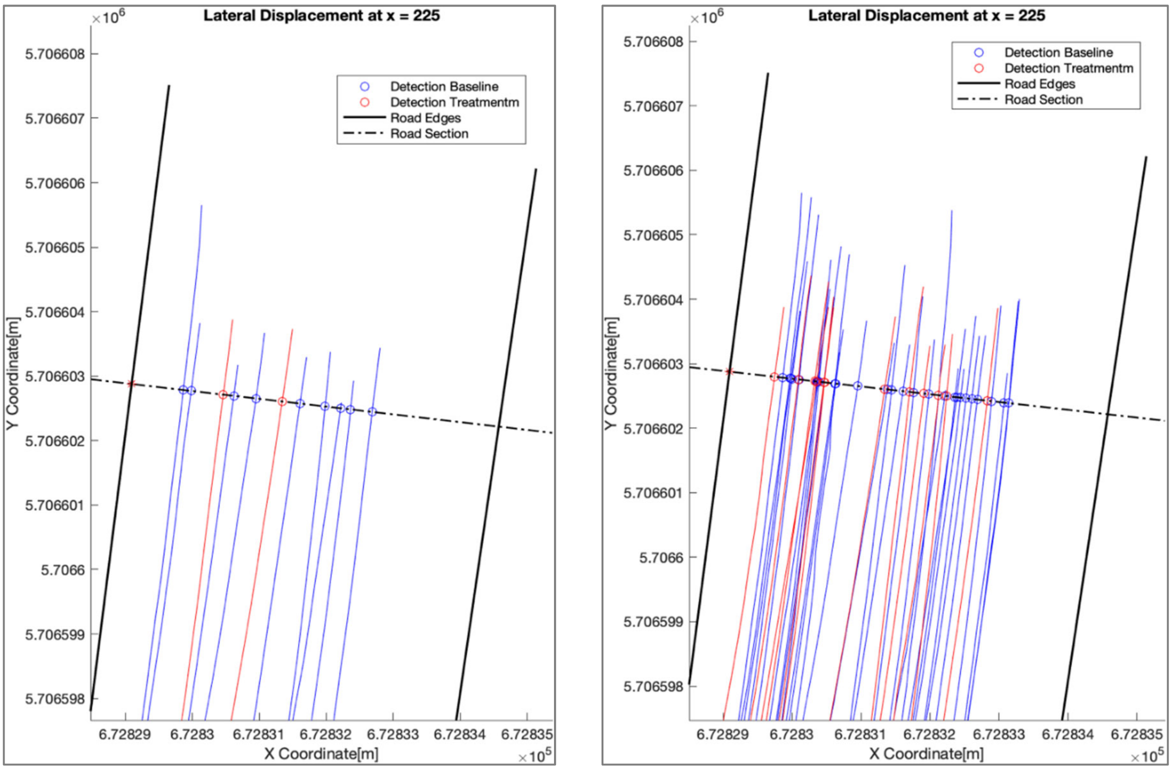

Figure 9-49: Comparison of rider lateral displacement for Q3 dataset and the whole dataset at x = 225.

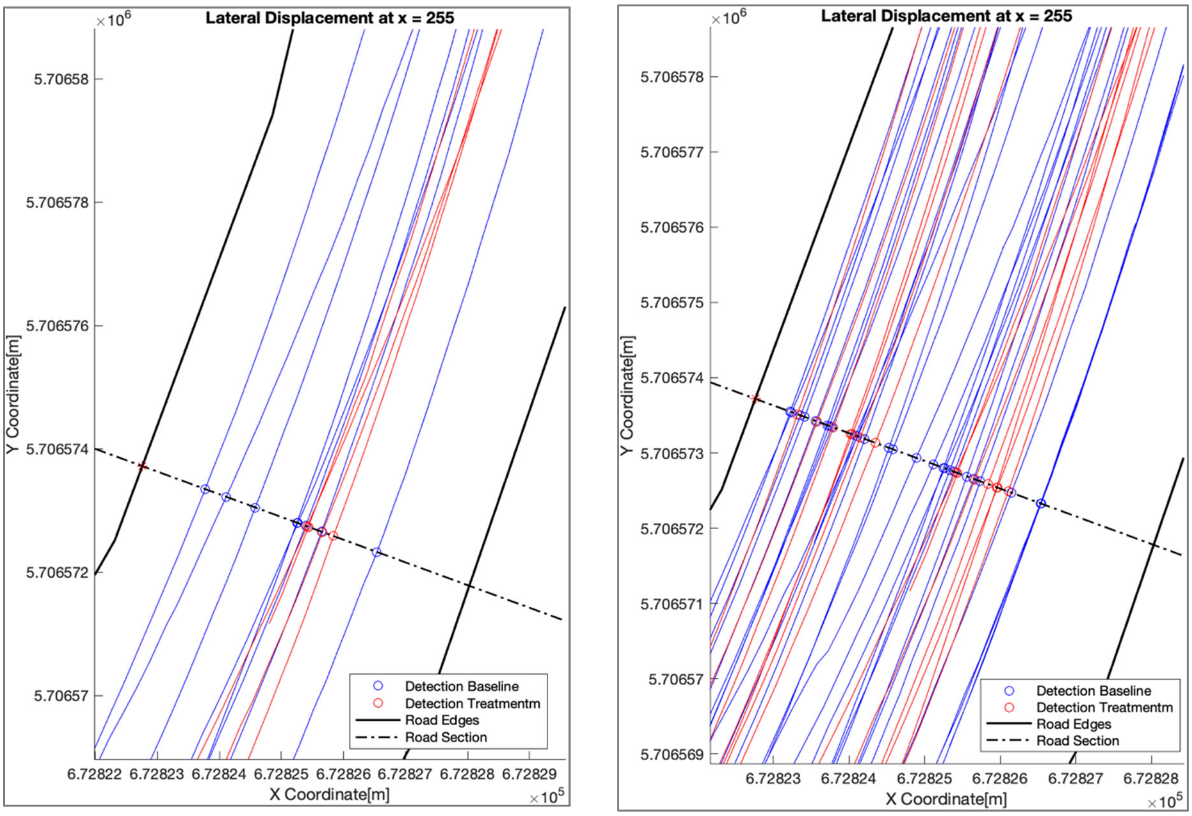

Figure 9-50: Comparison of rider lateral displacement for Q3 dataset and the whole dataset at x = 255.

An overall effect on lateral displacement for scenario was searched with an analysis of variance and four replications both for Q2 and Q3 (lateral displacement from CAM1 data were disregarded because of previous consideration on the intervention of the nudging system). The results are reported in Table 9-29.

Factors	Threshold	Scenario				Number of PTWs in the ANOVA test	
		P-values	F	d.f.	d.f. (*within*)	Baseline	Treatment
Lateral Displacement	Q3	0.708	0.14	1	47	N = 8	N = 3
	Q2	0.578	0.31	1	99	N = 16	N = 9

Table 9-29: ANOVA tests ('between' groups) for lateral displacement with four replications.

9.7.5 Residual effect of nudging system

Video acquisitions in the period June 21st to 23rd were used to define a 'post-treatment' group, as the light system was previously switched off for 16 weeks. Hence, the intention was to assess whether any residual effect of the nudging system could be detected on PTWs. To do this, a comparison between the baseline (October 2019) and the post-treatment group (June 2020) was produced. As specified in 9.7.1, we assumed that no residual effect had appeared after a month for the baseline group since the preliminary tests were conducted. However, in between the baseline group and the post-treatment group, the nudging system was active for 14 weeks (see Table 9-1).

Although the expected profile was similar to the previous treatment group, we found out a curve shifted by about 5÷6km/h towards higher velocity values (Figure 9-51). In addition, the percentage of riders above Q3 increased from the 26% (*N* = *9*) of the dataset for 'baseline' group to the 33% (*N* = *12*) of the overall amount of 'post-treatment' group.

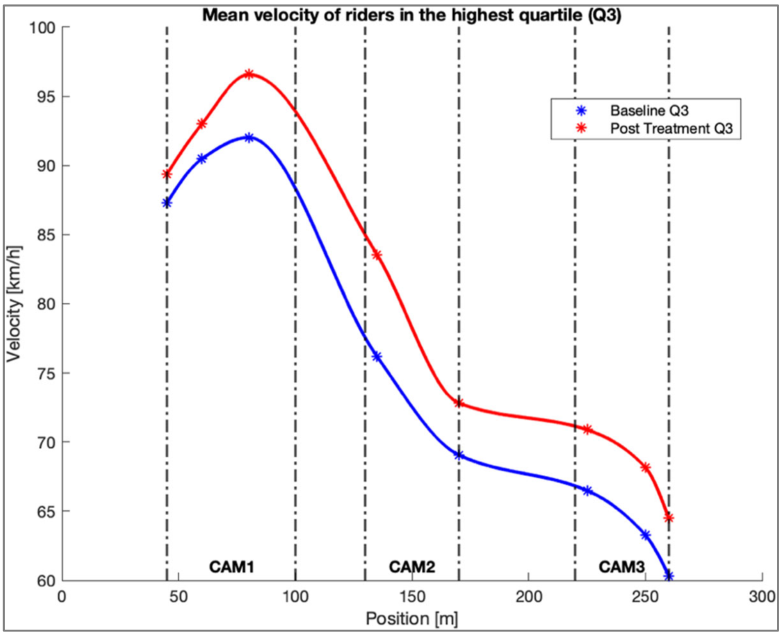

Figure 9-51: Instant mean velocity for drivers in Q3 quartile x = [45, 60, 80, 135, 170, 225, 250, 260]. Comparison between baseline and post-treatment groups.

An ANOVA was conducted using above Q2 and above Q3 datasets (Table 9-30) throughout 8 sections (i.e. x = [45, 60, 80, 135, 170, 225, 250, 260], see Table 9-32).

Criteria	Threshold	P-values			Number of PTWs in the ANOVA test	
		Longitudinal Position	Scenario	Interaction	Baseline	Post Treatment
Velocity at X	Q3	< .001	< .001	0.794	N = 9	N = 12
	Q2	< .001	< .001	0.145	N = 16	N = 16

Table 9-30: ANOVA test ('between groups') for velocity with eight replications

Factors	Statistics	Velocity at X	
		Q3	Q2
Scenario	F	11.83	23.28
	d.f.	1	1
	d.f. (*within*)	128	213
Longitudinal Position	F	53.09	70.15
	d.f.	7	7
	d.f. (*within*)	128	213
Interaction	F	0.55	1.57
	d.f.	7	7
	d.f. (*within*)	128	213

Table 9-31: Overall statistics 'between' groups throughout eight sections

Also, lateral displacement data were processed. The data for the above Q3 and above Q2 datasets is reported in Figure 9-52. An ANOVA test was also performed on the two datasets and the data are reported in Table 9-32.

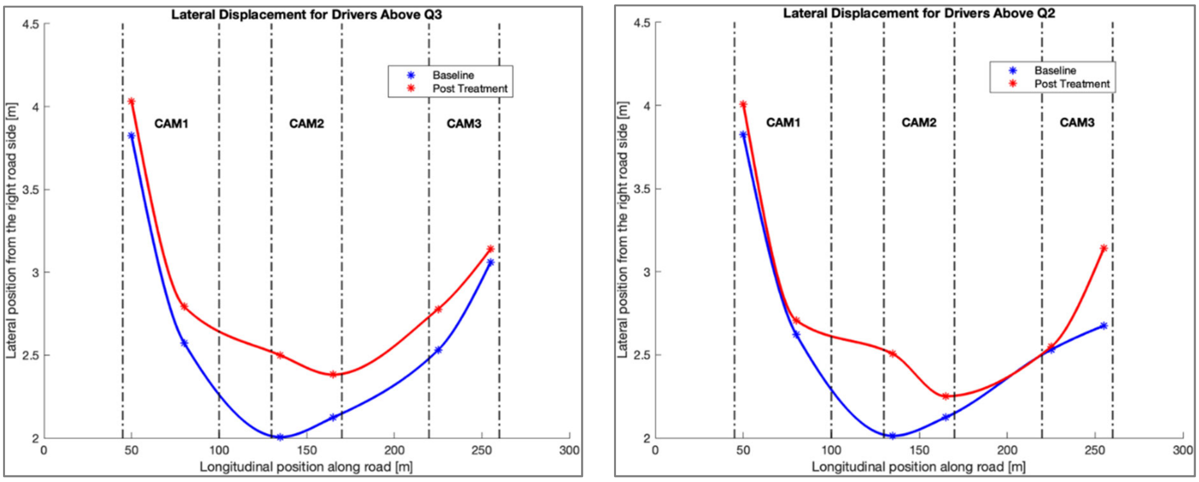

Figure 9-52: Lateral displacement development along the exit-lane throughout six sections for riders over Q3 (left side) and riders over Q2 (right side).

Factors	Threshold	Scenario				Number of PTWs in the ANOVA test	
		P-values	F	d.f.	d.f. (*within*)	Baseline	Post Treatment
Lateral Displacement	Q3	0.363	0.83	1	119	N = 9	N = 12
	Q2	0.158	2.01	1	179	N = 16	N = 16

Table 9-32: ANOVA tests for with six replications

9.7.6 General Discussion for PTW's Driver Results

The dataset with riders exposed to the nudging effect was recorded at the beginning of October 2019. When the system was active a large share of the riders activated the system at least in one section (89.5 %, i.e. $N = 17$ out of $N = 19$ riders). The use of different light scenarios during the observation period and the size of the population only allowed a lumped evaluation of the nudging effect, i.e. without the possibility to discriminate among different light scenarios.

Peak velocity in a section of the system and instant velocity were the two most sensitive parameters for investigating different rider behaviours, together with the vehicle position in the exit lane. The analysis of the trajectories demonstrated that (at x = 50) 80% of riders in the baseline group and 84% in the treatment group were not in the exit lane, but we could only see them all in it with the second camera view. The latter behaviour was observed only among riders and it caused the exclusion of the velocity and position data, derived from CAM1, from all the subsequent analyses. In fact, differences in velocity or in position data could not be an effect of the nudging system. Independently from other analyses, we can conclude that: 1) future infrastructure-based nudging systems for riders should consider this behaviour and, more generally, the different mobility of riders among lanes; 2) these systems should be designed to have an effect also on riders that enter the exit lane very late (e.g. extending the nudging area more than needed for cars).

Effects of the nudging both on velocity and the rider positioning in the exit lane were tested independently with an ANOVA comparing the baseline and treatment groups and using different segmentations of the dataset. Specifically, three different subsets were created using Q1, Q2 and Q3 quartiles of the velocity parameters in each section. These subsets were created to target increasingly faster riders, i.e. riders that should be more sensitive to the nudging system. Differences were found both in the peak velocity (Figure 9-39) and in the instant velocity (Figure 9-40), but they were not statistically significant. Similar results were found for the Q2 and Q1 subsets (Table 26). Also, the effect on the lateral positioning in the exit lane is not statistically significative although differences were noticed in the data (Figure 9-48). We can conclude that the tested nudging system doesn't produce any statistically relevant effect on riders. Nonetheless the size of the dataset is a limitation of the current study and a more extensive testing should be performed before drawing final conclusions.

A third dataset was created with data acquired in June 2020. This dataset, 'post-treatment', was recorded after 18 weeks of system activity. It was compared with the baseline group to check differences in rider's behaviour, which could be linked to the long-term activity of the nudging system (data recorded only for cars). The results showed higher velocity in the post-treatment group. The differences were statistically significative for ANOVA with scenario as independent parameter (Table 9-29). On the contrary the lateral positioning of the riders in the exit lane was not (statistically) different in the baseline and post-treatment groups (Table 9-32). The resulting change in velocity, between the baseline and post-treatment groups, would require more data both within the groups and in time for a robust interpretation.

With the available information we observe that: 1) there is no effect for the nudging in the treatment group for PTWs; 2) there is a velocity increase in the post-treatment group. We repute that the latter change is not an effect of the long-term presence of the nudging system, in the form of a risk compensation effect, since no beneficial effect was initially observed. We suppose that the change is linked to other factors, mostly environmental ones, which may influence riding behaviour:

1. seasonal effects: the baseline data were acquired in October 2019, during slightly rainy days (as confirmed from historical series of meteo data for the Eindhoven area by MeteoBlue's Archive), while the post-treatment data were recorded in June 2020 during sunny days. The environmental conditions influenced both the visibility and the road friction.

2. in April 2020, the road was partly re-paved.

Both the meteo conditions and the new tarmac may have produced a significative effect on the riders' behaviour, inducing a more confident attitude in June, which turned out in a higher speed.

In conclusion, the infrastructure-based nudging system, designed for car drivers, didn't produce any beneficial effect on riders. This result should be confirmed by future studies using larger datasets. Nonetheless, we suggest that infrastructure nudging systems should be designed taking into consideration the specific behaviour (incl. road usage) of all road users. In fact, because of specific behaviours, the design developed for a single group could not produce benefits for all road users. Lastly, seasonal effects should be investigated more in-depth and, in the meanwhile, they should be attentively considered in long term validation campaigns, since they could influence the validation of a system.

10 Final results for O8: Cyclists' speed reduction – Sweden (SAFER/ Chalmers University)

10.1Introduction

Crashes between cars and cyclists at urban intersections are common and their consequences are often severe (European Commission, 2018b). Typical causes for this type of crashes included excessive speed of the cyclist as well as car drivers failing to see the cyclist (Isaksson-Hellman & Werneke, 2017). Measures that decrease the cyclists' speed may lead towards safer car-cyclist interactions. The aim of this part of the project was to investigate the extent to which cyclists may approach intersections more safely when nudged to decrease their speed. This has been done by measuring the cyclist speed on the nudge before and after the nudge was installed and by conducting interviews with passing cyclists. We also investigated environmental factors that may influence the speed on the nudge.

10.2 Method

10.2.1 Locations

Several type of nudges (transverse stripes, lane narrowing stripes and digital, adaptive, speed signs) have been tested in previous pilot studies, and a transverse nudge was shown to be more feasible when cycling than the other tested nudges (MeBeSafe D3.1, Wallgren & Bergh-Alvergren, 2019). Consequently, the transverse nudge, shown in Figure 10-3, was selected for this field study. The nudge has a gap decrement of 7.25 % per gap from an initial gap of 2 metres, leading to 17 gaps and a total decrement of 70 % over 19.9 metres. The nudge was implemented on the bicycle lane by means of a white road tape which did not produce any vibrations or haptic feedback for the cyclist.

To investigate the effect of the visual nudge, two locations in the city of Gothenburg, Sweden, were selected that satisfied the criteria: a) cyclist lanes that are leading to an uncontrolled intersection between cyclist and vehicles, and b) crashes and/or incidents should have happened at the intersection to justify the nudge. The locations and the installed visual nudge are shown on Figure 10-1 and Figure 10-2. At location 1, Nobelplatsen, the bicycle lane is unidirectional with a 1.5 m lane width. The bicycle lane disappears soon after the intersection and the cyclist's view of the intersection is blocked until 10 m before the intersection. The bicycle lane is separated from the street and is at the same level as the pedestrian pathway. There is an on-street parking for vehicles on the left, and shops and restaurants on the right of the bicycle lane. The bicycle lane has a slight downwards slope. Location 2, Götaälvbron, has a two-way bicycle lane, 1.2 m lane in width, which is separated from the street and at the same level as a pedestrian pathway to the right. It has a downwards slope which continues from a bridge giving the bicyclists extra speed.

Figure 10-1: Site 1. The installed nudge (left). Nobelplatsen (57°42'49.6"N 12°00'23.4"E). The bike lane is unidirectional and the bikes comes from the low right corner of the picture moving towards the top left (right).

Figure 10-2: Site 2. The installed nudge (left), note the Viscando Otis measuring equipment mounted on the light pole nearest in the picture. The Götaälvbron site (57°43'12.4"N 11°57'45.5"E), the bike lane is the lane most to the right in picture (right).

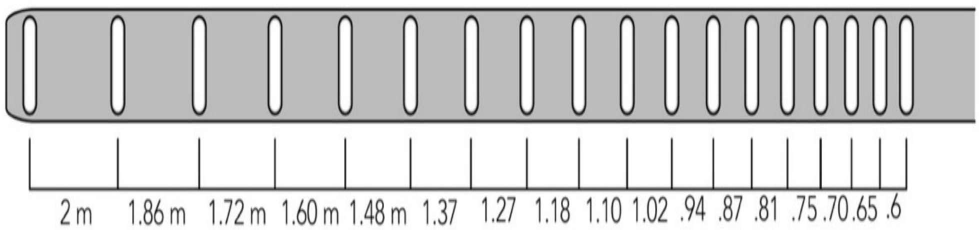

Figure 10-3. The nudge design consisting of transverse lines with decreasing distance. Total distance of the nudge is 19.9 m.

10.2.2 Camera-based system

Video data from the two locations were recorded with a site-based video recording system provided by Viscando ("Viscando," 2020). This consists of two OTUS3D FLEX units. Each unit has a pair of cameras producing a stereo image that is processed by the device resulting in tracks of individual road users. The processed tracks data are transferred wirelessly to Viscando. This makes the units GDPR compliant as the data are generated in real-time and the recorded images are neither sent nor stored.

10.2.3 Data

The data provided by the camera-based system consists of information about a road user with following attributes: timestamp, type of road user (cyclist, pedestrian, car and truck), position, and speed ("Viscando," 2020). The trajectories that were included in the analysis for this study were filtered to include: cyclists' trajectory on the cyclist's lane where the nudge was installed, the trajectory was straight (no turning) in a direction north (according to the road geometry, see Figure 10-1 and Figure 10-2) and the trajectory was at least 25 m long. The cyclist's data was then combined with data about weather (sunny/rain/cloudy), cyclist type (commuter/leisure), day of week (weekday/weekend) and wind (direction and speed). Regarding cyclist type, cyclists cycling on weekdays in the morning peak period (7-8:00) and evening peak period (16-17:00) were classified as commuters, while leisure cyclists were the ones who cycled on weekends in off-peak hours (12-18:00). A wind component was derived from wind direction and speed and categorized as neutral (between −1 and 1 km/h), headwind (>1 km/h) and tailwind (<−1 km/h).

10.2.4 Field Trial design

The experiment was designed to compare the cyclists' speed before (baseline) and after (treatment) the nudge was installed. The baseline and treatment periods were equivalent in terms of seasons, as shown in Table 10.1 and Figure 10-4. The data was collected for four consecutive days from Wednesday to Saturday, except for the baseline condition in location 1, which included data collected during 3 days (Thursday to Saturday). Furthermore, two treatment periods were recorded to capture the effect of the nudge over time in location 1. For location 2, the second treatment period was cancelled due to roadworks on the cyclist path.

10.2.5 Data analysis

The average cyclist speed was analysed for three positions along the nudge: at the beginning, middle, and at the end of the nudge. Furthermore, two measures: a) proportion of cyclists decreasing speed between the beginning and at the end of the nudge over a certain threshold (10 %, 20 % and 30 %) and b) percentage of cyclists at the end of the nudge at speeds greater than 20, 25 and 30 km/h were also investigated. These measures were compared between baseline and treatment. These types of measures have been previously used for evaluation of traffic-calming techniques for vehicles (Charlton, 2003; Gehlert, Schulze, & Schlag, 2012; Hallmark et al., 2007b). Different factors that may affect the cyclist speed at the end of the nudge were further investigated, since decreasing the speed while approaching the intersections may play a role in decreasing the conflicts with vehicles.

The statistical analysis of the mean speed at the different positions was conducted using a two-factor analysis of variance (ANOVA). To find out which groups are statistically different from one another, a Tukey's Honestly Significant Difference (Tukey's HSD) post-hoc test for multiple comparisons was performed. The threshold for statistical significance for the tests was set to = 0.05. A Chi-square test was performed to compare two proportions with alpha=0.05. The statistical analyses were performed on the whole dataset and on sub-datasets that had been divided according to different potential confounding factors, namely cyclist type, weather and wind. The rationale for this analysis was 1) to tell apart the effect of the nudge from factors that are known to affect cyclist speed and 2) to compare the effect size of the speed reduction from the nudge with that of these factors.

Location	Condition	Month
1) Nobelplatsen	Baseline (3 days)	September
	Treatment 1 (4 days)	September
	Treatment 2 (4 days)	October
2) Götaälvbron	Baseline (4 days)	April
	Treatment (4 days)	March

Table 10-1. Field trial design.

Figure 10-4. The timeline of the test; note that the nudge was present at the location for the whole treatment period.

10.2.6 Short interviews

Short interviews with passing bicyclists were conducted at both test locations on the first day of the treatment. The interviewers were standing just out of sight of the location where the nudge had been installed to assure that their presence didn't affect the behaviour of the cyclists. The locations were also chosen so that there was extra space to stop and where speed naturally would be a bit slower. The bicyclists were approached and asked if they could spare a minute to talk about cycling. They were then asked if they had seen anything special on the cyclist lane, if not they were shown a picture of the installed measure. They were then asked what they thought was the purpose of the marking, if they thought it had any effect on their behaviour, and if they would like to see such markings in the cyclist lane. In total 54 interviews were performed, 31 at location 1 and 23 at location 2. The nature of how the bicyclists were approached meant that few really fast bicyclists were interviewed. Furthermore, (and possibly related) more females than males stopped for interviews, 30 and 24, respectively.

10.2.7 Instrumented bikes study

In addition to the study on the particular selected nudge, an additional study was performed where 17 cyclists' bikes were instrumented with a GPS equipped action cam (Garmin VIRB Ultra 30). The cyclists were recruited among the ones who stopped for the short interviews. Seven were men and ten were women. All participants were regular bicyclists. The purpose of this study was to investigate how different designs of the bike infrastructure nudge the cyclists to different behaviour.

The cyclists were asked to record one of their daily commutes. After the trip was recorded, the cyclist was invited to an interview where they looked at the recording together with a researcher and discussed the trip. The interviews were semi-structured based on the participants' comments on circumstances observed in the film. Topics that were discussed were e.g. situations that the participant thought dangerous, pleasant, efficient et cetera, why they perceived the situations this way, and how they motivated their behaviour in different situations.

The interviews were transcribed, timestamped, and analysed with the software NVivo. The data was inductively coded in terms of objective aspects (e.g. objects, people, places, situations) and subjective aspects (e.g. valuation, priorities, feelings). The comments containing the subjective aspects were examined and generalized to a set of *behavioural factors.*

Additionally, a search-query was done to find comments relating to frequency (e.g. never, always, sometimes, rarely). Each comment and their corresponding video section were examined in order to recognize patterns in the bicycle environment. The analysis resulted in a set of *contextual factors* that were considered to affect cyclist behaviour. The contextual factors were combined to create generalized/typical *layouts* of the cyclist environment.

10.3 Results

10.3.1 Speed data analysis

The number of cyclist trajectories that satisfied the criteria explained in Section 10.2.3 for baseline, treatment 1 and treatment 2 for location 1, were 740, 1151 and 995, respectively, while for location 2 they were 1301 and 1292. The speed distribution at three positions for baseline and treatment at the respective locations is shown in Figure 3. An overview of the ANOVA including the main effects and interactions for each location, can be found in Table 2 and Table 3, respectively. As can be seen the main effects condition (baseline, treatment) and position, as well the interaction effect between them were significant for both locations. The effect of the nudge on average speed at the end of nudge was different across locations and treatment repetition, though. For location 1, the speed at baseline was higher than at treatment 1 and lower than at treatment 2, both $p < .001$. For location 2, the speeds at treatment were higher than the baseline (see table 10.3).

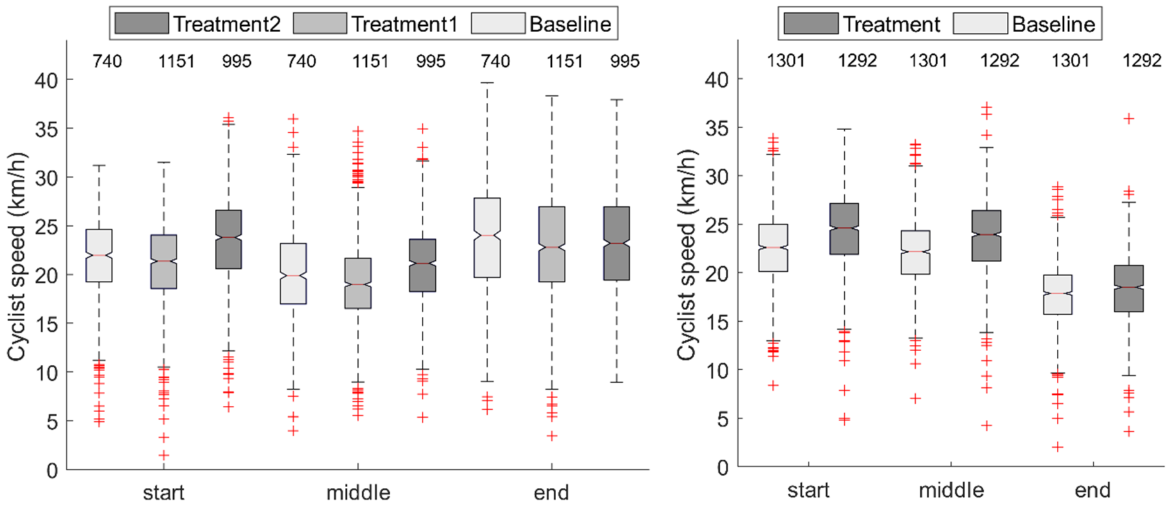

Figure 10-5. Distribution of cyclist speed at different positions and conditions for location 1 (left) and location 2 (right). The numbers on the top report the sample size for each boxplot.

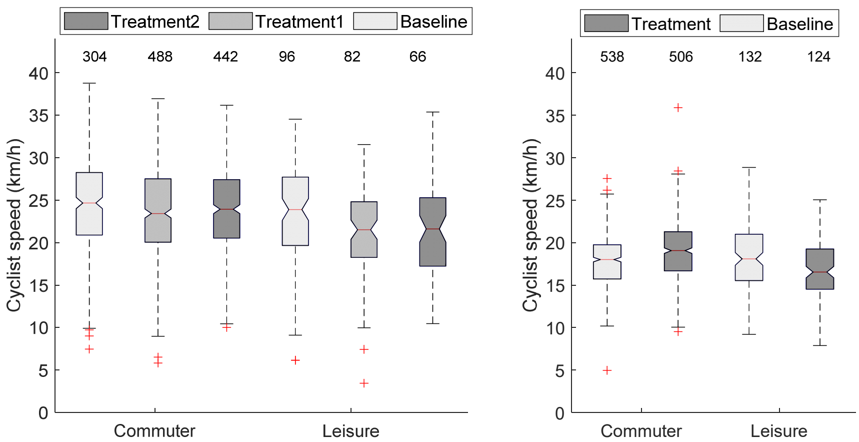

Figure 10-6. Distribution of cyclist speed for commuter and leisure cyclist at the end of the nudge, for location 1 (left) and location 2 (right).

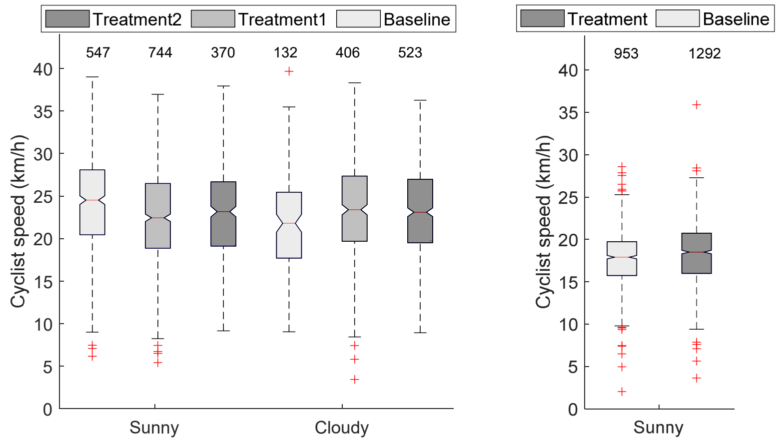

Figure 10-7. Distribution of cyclist speed at the end of the nudge in different weather conditions for location 1 (left) and for sunny weather for location 2 (right).

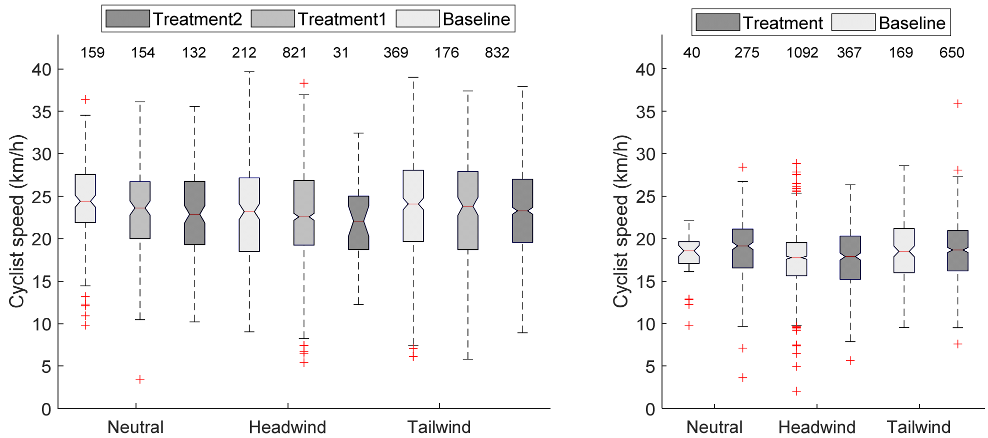

Figure 10-8. Distribution of cyclist speed at the end of the nudge for different wind conditions for location 1 (left) and location 2 (right).

	F	*p*
Condition	82.04	< .001
Position	297.89	< .001
Condition x Position	17.12	< .001

Table 10-2. Summary of ANOVA results for location 1.

	F	*p*
Condition	267.30	< .001
Position	1802.47	< .001
Condition x Position	18.85	< .001

Table 10-3. Summary of ANOVA results for location 2.

We investigated also the different factors that may affect the speeds at the end of the nudge.

Regarding cyclist type, commuters were less affected by the nudge than leisure cyclists, see Figure 10-6. The main effects condition and cyclist type were significant for location 1, see Table 10-5. At location 2, the cyclist type and the interaction between condition and cyclist type were significant, $F(1,1296) = 16.71$, $p < 0.001$ and $F(1,1296) = 26.34$, $p < 0.001$, see Table 10-6. At this location, leisure cyclist had lower speeds in treatment than in baseline, $p = 0.0211$. This effect was opposite for the commuters, namely the commuters had higher speeds in treatment than in baseline, the result was statistically significant, $p < .001$.

Regarding weather conditions for location 1, there was no overall effect of either condition or weather, but there was a crossover interaction $F(2,2716) = 13.37$, $p < 0.001$, see table 10.4.

The effect of weather on the speed was opposite, depending on the value of the condition. Post-hoc comparison revealed that speeds in treatment 1 and treatment 2 for sunny weather were lower than in baseline, $p < 0.001$ and $p = 0.0213$, respectively. However, the speeds in treatment 1 and treatment 2 were higher than in baseline for cloudy weather, $p = 0.0197$ and $p = 0.0371$, respectively. For location 2 all cyclist passages in treatment were in sunny weather, warranting only comparisons for this condition. In this location, the treatment speeds were higher than baseline speeds for sunny weather ($t = -4.49$, $p < 0.001$).

	F	p
Condition	0.21	0.8107
Weather	2.31	0.1287
Condition x Weather	13.37	< .001

Table 10-4. Summary of ANOVA results for location 1 for factors condition and weather. Significant effects in boldface.

	F	p
Condition	3.34	0.0354
Cyclist type	26.51	< .001
Condition x Cyclist type	0.46	0.6306

Table 10-5. Summary of ANOVA results for location 1 for factors condition and cyclist type. Significant effects in boldface.

	F	p
Condition	0.0002	0.9868
Cyclist type	16.72	< .001
Condition x Cyclist type	26.34	< .001

Table 10-6. Summary of ANOVA results for location 2 for factors comparison situation and cyclist type. Significant effects in boldface.

When taking into consideration the wind, the contradicting results across locations were not evident or statistically significant any longer. The main effect of wind was statistically significant, both for location 1, $F(2,2877) = 3.66$, $p = 0.0257$ and location 2, $F(2,2587) = 16.42$, $p < 0.001$, see table 10.7 and table 10.8, respectively, confirming that tailwind increases speed while headwind reduces it. The main effect of condition was not statistically significant anymore..

	F	*p*
Condition	2.46	0.0853
Wind	3.66	**0.0257**
Condition x Wind	0.75	0.5572

Table 10-7. Summary of ANOVA results for location 1 for factors condition and wind (wind threshold = 1 km/h). Significant effects in boldface.

	F	*p*
Condition	1.07	0.2991
Wind	16.42	< .001
Condition x Wind	0.42	0.6561

Table 10-8. Summary of ANOVA results for location 2 for factors comparison situation and wind (wind threshold = 1 km/h). Significant effects in boldface.

Individual cyclists decreased their speed, from the beginning to the end of the nudge, more in treatment than in baseline, see Table 10-9. For location 1, the proportion of cyclist decreasing their speed more than 10% was greater in treatment 2 in comparison to baseline, p <.001. For location 2, the proportion of cyclist decreasing their speed more than 20% (p <.001) and 30% (p <.001) was greater in treatment than in baseline.

	Percent threshold	10%	20%	30%
Location 1	Baseline	**92 (12%)**	50 (7%)	29 (4%)
	Treatment 1	152 (13%)	80 (7%)	37 (3%)
	Treatment 2	**211 (21%)**	87 (9%)	32 (3%)
Location 2	Baseline	1253 (96%)	**715 (55%)**	**154 (12%)**
	Treatment	1257 (97%)	**927 (72%)**	**326 (25%)**

Table 10-9. Number and percent (in brackets) of cyclists decreasing their speed from the start to the end of the nudge for more than percent threshold. The boldface indicates significance using test of proportionality.

10.3.2 Short interviews

The majority of the participants (44 out of 54) noted or recognized the nudge when shown a picture of it. More than 70% (N = 39) of the participants interpreted the nudge as something that intended to slow down bicyclists and/or warn for a dangerous intersection. Half of the participants thought that the nudge affected their behaviour in that they slowed down more and were more careful than usual. Interestingly, almost 90% (48 of 54) participants accepted this type of markings in bicycle lanes, often stating that everything that makes the traffic situation safer is good. The reason stated for not accepting these types of markings in the cyclist lane was, without exception, that one did not understand their purpose.

Noticed the nudge	Number of responses
Saw the correct nudge	24
Recognised the nudge from picture	20
Did not recognise the nudge	10

Purpose of the markings	Number of responses
Slow down	24
Warn for intersection	25
Other/Don't know	14

Acceptance	Number of responses
Would like to see these type of markings before dangerous intersections	48
Don't want the markings	6

Table 10-10: TABLE on interview answers

10.3.3 The instrumented bikes study

A group of factors that affects how cyclists behave in traffic, according to our tentative model, are what we choose to call *contextual factors (CF).* These factors are divided into two sets (see Table 10-11) of which one relates to fewer interactions and less effort for cyclists (CF2, CF4, CF7, CF6b) and the other relates to more interactions and higher effort (CF1, CF3, CF5, CF6a, CF6c). They exist either by intentional design or by chance.

Contextual Factor	Description	Examples	E[1]
CF1. Destinations for pedestrians (D_P)	Popular locations where people go to and from	Shops, residential houses, doors (in general), trash bins, benches, school buildings, shopping malls, public transport stops, parked cars[2]	+
CF2. Obstacles for pedestrians (O_P)	Longitudinal elements creating non-traversable barriers	Rivers, high fences, busy highways, buildings	−
CF3. Obstacles for cyclists (O_C)	Elements located on or next to the bicycle infrastructure affecting passage or vision	Holes, icy patches, maintenance holes, uneven ground, edges of asphalt, leaves, gravel, pools of water, fruits or nuts from trees, vehicles, 'zig-zag' railing before road crossing, rumble stripes, tunnels, buildings	+
CF4. Dividers between lanes (V)	Elements increasing the distance between lanes	Stones, trees, cobble stones, spacing, railings, fences	−
CF5. Elevations for cyclist (E)	Elevation changes from one point to another	Hills, bridges, high ground to low ground and back to high ground again	+
CF6a. Lanes for car drivers (L_D)	Travel paths for car drivers	Car roads, highways, cyclist boulevards, Shared roads with car drivers and cyclists	+
CF6b. Lanes for cyclists (L_C)	Travel paths for cyclists	Bike lanes, cyclist boulevards, shared roads with pedestrians and cyclists, shared roads with car drivers and cyclists	−
CF6c. Lanes for pedestrians (L_P)	Travel paths for pedestrians	Pedestrian roads, shared roads with pedestrians and cyclists	+
CF7. Shortcuts for cyclists (S_C)	Short trajectory segments allowing for easier passage	Segments having less interaction with other road users, with less obstacles, being less uphill	−

1. Relation to number of interactions and amount of effort. Plus sign implies more and minus sign implies less.

2. Parked vehicles is a dynamic destination. Car drivers are pedestrians after they step out or before they step into the vehicle.

Table 10-11: Definitions and examples of contextual factors (CF) of bicycle infrastructure.

The importance of the *contextual factors (CF)* is that they result in different behaviours (see Figure 10-9 to *Figure* 10-20 for some examples). Cyclists will generally keep their speed if they perceive it possible and change their trajectory to avoid obstacles. If they don't perceive it possible, they will decrease their speed or stop. Most CF:s will likely result in a trajectory-changing behaviour, if placed on one side of a bike lane (e.g. Figure 10-9, Figure 10-11) while if they are placed on both sides the resulting behaviour will likely be to decrease speed.

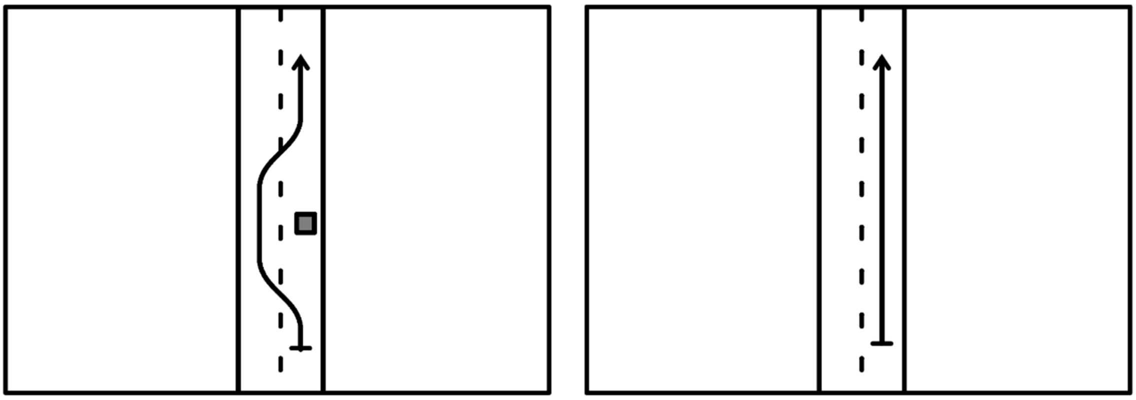

Figure 10-9: Obstacles for cyclists. Left: Cyclists are more likely to change trajectory as they wish to ride more comfortably or safely, or both (e.g. due to a hole in the cycle path). Right: Cyclists are less likely to change trajectory as there exist no apparent reason.

Figure 10-10: The rugged maintenance holes on the ground to the right act as obstacles for cyclists. The cyclists travels to the left.

Nothing acts as obstacles for cyclists. The cyclist travels to the right.

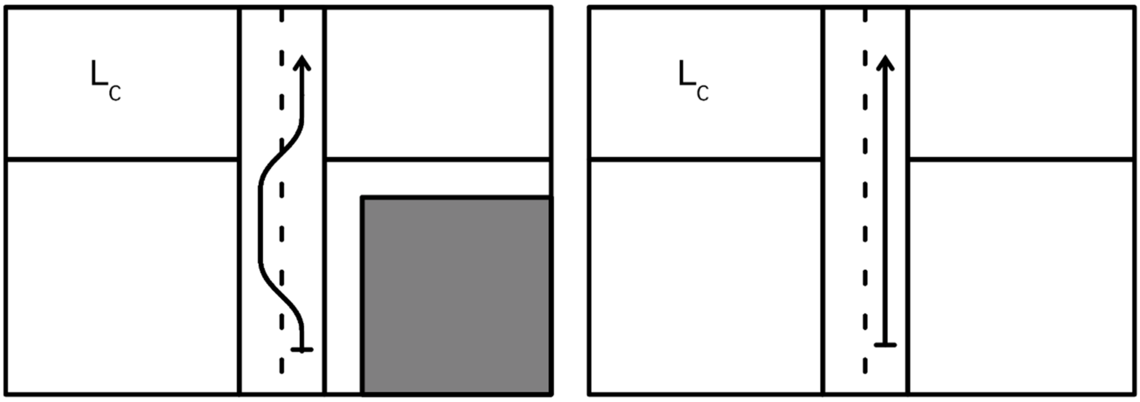

Figure 10-11: Obstacles for cyclists. Left: Cyclists are more likely to change trajectory as they anticipate crossing traffic (e.g. view-obstructing building). Right: Cyclists are less likely to change trajectory as there exists no apparent reason.

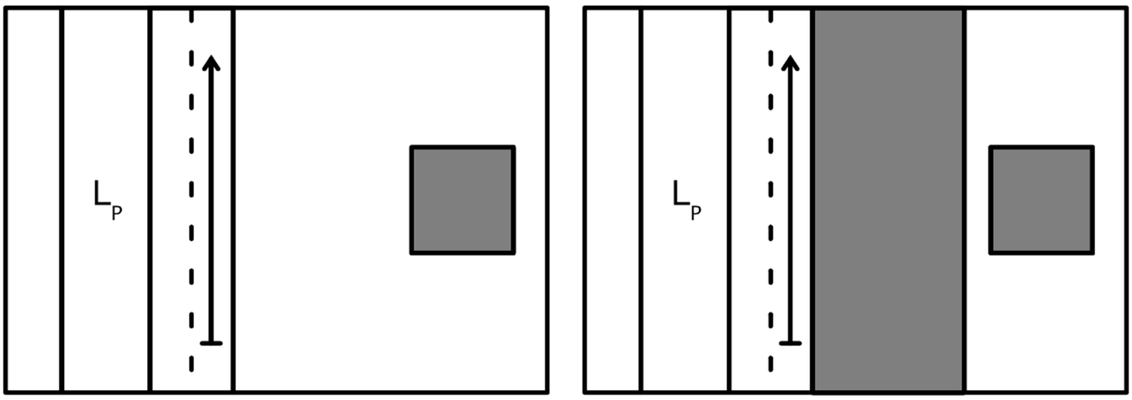

Figure 10-12: Obstacles for pedestrians. Left: Cyclists are more likely to interact with pedestrians, as they are more likely to cross (e.g. shop). Right: Cyclists are less likely to interact with pedestrians as they have less reason to cross (e.g. river).

Figure 10-13: The narrow low-speed road does not act as an obstacle for the pedestrians to the left.

The wide high-speed road to the right acts as an obstacle for the pedestrians on the left.

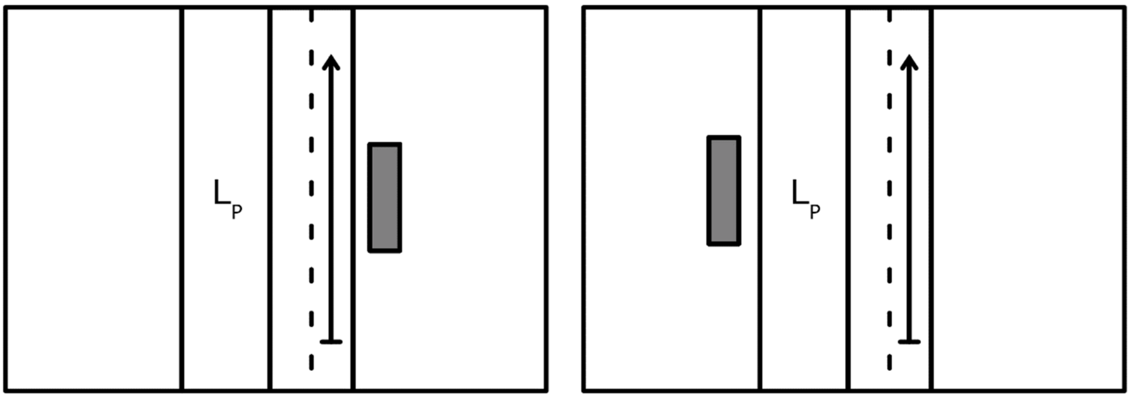

Figure 10-14: Destinations for pedestrians. Left: Cyclists are more likely to interact with pedestrians, as they are more likely to cross (e.g. bench). Right: Cyclists are less likely to interact with pedestrians as they have less reason to cross.

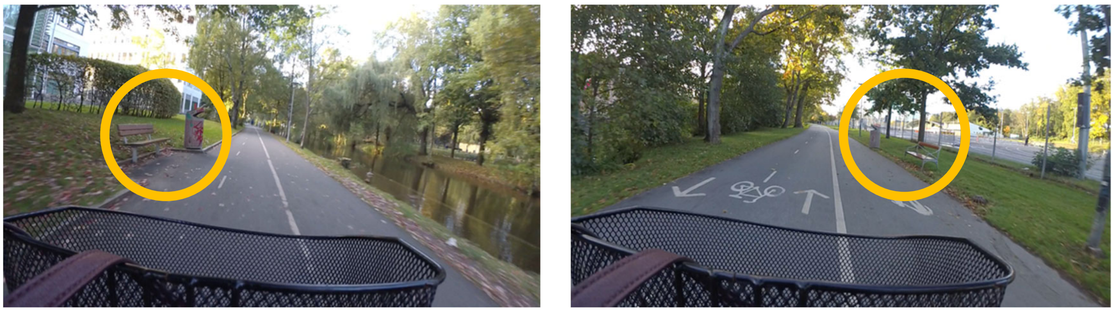

Figure 10-15: The bench and waste bin to the left act as destinations for the pedestrians walking to the right. The bench and waste bin to the right act as destinations for the pedestrians walking to the right.

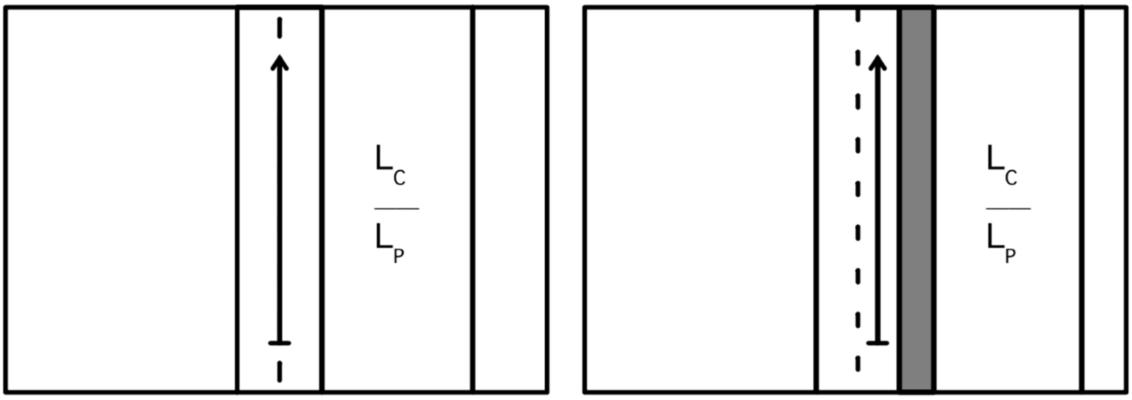

Figure 10-16: Dividers between lanes. Left: Cyclists are more likely to change trajectory as they prefer less interaction with other road users (e.g. open car doors, pedestrians entering bike lane). Right: Cyclists are more likely to evade crossing if there's an alternative path nearby as they prefer to travel with less effort and/or risk (e.g. a crowded and elevated crossing).

Figure 10-17: The lane edge to the right acts as an insufficient divider. Cyclists travel in the middle of lane. *The grass to the right acts as a divider between lanes. Cyclists travel on the right side of lane.*

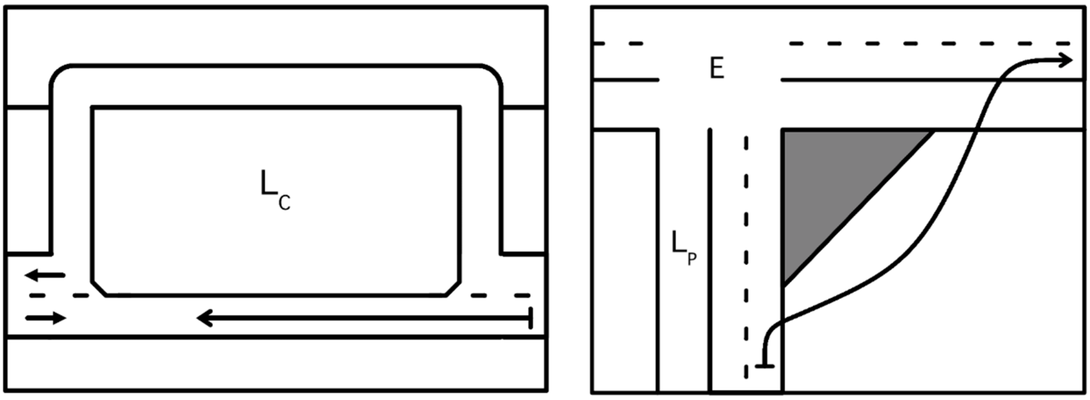

Figure 10-18: Shortcuts for cyclists. Left: Cyclists are likely to travel against the direction as they prefer to travel with less effort and/or risk (e.g. not crossing car road instead of crossing twice). Right: Cyclists are more likely to evade crossing if there's an alternative path nearby as they prefer to travel with less effort and/or risk (e.g. a crowded and elevated crossing).

Figure 10-19: Shortcut. Travelling to the right across a parking lot that eventually connects to the bike lane… *…instead of traveling straight forward, slightly uphill and more interactions with other road users.*

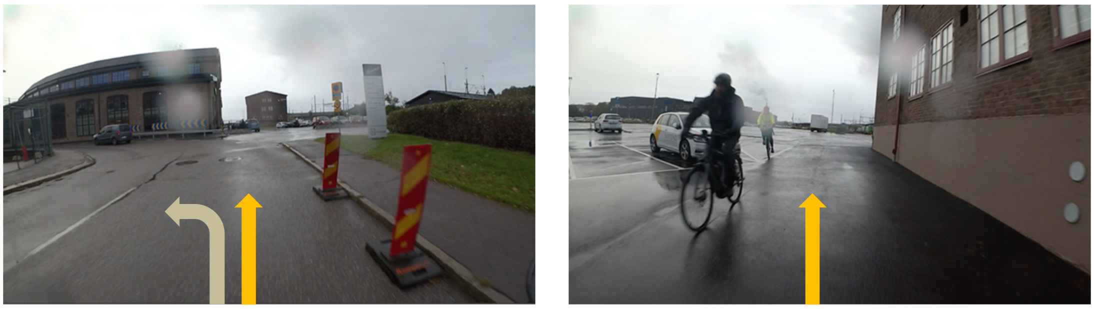

Figure 10-20: Shortcut. Instead of travelling to the left along an S-shaped and narrow road…

…the cyclists travel straight forward across a parking lot that eventually connects to the bike lane.

The contextual factors will in themselves act as nudges, giving higher probability of a certain action. Another set of factors that has been observed in the study are the *behavioural factors* (see Table 10-12). They describe cyclists' perceived action space, which depend on both the infrastructure and other road users. In summary, the traffic situation, the actions of other road users, the cyclists' personalities etc. will all contribute to what actions a certain cyclist will take in a certain situation.

Behavioural factors	*… related to bicycle infrastructure (BI)*	*… related to other road users (ORU)*
… related to external elements	(BF1) Ambiguity of BI (BF2) Reasonableness of BI	(BF5) Distance to ORU (BF6) Timing to ORU (BF7) Understanding by ORU
	(BF3) Ease of sharing BI with ORU (BF4) Visibility of ORU from BI	
… related to internal elements	(BF8) Values and beliefs of cyclist (BF9) Culture among cyclists	

Table 10-12: Categories of cyclist behavioural factors (BF). They relate to bicycle infrastructure (BI) and other road users (ORU).

10.4 Discussion

One big advantage of the implemented measure, i.e. the visual nudge, is that acceptance is high among cyclists. Most cyclists are positive to the idea of lane markings to reduce speed and warn for dangerous intersections. This can be compared to commonly used solutions such as rumble strips, speed humps and chicanes, which all have very low acceptance and are perceived as unsafe by cyclists (e.g. MeBeSafe D3.1). The tested visual nudge, on the other hand, shows none of these negative impacts. This means that even if the observed effect on speed is not very high, the cost (both in acceptance and in monetary terms) is very low, which makes an investment in the solution very low risk.

If one looks at the speed distribution at location 1, it is clear that minimum speed is obtained about midway down the nudge and that cyclists increase their speed after this point. This make sense if one considers the results from the instrumented bike study which shows that obstruction of sight, e.g. from buildings, makes cyclists move left to increase the observable area, and when this isn't possible (as at location 1 which has a one-way bike lane) decrease speed. The lack of sight due to the building to the right works together with the nudge to decrease speed, and when the building is passed and the cyclists have a clear view of the intersection again, they increase their speed counteracting the effects of the nudge.

The nudge reduced cyclist speed at intersections; however, this effect was not as large as expected and similar (or smaller than) the effects of other factors, such as wind, that are known to influence cyclist speed. Indeed, the wind direction proved to be a crucial confounding factor in our analysis, and, once the data were filtered according to the wind direction, results became consistent across locations.

Furthermore, the nudge was more effective on leisure cyclists than commuters, possibly because of their different motivations. We interpret this as less experienced cyclists may be easier to nudge. The number of cyclists decreasing their speed while approaching the intersection increased with the nudge; however, the nudge was *not* more effective the faster the cyclists were, although fast cyclists had more margin for speed reduction. If we want to increase cycling without an increase in the number of accidents it is important to help new cyclists to adapt a safe cycling style. Nudges can work as an aid to reach these goals.

The results in terms of effect on speed was lower in the field trial than in the pre-study where recruited cyclists cycled a pre-defined route with instrumented bikes. We attribute this in part to the locations chosen. In the pre-study, the nudges were located before intersections in the city centre where the road is flat and speeds are in general a bit low due to the traffic situation. For the field trial we wanted to go with intersections that were documented as being particularly dangerous. This resulted in both intersections chosen being where the bicycle lane had a downwards slope, a bit outside the immediate city centre, and consequently speeds were higher than in the pre-study. Moreover, in the pre-study the participants were out on a bike lane they necessarily didn't use very often and they were aware that there would probably be something happening on the route that they were asked to cycle. Consequently, one can assume that they were more on 'tip toe' actively looking for something to react to. In the field test, on the other hand, most of the cyclist were commuters riding on a route that they use a lot and therefore were accustomed to, and as previously discussed commuters have been shown to be more difficult to nudge.

11 Cyclists' speed reduction – the Netherlands (TNO/ SWOV)

11.1 Introduction

In the previous chapter, the reasons for applying a nudge measure to decrease cyclists' speed in the approach of an intersection were explained. SAFER/Chalmers University have developed and applied a nudge measure based on flat transverse stripes on the road giving the cyclist the illusion to ride at a higher speed than they actually do. The measure has been applied at several locations in the Gothenburg area and the results thereof have been reported in Chapter 10.

The ambition of the MeBeSafe project was to study how the infrastructure nudge measure to slow down cyclists in the approach of an intersection that has been developed in Sweden would influence cyclists in another country known for the large number of cyclists in traffic: the Netherlands. To this end, the Swedish nudge has been applied at busy intersections in Eindhoven for another field trial.

In the Netherlands, cyclists' speed in relation to hazardous interactions with motorized vehicles does not seem to be an issue. There are not many down-hill situations for cyclists that end up in an intersection with motorized vehicles and often the infrastructure has already been adapted to reduce the speed of cyclists, especially in accident-prone locations. In many cases, separate cycle lanes that cross a side road are curved in a way that the cyclist needs to reduce speed and becomes more easily visible to approaching cars that have to give priority to the cyclist.

Cyclist-cyclist interactions have become increasingly important in recent years, especially in dedicated (double) cycling lanes in inner cities. These lanes can become congested during rush hour, making it difficult for cyclists to merge safely as safety margins become small. In such cases, measures are helpful that increase the level of attention of cyclists in an approach of an intersection with other cyclists. It has been investigated how the nudge developed in Sweden can be applied to reduce the speed of cyclists in the approach of an intersection with other cyclists. A decrease of speed increases the safety margins at the intersection, and it is believed to support the increase of the level of attention of cyclists.

11.2 Method

11.2.1 Location

Similar to Sweden, the transverse nudge, shown in Figure 10-3, was selected for this field study. The nudge design has a gap decrement of 7.25 % per gap from an initial gap of 2 metres, leading to 17 gaps and a total decrement of 70 % over 19.9 metres. The nudge was implemented on the bicycle lane by means of a white road tape which did not produce any vibrations or haptic feedback for the cyclist.

The field trial involved a random sample of cyclists who passed the test site located at the cyclist path at the Kruisstraattunnel in Eindhoven during a 14-day period (to cover both baseline and treatment at the same days of the week). This location was selected as there are many cyclist-cyclist interactions in the Netherlands which is a safety concern. The location is a T-intersection of two dedicated cycling facilities with no car traffic at the intersection of the Kruisstraattunnel and Fellenoord in Eindhoven. It is the main cycling facility leading to the train station and therefore has a high cyclist traffic volume especially during rush hour, with up to almost 11.000 cyclists travelling through this intersection per day (Dufec/Sweco, 2018).

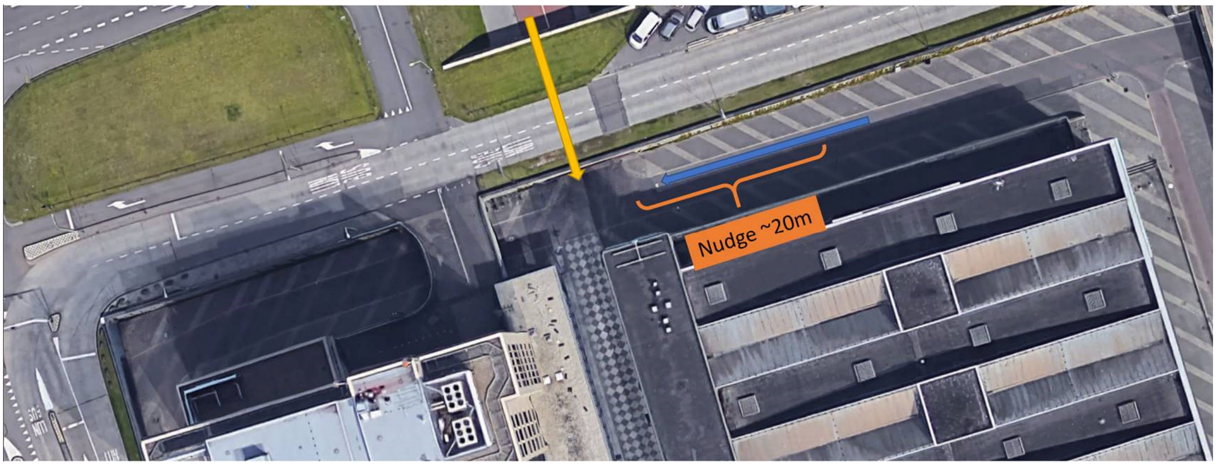

Figure 11-1: Location of study indicating the cyclists traveling through the underpass that will turn right (yellow arrow), the through cyclists (blue arrow), and the location of the nudge (orange)

One leg of the T-intersection is an underpass as indicated with the yellow arrow in *Figure* 11-1. As a result, cyclists travelling along the blue arrow with high speeds do not have a clear view of the cyclists coming from the right. This leads to conflicts between the through travelling and right turning cyclists at this location, especially since through traveling cyclist must give way to the right turning cyclists, which is not the case in practice. The implementation of the nudge along the through-traveling direction aims to reduce the speed of cyclists approaching the intersection in order to reduce their speeds, providing them with more time to see and give way to the right turning cyclists. The location and length of the nudge is shown in orange in *Figure* 11-1.

The width of the cyclist lane is 2.25 m and the width of the applied transverse lane marking nudge is 2.45 m. *Figure* 11-2 shows the implemented nudge and a through cyclist traveling along the nudge approaching the intersection with the underpass cycling facility on the right.

Figure 11-2: Implemented nudge along the through traveling cycling facility, showing two of the three implemented cameras (red boxes)

11.2.2 Video data collection and pre-processing

Video data collection was performed by an external company "Connection Systems" (www.connectionsystems.nl). They installed three temporary cameras and collected video data from different angles for two weeks. The cameras were setup on existing poles overlooking the location as shown in Figure 11-3, Figure 11-4 and Figure 11-5.

Connection systems provides road user trajectory files using an object detection method and no video files are transferred to comply with the GDPR rules for privacy. Road users are detected and classified, in our case into cyclists, motorcyclists (mopeds and scooters), and pedestrians. From the provided trajectories, we are able to analyse potential speed and safety changes between the before and after nudge scenarios.

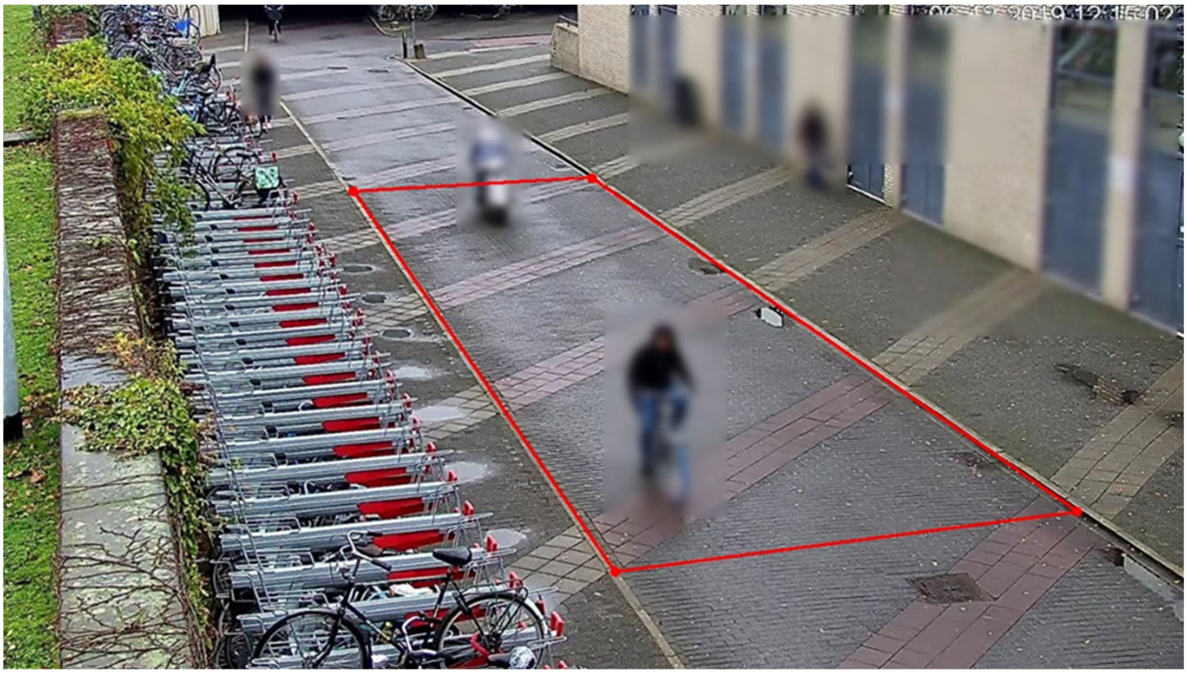

Figure 11-3: Camera 1 view, indicating the through traveling cyclists where the nudge will be implemented

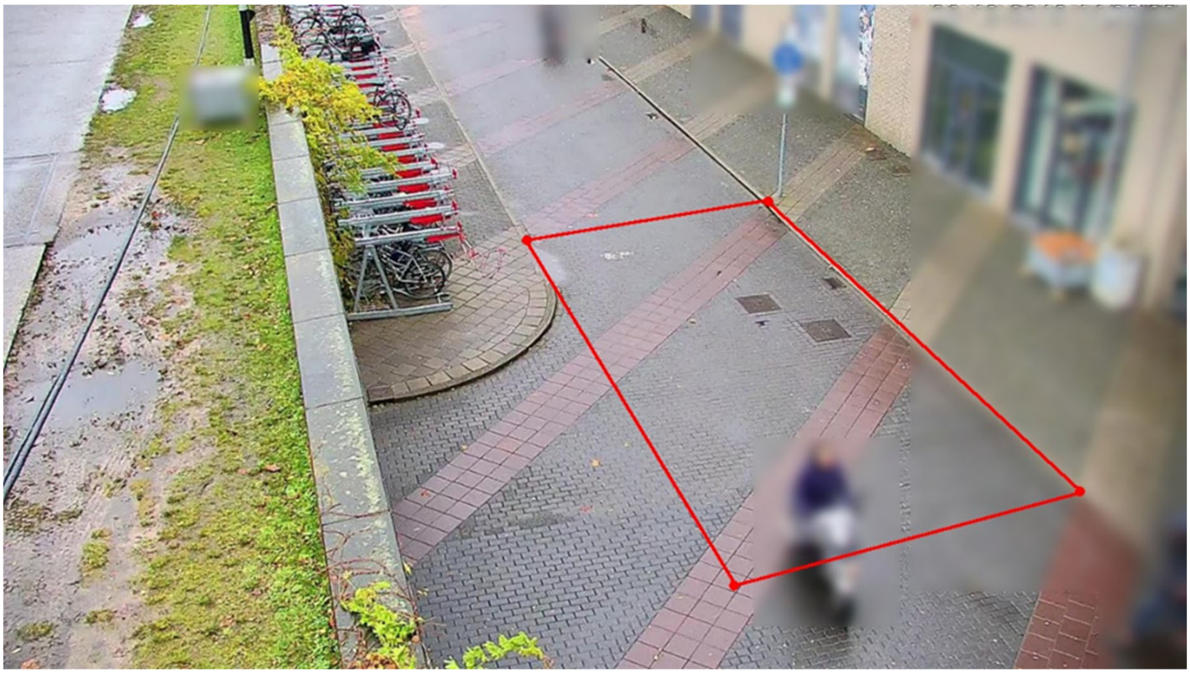

Figure 11-4: Camera 2 view at the intersection

Figure 11-5: Camera 3 view showing the intersection from an angle where the right turning cyclist approaching from the underpass is more clearly visible

The data collection period for the nudge scenario is from December 1st, 2019 at 12:00AM until December 3rd at 10:00AM, and for the base scenario without the nudge, the same weekdays (Sunday through Tuesday), were selected on December 8th at 12:00AM until December 10th at 10:00AM[6]. The trajectory processing includes the evaluation of the location where cyclists are riding along both approaches and the change in speed of cyclists going through the nudge. The speeds of the through travelling cyclists are computed from Camera 1 (Figure 11-3) to focus only on cyclists traveling along the nudge.

[6] A larger period for baseline and treatment had been foreseen, but the applied line markers came loose from the pavement as a result of the cold and humid conditions during the application of the lines, shortening the treatment period to just over 2 days. As a results of the high cyclist density in this area of the city, still close to 10.000 cyclists passed the site both for the treatment as for the baseline period.

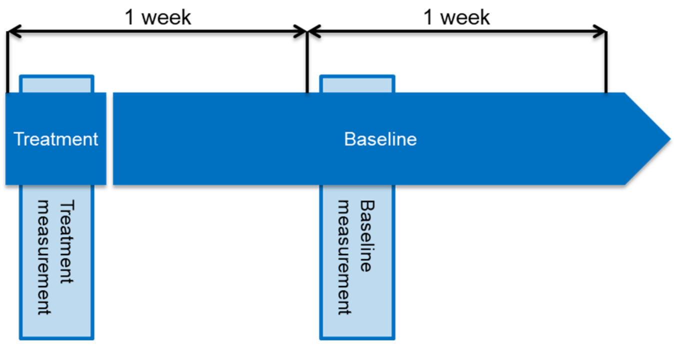

Figure 11-6 The timeline of the test. The treatment measurement continued until the lines came loose from the pavement. The baseline situation continued from there. The baseline measurement was conducted during the same days of the week as the treatment measurement; weather conditions for treatment and baseline period were very similar.

11.3 Results

The results from the Dutch study indicate no significant change from the before and after nudge-implementation. Figure 11-7 and Figure 11-8 show a histogram of mean velocity of cyclists and mopeds going through the nudge section, where Figure 11-7 shows the speeds in the baseline conditions without nudge and Figure 11-8 shows the speeds for the treatment condition with the nudge as a line pattern. The difference in speed distribution with and without nudge is not statistically significant. The similar speed distribution could be associated with the several existing maneuvers that also have an effect on the through-cyclists speeds. For example, left-turning cyclists from the opposite approach, and right turning cyclists towards the underpass would have an effect on the through-cyclist speeds and therefore the effects of the nudge cannot be isolated.

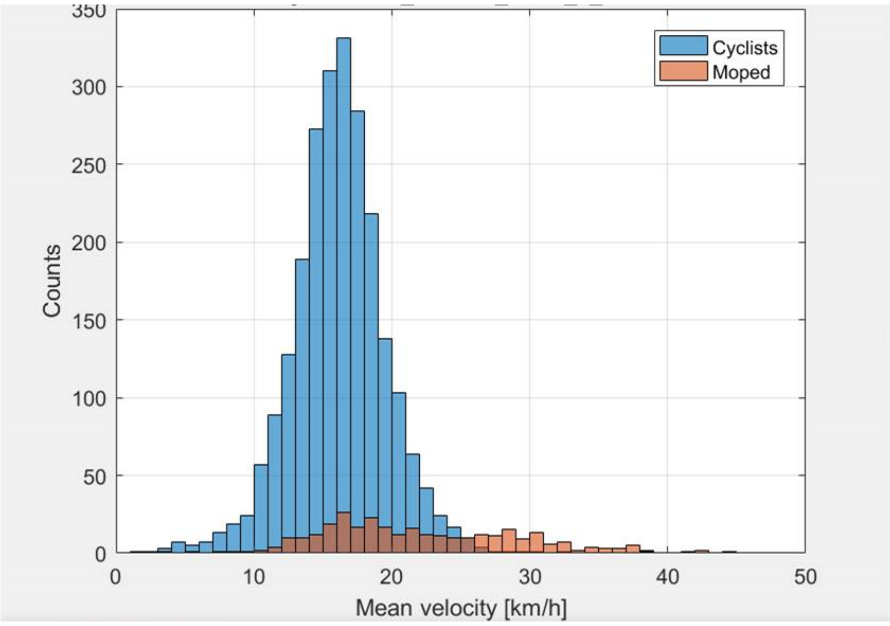

Figure 11-7 Speed distribution of cyclists and mopeds in the baseline situation without the infrastructure cycling nudge applied. The blue bars show the speed distribution of the cyclists, the orange bars that of mopeds.

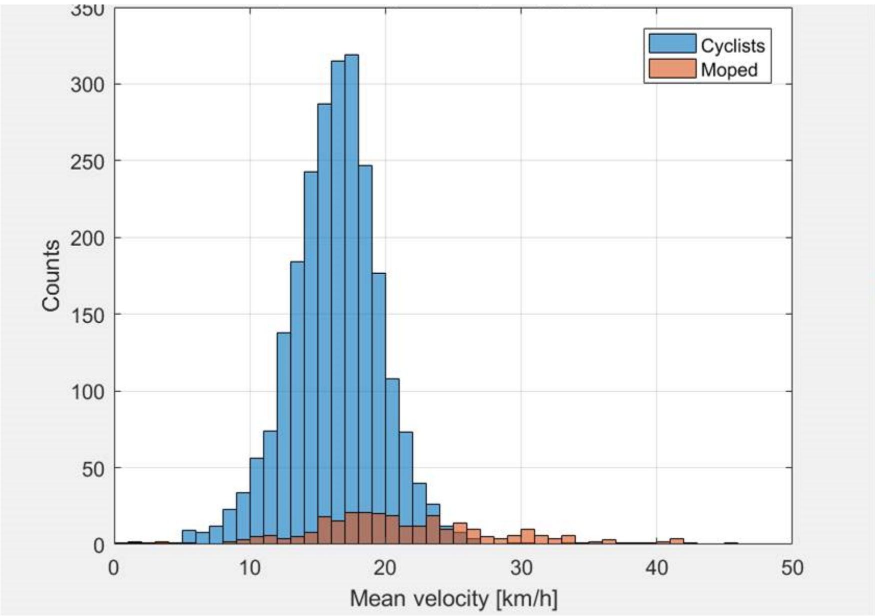

Figure 11-8 Speed distribution of cyclists and mopeds in the treatment situation with the infrastructure cycling nudge being applied. The blue bars show the speed distribution of the cyclists, the orange bars that of mopeds.

11.4 Conclusions

In conclusion, the implemented nudge aiming to reduce the speed for through-cyclists was not able to fully influence cyclist speeds. Other factors may have played a role in this. Both in the before and after scenario (with and without nudge), other cyclist movements affected the through-cyclist speeds and trajectories and as a result the influences of the nudge could not be isolated. This approach however has been shown to have a positive effect on the Swedish site where there were no other cyclist maneuvers affecting the through-cyclist speeds, indicating that the nudge will be most effective when targeting cyclists with no interactions with other cyclists.

12 Impact assessment of MeBeSafe on the European Union

The impact assessment of the MeBeSafe project bases on the results of the field trails by each measure and gives an overview about the expected impact on road safety in the EU-27 by 2025 and 2030.

The chapter shows the methodology and its application for the estimation of safety impacts in terms of crashes addressed. The method bases on the safety benefit evaluation within the "European New Car Assessment Programme Advanced" (Euro NCAP Advanced) and the assessment process was established by the "Beyond NCAP" subgroup. For this purpose, the impact assessment is limited to casualties of road traffic accidents where at least one person was injured. The aim is to generate the number of reduced casualties for the categories "slightly injured", "seriously injured" as well as "fatalities". Please note that this is only one indicator for the effectiveness of the measures developed in MeBeSafe, as they target driving behaviour before the actual risky situations occur that may lead to accidents. Accidents and fatalities can be viewed as the final outcomes in a cascade of critical events, which MeBeSafe aims to stop before a situation becomes risky at all. These factors base on the latest published CARE data (2018) and have been provided by the European Commission - Directorate-General for Mobility and Transport (DG Move) for Road Safety.

2018 EU-27 - CARE (the accident data refer to 2016)			CITY (urban)		RURAL (w/o motorway)		MOTORWAY		TOTAL	
			n	%	n	%	n	%	n	%
CASUALTIES	Car Occupants	slightly	361,525	63.6%	229,459	40.4%	74,713	13.1%	665,697	100.0%
		seriously	33,080	39.0%	54,109	63.8%	11,449	13.5%	98,638	100.0%
		fatally	2,433	23.4%	7,738	74.3%	1,150	11.0%	11,321	100.0%
	Goods Vehicle Occupants	slightly	15,429	44.1%	15,847	45.3%	8,781	25.1%	40,057	100.0%
		seriously	1,613	25.2%	3,532	55.1%	2,185	34.1%	7,330	100.0%
		fatally	181	16.4%	598	54.0%	392	35.4%	1,171	100.0%
	Motorised Two-Wheelers	slightly	139,921	85.9%	29,621	18.2%	5,499	3.4%	175,041	100.0%
		seriously	31,997	67.4%	22,349	47.1%	1,877	4.0%	56,223	100.0%
		fatally	1,746	41.9%	2,591	62.1%	247	5.9%	4,584	100.0%
	Cyclists	slightly	127,260	99.0%	17,160	13.4%	144	0.1%	144,564	100.0%
		seriously	35,279	91.8%	9,467	24.6%	31	0.1%	44,777	100.0%
		fatally	1,180	62.0%	854	44.9%	7	0.4%	2,041	100.0%
	Pedestrians	slightly	104,371	111.0%	5,963	6.3%	232	0.2%	110,566	100.0%
		seriously	35,998	115.3%	3,438	11.0%	217	0.7%	39,653	100.0%
		fatally	3,802	79.3%	1,261	26.3%	254	5.3%	5,317	100.0%
	Other	slightly	10,023	31.3%	5,233	16.3%	1,285	4.0%	16,541	100.0%
		seriously	1,882	23.6%	1,455	18.3%	163	2.0%	3,500	100.0%
		fatally	355	36.2%	485	49.5%	99	10.1%	939	100.0%
	TOTAL	slightly	758,529	65.8%	303,283	26.3%	90,654	7.9%	**1,152,466**	**100.0%**
		seriously	139,849	55.9%	94,350	37.7%	15,922	6.4%	**250,121**	**100.0%**
		fatally	9,697	38.2%	13,527	53.3%	2,149	8.5%	**25,373**	**100.0%**

Table 12-1: EU-27 accident scenario based on the CARE dataset from 2018

The data for the publication of the EU accident scenario for 2018 refers to the accident year 2016 for the most member states. For the extrapolation to the European accident scenario in 2030, the development of the European accident scenario from 2012 until 2018 is used. Table 12-2 shows the accident scenario for the EU-27 in 2012 by accident site and kind of road user on personal level.

2012 EU-27 - CARE (the accident data refer to 2010)			CITY (urban)		RURAL (w/o motorway)		MOTORWAY		TOTAL	
			n	%	n	%	n	%	n	%
CASUALTIES	Car Occupants	slightly	412,085	56.8%	251,711	34.7%	61,725	8.5%	725,521	100.0%
		seriously	50,691	42.6%	56,436	47.4%	11,845	10.0%	118,972	100.0%
		fatally	3,336	23.0%	9,963	68.6%	1,222	8.4%	14,521	100.0%
	Goods Vehicle Occupants	slightly	16,789	42.2%	17,462	43.8%	5,574	14.0%	39,825	100.0%
		seriously	2,027	27.2%	3,970	53.2%	1,459	19.6%	7,456	100.0%
		fatally	266	21.1%	766	60.9%	226	18.0%	1,258	100.0%
	Motorised Two-Wheelers	slightly	155,072	81.5%	31,859	16.7%	3,311	1.7%	190,242	100.0%
		seriously	38,405	66.5%	17,982	31.1%	1,381	2.4%	57,768	100.0%
		fatally	2,403	43.3%	2,955	53.2%	197	3.5%	5,555	100.0%
	Cyclists	slightly	101,094	89.6%	11,675	10.3%	48	0.0%	112,817	100.0%
		seriously	22,348	81.2%	5,173	18.8%	14	0.1%	27,535	100.0%
		fatally	1,122	54.5%	933	45.3%	5	0.2%	2,060	100.0%
	Pedestrians	slightly	108,219	94.4%	6,173	5.4%	226	0.2%	114,618	100.0%
		seriously	32,469	90.4%	3,318	9.2%	142	0.4%	35,929	100.0%
		fatally	4,263	69.5%	1,695	27.6%	175	2.9%	6,133	100.0%
	Other	slightly	32,906	65.9%	13,582	27.2%	3,455	6.9%	49,943	100.0%
		seriously	5,287	55.0%	3,436	35.8%	888	9.2%	9,611	100.0%
		fatally	875	44.4%	714	36.2%	381	19.3%	1,970	100.0%
	TOTAL	slightly	826,165	67.0%	332,462	27.0%	74,339	6.0%	**1,232,966**	**100.0%**
		seriously	151,227	58.8%	90,315	35.1%	15,729	6.1%	**257,271**	**100.0%**
		fatally	12,265	38.9%	17,026	54.1%	2,206	7.0%	**31,497**	**100.0%**

Table 12-2: EU-27 accident scenario based on the CARE dataset from 2012

Then, an annual change value is calculated according to the six-year interval using the following formula:

$$\begin{matrix}\Delta\, \boldsymbol{injured\ persons} \\ (\%\ per\ year)\end{matrix} = \frac{1}{6} \times \left(\frac{\begin{matrix}\boldsymbol{CARE\ data}\ \mathbf{2018} \\ (accident\ site, kind\ of\ road\ user, injury\ severity)\end{matrix}}{\begin{matrix}\boldsymbol{CARE\ data}\ \mathbf{2012} \\ (accident\ site, kind\ of\ road\ user, injury\ severity)\end{matrix}} - 1 \right) \times 100\%$$

The results from Table 12-3 are the basis for the extrapolations of the European accident scenario on personal level up to the year 2030. Starting with the latest publication of the European accident scenario (accident year 2016), the factors are multiplied with the numbers of injured persons and lead to the accident year 2017. Afterwards, the accident year 2017 serves as basis for the extrapolation to the accident year 2018, by using the multiplication factors from Table 12-3. This procedure is continued until the accident year 2030.

Of course, this is a rather simple form of extrapolation. The actual development of road accident victims in Europe is subject to many influences, such as the renewal of vehicle fleets, the introduction of mandatory safety systems, the progress in automated driving, legislation changes, the development of infrastructure, the development of the modal split and many more. As this is true (and different) for each single country, it is impossible to make a robust estimate of this.

Development of EU accidents from 2012 to 2018 per year [%] (the accident data refer to 2010 and 2016)			**CITY** (urban)	**RURAL** (w/o motorway)	**MOTORWAY**	**TOTAL**
CASUALTIES	Car Occupants	slightly	-2,04%	-1,47%	3,51%	-1,37%
		seriously	-5,79%	-0,69%	-0,56%	-2,85%
		fatally	-4,51%	-3,72%	-0,98%	-3,67%
	Goods Vehicle Occupants	slightly	-1,35%	-1,54%	9,59%	0,10%
		seriously	-3,40%	-1,84%	8,29%	-0,28%
		fatally	-5,33%	-3,66%	12,24%	-1,15%
	Motorised Two-Wheelers	slightly	-1,63%	-1,17%	11,01%	-1,33%
		seriously	-2,78%	4,05%	5,99%	-0,45%
		fatally	-4,56%	-2,05%	4,23%	-2,91%
	Cyclists	slightly	4,31%	7,83%	33,33%	4,69%
		seriously	9,64%	13,83%	20,24%	10,44%
		fatally	0,86%	-1,41%	6,67%	-0,15%
	Pedestrians	slightly	-0,59%	-0,57%	0,44%	-0,59%
		seriously	1,81%	0,60%	8,80%	1,73%
		fatally	-1,80%	-4,27%	7,52%	-2,22%
	Other	slightly	-11,59%	-10,25%	-10,47%	-11,15%
		seriously	-10,73%	-9,61%	-13,61%	-10,60%
		fatally	-9,90%	-5,35%	-12,34%	-8,72%
	TOTAL	**slightly**	-1,36%	-1,46%	3,66%	-1,09%
		seriously	-1,25%	0,74%	0,20%	-0,46%
		fatally	-3,49%	-3,43%	-0,43%	-3,24%

Table 12-3: Development of the European accident scenario per year based on 2012 and 2018

For the accident years 2020, 2025 and 2030, the following numbers of injured persons in the EU-27 (Table 12-4) are expected, distinguished by accident site, kind of road user and injury severity.

Expected number of injured persons in the EU *by 2020, 2025 and 2030*			2020				2025				2030			
			CITY (urban)	RURAL (w/o motorway)	MOTORWAY	TOTAL	CITY (urban)	RURAL (w/o motorway)	MOTORWAY	TOTAL	CITY (urban)	RURAL (w/o motorway)	MOTORWAY	TOTAL
CASUALTIES	Car Occupants	slightly	332,849	216,232	85,758	**634,838**	300,180	200,765	101,888	**602,833**	270,719	186,404	121,051	**578,174**
		seriously	26,058	52,637	11,196	**89,891**	19,339	50,853	10,887	**81,079**	14,352	49,129	10,588	**74,069**
		fatally	2,023	6,649	1,105	**9,777**	1,606	5,500	1,052	**8,158**	1,275	4,550	1,002	**6,826**
	Goods Vehicle Occupants	slightly	14,613	14,892	12,665	**42,170**	13,652	13,779	20,019	**47,451**	12,755	12,750	31,644	**57,149**
		seriously	1,404	3,279	3,005	**7,689**	1,181	2,989	4,476	**8,645**	993	2,724	6,666	**10,383**
		fatally	145	515	622	**1,283**	111	428	1,108	**1,647**	84	355	1,974	**2,414**
	Motorised Two-Wheelers	slightly	131,027	28,258	8,352	**167,637**	120,701	26,642	14,082	**161,426**	111,189	25,119	23,744	**160,052**
		seriously	28,584	26,193	2,368	**57,145**	24,824	31,941	3,167	**59,932**	21,559	38,950	4,236	**64,745**
		fatally	1,449	2,385	292	**4,125**	1,147	2,150	359	**3,656**	909	1,938	441	**3,288**
	Cyclists	slightly	150,681	23,199	455	**174,336**	186,109	33,820	1,918	**221,847**	229,867	49,304	8,082	**287,253**
		seriously	50,986	15,897	65	**66,948**	80,792	30,387	163	**111,341**	128,022	58,084	409	**186,515**
		fatally	1,221	807	9	**2,037**	1,275	751	13	**2,039**	1,331	700	17	**2,048**
	Pedestrians	slightly	101,919	5,829	236	**107,984**	98,934	5,666	241	**104,841**	96,037	5,507	247	**101,791**
		seriously	38,678	3,522	304	**42,504**	42,311	3,629	464	**46,403**	46,284	3,740	707	**50,731**
		fatally	3,535	1,059	340	**4,934**	3,228	852	488	**4,568**	2,947	685	701	**4,333**
	Other	slightly	6,124	3,396	826	**10,345**	3,308	1,978	475	**5,761**	1,787	1,152	273	**3,212**
		seriously	1,195	971	91	**2,257**	677	586	44	**1,307**	384	354	21	**759**
		fatally	234	389	58	**682**	139	296	30	**465**	82	225	16	**323**
	TOTAL	**slightly**	**737,212**	**291,806**	**108,292**	**1,137,311**	**722,885**	**282,650**	**138,624**	**1,144,159**	**722,354**	**280,235**	**185,041**	**1,187,630**
		seriously	**146,905**	**102,499**	**17,029**	**266,433**	**169,124**	**120,384**	**19,201**	**308,709**	**211,595**	**152,980**	**22,627**	**387,202**
		fatally	**8,607**	**11,804**	**2,426**	**22,837**	**7,505**	**9,976**	**3,050**	**20,532**	**6,628**	**8,452**	**4,152**	**19,232**

Table 12-4: Expected number of injured persons in the EU by 2020, 2025 and 2030

12.1.1 Methodology

The methodology for the impact assessment of the MeBeSafe nudging measures bases on the "European New Car Assessment Programme Advanced" (Euro NCAP Advanced). It was established by the "Beyond NCAP" subgroup.

In preparation of the impact assessment, several methodologies were discussed within workshops. The recursive decision tree method is one of these methods that is often used in different European projects. However, it has been found that the safety potentials of the MeBeSafe nudging measures are too individual for the decision tree method. Furthermore, the data depth of CARE data is by far not sufficient for the application of this method within MeBeSafe.

Finally, we decided to use the Euro NCAP methodology for the impact assessment as this is an established method for the evaluation of new safety systems. It can be also applied for the different nudging measures as well as coaching in the MeBeSafe project. The process is described in the “Beyond NCAP assessment protocol” (Euro NCAP – Beyond NCAP Assessment Protocol,V2.0, 2012) and is divided into two phases. The aim of the first phase is to establish an understanding of the innovation/system and its safety potential. Therefore, the safety issues have to be described, which the innovation is seeking to address. To determine the safety issue, the GIDAS database German In-Depth Accident Study (GIDAS) is to be used and it is assumed to be representative for the EU-27. Therefore, the scenarios have to be selected from GIDAS which are applicable for the innovation/measure. This is called the “problem at large”. In the next step, the expected safety potential is determined. This is done by filtering the problem at large using the system’s specifications and limitations. The European database CARE serves as the basis for the extrapolation of the in-depth database GIDAS to the EU-27.

In the second phase, the detailed technical assessment of the measure is provided. For this purpose, the possible safety potential established in the first phase needs to be adjusted, e.g. by test results and the expected benefit. At the end of the second phase, a number of addressed casualties is available.

The basis of the impact assessment is the GIDAS dataset from December 2019. The dedicated GIDAS database includes all reconstructed accidents from 1999 to 2019. In addition, uninjured persons have been excluded. For representative statements, the entire GIDAS dataset is weighted to the official German traffic accident statistics (DESTATIS, 2019). Weighting of GIDAS data is important due to some bias in the data. This bias comes from several reasons. The investigation teams are not thoroughly informed about all accidents (e.g. alarming rate depends on accident severity) and the information about the accident severity cannot always be obtained immediately on the accident site or on the day of the accident.

The GIDAS database is usually weighted on basis of the following parameters:

- accident site (urban / rural w/o motorway / motorway)

- o accident category (accident with slightly / seriously / fatally injured persons)
- o type of accident (seven different categories)

Using these parameters gives 63 different combinations (weighting categories). For every category, the number of accidents in GIDAS is compared to the numbers in the official statistics and a weighting factor is calculated for each category.

For the impact assessment, the "relative weighting factor" is used. This factor is a correction factor of the GIDAS accidents to the German accident scenario. Due to the use of weighting factors rounding differences from ± 1 accidents (resp. persons) may occur.

$$\boldsymbol{relative\ weighting\ factor} = \frac{\textbf{German accidents scenario}\ (UTYP, PVERL, ORTSL)}{\textbf{All accidents GIDAS}} \times \frac{\textbf{All accidents GIDAS}}{\textbf{accidents GIDAS}\ (UTYP, PVERL, ORTSL)}$$

$\boldsymbol{rel.weighting\ factor}$	*Correction factor of the GIDAS database*
$\boldsymbol{TYP}$	*Type of accident*
$\boldsymbol{PVERL}$	*Accident category*
$\boldsymbol{ORTSL}$	*Accident site*

Table 12-5 shows the figures in the weighted GIDAS dataset, filtered by accident site and kind of road user on personal level.

GIDAS 1999 - 2019 (December 2019) - relative weighted -			CITY (urban)		RURAL (w/o motorway)		MOTORWAY		TOTAL	
			n	%	n	%	n	%	n	%
CASUALTIES	Car Occupants	slightly	12,470	52.2%	8,332	34.9%	3,105	13.0%	23,907	100.0%
		seriously	1,180	29.0%	2,302	56.5%	593	14.5%	4,075	100.0%
		fatally	38	16.4%	154	66.5%	39	17.1%	231	100.0%
	Goods Vehicle Occupants	slightly	97	20.0%	140	29.0%	247	51.0%	485	100.0%
		seriously	16	12.2%	32	24.5%	84	63.3%	132	100.0%
		fatally	2	15.6%	2	15.0%	7	69.4%	10	100.0%
	Motorised Two-Wheelers	slightly	3,110	77.6%	836	20.9%	60	1.5%	4,006	100.0%
		seriously	783	56.5%	567	40.9%	35	2.6%	1,385	100.0%
		fatally	22	28.2%	52	66.5%	4	5.3%	79	100.0%
	Cyclists	slightly	8,178	94.4%	488	5.6%	0	0.0%	8,665	100.0%
		seriously	1,429	87.6%	202	12.4%	0	0.0%	1,631	100.0%
		fatally	26	60.1%	17	38.9%	0	1.0%	43	100.0%
	Pedestrians	slightly	2,449	95.8%	101	3.9%	7	0.3%	2,557	100.0%
		seriously	840	92.1%	64	7.0%	8	0.9%	911	100.0%
		fatally	45	70.5%	15	23.5%	4	6.0%	64	100.0%
	Other	slightly	883	84.1%	142	13.5%	25	2.3%	1,049	100.0%
		seriously	70	73.6%	24	24.7%	2	1.7%	96	100.0%
		fatally	1	32.8%	2	53.1%	0	14.1%	3	100.0%
	TOTAL	slightly	27,187	66.8%	10,039	24.7%	3,444	8.5%	**40,670**	**100.0%**
		seriously	4,318	52.5%	3,191	38.8%	722	8.8%	**8,230**	**100.0%**
		fatally	133	31.0%	241	56.1%	55	12.9%	**430**	**100.0%**

Table 12-5: Weighted GIDAS dataset with accidents from 1999 to 2019 (numbers on personal level)

For the impact assessment within MeBeSafe, the process of the Euro NCAP Advanced is adapted. The filtering of the problem at large and the safety potential is replaced by one overall filtering process of the GIDAS database for each nudging measure. This dataset is defined for the MeBeSafe project as the safety potential group ($GIDAS_{SP}$). The second phase of the Euro NCAP assessment for the MeBeSafe project is then determined by the specifications and limitations of the measures.

Additional filter criteria, representing the system characteristics and individual performance limits (e.g. accident constellations, accident site, speed etc.), are applied to the database to identify the general safety potential of the nudging measure. The filter criteria of the respective nudging objects are described in 12.2 - Impact assessment for each measure in detail. The results of the safety potential are subdivided by the accident site, kind of road user and injury severity.

The proportion between the total weighted GIDAS accident scenarios on personal level ($GIDAS_{Total}$) and the safety potential group according to the accident site, kind of road user and injury severity represents the percentage of safety potential (SP).Table 12-1 serves as basis for the total number of injured people ($GIDAS_{Total}$).

$$SP = \frac{GIDAS_{SP}}{GIDAS_{Total}}$$

SP	*Safety potential [%]*
$GIDAS_{SP}$	*Number of casualties in GIDAS addressed by the nudging measure*
$GIDAS_{Total}$	*Total number of GIDAS casualties (weighted)*

The safety potential (SP) is then used for the extrapolation to the EU level. Therefore, the safety potential is multiplied with the numbers of injured persons on the EU level (EU_{Total}) according to the accident site, kind of road user and injury severity.

The calculated EU safety potential (EU_{SP}) indicates the number of persons addressed on the EU level depending on the accident year (20xx).

$$EU_{SP,20xx} = EU_{Total,20xx} \cdot SP$$

$EU_{SP,20xx}$	*Total number of addressed persons in the EU*
$EU_{Total,20xx}$	*Total number of causalities in the EU*
SP	*Safety potential [%]*

Table 12-1 serves as basis for the extrapolation to the EU level for the accident year 2016. For the extrapolations to the accident years 2025 and 2030, the safety potential from GIDAS remains the same, but the numbers of injured persons per year are adjusted by the annual changes from Table 12-3.

The numbers of persons on EU level that can be addressed by MeBeSafe nudging measures and the accident year serve as input parameters for the further calculation. However, there is one important aspect that has to be considered to avoid over-estimations of benefits: Some accidents can be addressed by different nudging measures and should not be counted multiple times. As an example, this is true for accidents with cyclists at a crossing where the car driver did not recognize the cyclist. These accidents can be addressed by the in-vehicle nudge (increasing the driver's attention to a potentially dangerous crossing) and by the cyclist nudge (reducing the speed of the cyclist in front of the dangerous crossing).

To avoid multiple counting of benefits for single cases a reduction by a fixed percentage is applied, which is discussed in more detail in 12.1.2 - Influence factors.

12.1.2 Influence factors

Influence factors are necessary to put the absolute numbers of addressable persons by each nudging measure into perspective. In order to obtain a realistic estimation for the impact assessment, several influencing factors on the impact calculation are discussed and described.

Benefit

In general, the calculated benefit of each nudge is based on the results of the field tests. Then, the investigations without nudging measure or coaching ("baseline") are compared with the investigations after the application of the measure ("treatment"). The difference between the baseline and the results of the treatment forms the benefit (X-factor).

Depending on the measure, different types of behaviour are addressed. The speed reduction is one of these variables. The percentage of speed reduction is used to identify those accidents from the GIDAS master dataset, which could have been addressed by the reduction of initial speed. For this purpose, the spatial and temporal avoidance speed from GIDAS is compared with the initial speed at the time before the accident happened. An accident is defined as "addressed" when the initial speed is equal to the spatial or temporal avoidance speed.

The spatial avoidance or temporal avoidance applies when the accident participant would not have reached the collision point. According to the definition, an accident is avoided when the vehicle would have come to a stop in front of the collision point (spatial avoidance) or when the vehicle would have reached the collision point after the collision partner had already left the accident site (temporal avoidance). For this purpose, the same driver/rider reactions and boundary conditions are assumed.

Nudging measures and coaching could influence also other behavioural aspects. For instance, they could lead to less distraction or to a general improvement of driver skills. Depending on the different measures, the factors that are influenced by the measures must be individually identified and queried from the GIDAS database. The respective addressed behaviours and the relevant GIDAS filter criteria for each nudging measure are described more in detail in 12.2 - Impact assessment.

In addition to the benefit factor, the impact assessment considers the percentage of people addressed by the nudging measure (Y-factor). But the factor varies depending on the measure. For example, for coaching measures the factor describes the percentage of coachable persons. For the infrastructure measure on motorway exits, the factor describes the percentage of speeding drivers that could be nudged with a headway of at least 90 m to the leading vehicle. Further details of all single factors are described in 12.2 - Impact assessment for each nudging measure.

Non double-addressed accidents

As described above, accidents may be potentially addressed several times by different nudging measures. The example for the cyclist nudge and in-Vehicle nudge is shown in Figure 12-1. If one of the measures addresses an accident, this accident may only be counted once.

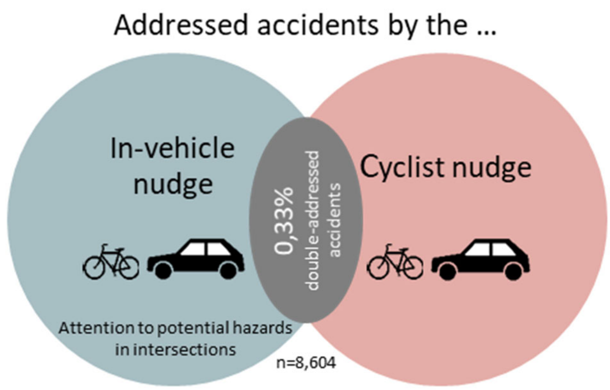

Figure 12-1 Scheme of double-addressed accidents for a conflict between car and cyclist

In order to avoid double-addressed accidents the actual number of double-addressed accidents is determined on a single-case basis for each combination of two nudges. Then, the percentage of accidents per nudge is calculated (see Table 12-6). Finally, this percentage is then deducted during the impact calculation for each nudge separately.

		O1	O2=O4	O3	O5	O6/O7	O8 - SWE	O8 - NL
Driver alertness feedback	O1		0.97% (n=1,936)		0.19% (n=2,583)	0.09% (n=356)		
Usage of safety ADAS to prevent close following= Behavioural change through online private driver coaching	O2=O4	0.97% (n=1,936)			1.18% (n=3,787)			
Attention to potential hazards in intersections	O3				1.28% (n=8,797)		0.30% (n=4,025)	0.03% (n=4,579)
HGV driver behavioural change through online coaching	O5	0.19% (n=2,583)	1.18% (n=3,787)	1.28% (n=8,797)			0.02% (n=2,262)	0.01% (n=2,284)
Safe speed/trajectory on inter-urban roads	O6/O7	0.09% (n=356)						
Cyclists' speed reduction – Sweden	O8 - SWE			0.30% (n=4,025)	0.02% (n=2,262)			0.70% (n=51)
Cyclists' speed reduction – Netherlands	O8 - NL			0.03% (n=4,579)	0.01% (n=2,284)		0.70% (n=51)	
	Σ	1.25%	2.15%	2.61%	3.67%	0.09%	1.02%	0.74%
Share of non double-addressed accidents	Z	98.75%	97.85%	97.39%	96.33%	99.91%	98.97%	99.26%

Table 12-6: Share of non double-addressed GIDAS accidents per nudging measure

The share of non double-addressed accidents (Z) is the difference of all accidents and the total share of all double-addressed accidents per nudging measure.

Market penetration

In the MeBeSafe project, the market penetration describes the frequency/presence of a technology compared to the total market (M). For the three measures (In-vehicle measure, coaching, infrastructure measures) the market penetration for the EU-27 is assumed for the years 2025 and 2030. Therefore, two different scenarios and the total number of addressable casualties are considered. For the total number of addressable casualties, a market penetration of 100 % by 2025 and 2030 is assumed. Then, an optimistic scenario and a pessimistic scenario are defined. They are later described in detail for each nudging measure.

In-vehicle measures

In-vehicle measures contain applications for the use in the automotive sector. If the proposed measures are made mandatory for new cars sold in the EU from 2020 onward, the number of cars equipped with our measures can be expected to be 20 % of the EU fleet by 2025 for the optimistic scenario. It is assumed that 20 % of the EU vehicle fleet is less than 3 years old. The market penetration of new automotive technology in German cars is increasing by 4-5 % per year after a certain initiation phase (Liers, 2019). For the impact assessment of the In-vehicle measures, a smaller penetration of 2.5 % per year for the EU is assumed, because the penetration varies across the EU. In the optimistic scenario, 32.5 % of the EU fleet will be equipped with the new technology by 2030. Depending on the type of In-vehicle measure, the market penetration values differ at the starting point (2020). For this purpose, a distinction is made between technologies that already exist on the market (e.g. ACC, driver drowsiness detection) and new innovations.

The pessimistic scenario for the In-vehicle measures is based on the combined EU sales of passenger cars, trucks and buses of 15 million units per year. (ACEA, 2016) The partner OEMs (BMW, Fiat, Volvo) estimate the combined EU market share of about 15 %. It is assumed that this share will remain constant and that on average 50 % of their new car sales will include results from the MeBeSafe project.

This estimation leads to the following numbers of vehicles with the In-vehicle measure for the partner OEMs by…

2025: 15M (vehicles) x 5 (years) x 15 % (market share) x 50 % (share of vehicles with nudging measures) = **5.6M** (vehicles)

2030: 15M (vehicles) x 10 (years) x 15 % (market share) x 50 % (share of vehicles with nudging measures) = **11.2M** (vehicles)

Other OEMs are expected to introduce measures that are found to be effective in a lower percentage of their new vehicle sales, starting from 2022 onward. From the 85 % market share of the other OEMs, it is expected that 20 % of their new vehicles will be equipped with In-vehicle nudging measures from MeBeSafe.

This estimation leads to the following numbers of vehicles with the In-vehicle measure for the other OEMs by…

2025: 15M (vehicles) x 3 (years) x 85 % (market share) x 20 % (share of vehicles with nudging measures) = **7.7M** (vehicles)

2030: 15M (vehicles) x 8 (years) x 85 % (market share) x 20 % (share of vehicles with nudging measures) = **20.4M** (vehicles)

For 2025, it is assumed that 273 million vehicles will be part of the EU fleet (Digital Auto Report, 2019). Compared to the estimated numbers of vehicles equipped with the In-vehicles measures (5.6M + 7.7M = 13.3M), the market share for the pessimistic scenario is assumed to be about 5 % of the EU fleet by 2025.

For the EU fleet in 2030, estimations say that fewer vehicles will be on the EU roads (e.g. due to the increased availability of car sharing) and a total number of 258M is assumed (Digital Auto Report, 2019). Consequently, about 12 % of the vehicles in the

EU fleet will be equipped with the In-vehicle measures (11.2M + 20.4M = 31.6M) by 2030 in the pessimistic scenario.

Coaching

For the HGV coaching, the same market penetration rates are assumed for the optimistic and pessimistic scenario as for the In-vehicle measures. Consequently, it is expected that in the pessimistic scenario, 5 % of the HGV drivers in the EU will be coached through this measure by 2025 and 12.3 % by 2030. In the optimistic scenario, 20 % of HGV drivers will be coached by 2025 and one third (32.5 %) of all drivers by 2030.

Infrastructure measures

The estimation for the infrastructure measures is difficult to implement, because there are no established studies available on EU level. Consequently, the market penetration rate for infrastructure measures are replaced by the equipment rate for the accident hotspots.

The impact assessment is again done using a pessimistic and an optimistic scenario. In the pessimistic scenario, it is expected that infrastructural measures will be implemented in 10% of all critical locations by 2025 and 20% by 2030. In the optimistic scenario, it is assumed that one quarter of the accident hotspots will be equipped with the measures by 2025 and 50% by 2030.

The total number of addressable casualties will be reached if 100% of the accident hot spots are equipped with the infrastructural measures for 2025 and 2030.

Usage rate

The usage rate describes the proportion of time when the measure is used (U). Due to the fact that the infrastructure measures are always present and for the other nudging measures the usage times are not documented, it is assumed that the usage rate for all MeBeSafe measures is 100%.

12.1.3 Impact calculation

The impact calculation is the process that leads to the results of the impact assessment. The results represent the addressed casualties (slightly, seriously and fatally injured persons) in relation to the year (EU_{20xx}).

For this purpose, the extrapolated safety potential for the EU is multiplied by the influencing factors. In addition to the extrapolated accident year and the assumed influencing factors, the results depend on the accident location, the type of road user, the injury severity and the measure.

$$EU_{20xx} = EU_{SP,20xx} \cdot X \cdot Y \cdot Z \cdot M_{20xx} \cdot U$$

EU_{20xx}	*Target figure of the addressed persons in the EU depending on the year, accident location, the type of road user, the injury severity*
$EU_{SP,20xx}$	*Total number of addressed persons in the EU*
X	*Benefit of the measure [%]*
Y	*Person addressed by the measure; coachable persons [%]*
Z	*Non double-addressed accidents [%]*
M_{20xx}	*Market penetration [%]*
U	*Usage rate [%]*

12.2 Impact assessment

The impact assessment describes the accident selection of the GIDAS database for the individual measures and calculates the number of addressed casualties by 2025 and 2030 for EU-27 according to the methodology from 12.1.1 - Methodology.

In the first step, the absolute number of the addressed casualties is calculated. Afterwards the absolute number is adjusted to the three market penetration scenarios (total number, optimistic and pessimistic scenario). The impact assessment is divided into the In-vehicle measures, the coaching part and the infrastructure measures.

12.2.1 In-vehicle measures

The aim of the In-vehicle measures is to develop and implement hardware and software solutions to encourage passenger car drivers to behave more safely in traffic. The following measures have been developed in the MeBeSafe project for this purpose:

- **Driver alertness feedback** - Nudge the driver to take a break when the driver alert system indicates driver fatigue
- **Usage of safety ADAS to prevent close following** - Nudge the driver to use the ADAS more often
- **Attention to potential hazards in intersections** - Nudge drivers into safer behaviour at non-signalized intersections

If the three In-vehicle measures would be launched in the EU-27 with a market penetration of 100 %, it could be expected that up to 920 fatalities in 2025 and about 825 fatalities in 2030 will be addressed. In addition, 77,300 slightly and seriously injured persons could be addressed by 2025 and up to 87,800 persons by 2030.

Regarding the analyses on the market penetration of new automotive technology, especially for active safety technologies (Liers, 2019), it is assumed that the results of the pessimistic scenario are more realistic for the driver alert nudge and ACC nudge. For the attention nudge, the optimistic scenario is the more realistic assumption for the impact assessment, if the measure is launched as smartphone application, similar to the developed application in the MeBeSafe project. The sum of the realistic estimations indicate that 69 fatalities could be addressed in 2025 and up to 135 fatalities in 2030. In addition, 8,000 slightly and seriously injured persons could be addressed in 2025 and up to 18,400 persons in 2030. Further details on the in-vehicle nudging measures and the impact assessments are describe in the following sub-chapters.

The current In-vehicle measures have only been validated and tested on passenger cars yet. Some of these systems such as ACC or the driver alert system are already equipped in commercial vehicles. If the In-vehicle measures are also installed in commercial vehicles, the number of addressed persons would be increased. The additional installation of the ACC nudge in commercial vehicles would result in a five times higher number of addressed fatally injured persons by 2025 and 2030.

Driver alertness feedback

The driver alertness measure is a supplement to the driver drowsiness detection and should motivate the driver to take a break within the next 20 minutes after the system detects signs of driver fatigue. The main objective of the measure is to prevent accidents due to fatigue or microsleep.

From the GIDAS database all accidents with fatigue as an accident cause are filtered. Fatigue must not necessarily be the main accident cause, but at least coded for one of the participants. In addition to the accident causation, the accident types for fatigue accidents (code 761) is selected (Ortlepp, 2016). The type of accident describes the conflict situation which resulted in the accident.

Currently, fatigue warning systems are available in passenger cars, busses and trucks. Due to the fact that the measure was tested only in passenger cars, fatigue drivers of passenger cars and fatigue drivers of commercial vehicles (up to 3.5 t) are filtered from GIDAS. Further restrictions result from the system requirements of fatigue warning systems. Currently, the availability of the driver alert functions is only active at speeds above 70 km/h. For this purpose, the GIDAS selection focused on accidents happened on rural roads and motorways.

Driver alertness feedback GIDAS 1999 - 2019* - relative weighted -			CITY (URBAN)						RURAL (w/o motorway)						MOTORWAY						TOTAL					
			ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$
			n	%	n	%	n	n	n	%	n	%	n	n	n	%	n	%	n	n	n	%	n	%	n	n
CASUALTIES	Car Occupants	slightly	12,470	52.2%					8,332	34.9%	177	2.1%	4,264	3,959	3,105	13.0%	172	5.6%	5,655	6,719	23,907	100%	349	1.5%	9,919	10,678
		seriously	1,180	29.0%					2,302	56.5%	82	3.6%	1,809	1,747	593	14.5%	59	10.0%	1,089	1,059	4.075	100%	141	3.5%	2,897	2,806
		fatally	38	16.4%					154	66.5%	8	5.5%	301	249	39	17.1%	6	14.5%	153	145	231	100%	14	6.1%	453	394
	Goods Vehicle Occupants	slightly	97	20.0%					140	29.0%	1	0.9%	120	111	247	51.0%	1	0.4%	88	139	485	100%	2	0.5%	209	251
		seriously	16	12.2%					32	24.5%					84	63.3%					132	100%				
		fatally	2	15.6%					2	15.0%					7	69.4%					10	100%				
	Motorised Two-Wheelers	slightly	3,110	77.6%					836	20.9%					60	1.5%					4,006	100%				
		seriously	783	56.5%					567	40.9%					35	2.6%					1,385	100%				
		fatally	22	28.2%					52	66.5%					4	5.3%					79	100%				
	Cyclists	slightly	8,178	94.4%					488	5.6%					0	0%					8,665	100%				
		seriously	1,429	87.6%					202	12.4%					0	0%					1,631	100%				
		fatally	26	60.1%					17	38.9%					1	1.0%					43	100%				
	Pedestrians	slightly	2,449	95.8%					101	3.9%					7	0.3%					2,557	100%				
		seriously	840	92.1%					64	7.0%					8	0.9%					911	100%				
		fatally	45	70.5%					15	23.5%					4	6.0%					64	100%				
	Other	slightly	883	84.1%					142	13.5%					25	2.3%					1,049	100%				
		seriously	70	73.6%					24	24.7%					2	1.7%					96	100%				
		fatally	1	32.8%					2	53.1%					0	14.1%					3	100%				
	TOTAL	**slightly**	27,187	66.8%					10,039	24.7%	178	1.8%	4,385	4,071	3,444	8.5%	173	5.0%	5,743	6,858	40,670	100%	352	0.9%	**10,128**	**10,929**
		seriously	4,318	52.5%					3,191	38.8%	82	2.6%	1,809	1,747	722	8.8%	59	8.2%	1,089	1,059	8,230	100%	141	1.7%	**2,897**	**2,806**
		fatally	133	31.0%					241	56.1%	8	3.5%	301	249	55	12.9%	6	10.3%	153	145	430	100%	14	3.3%	**453**	**394**

*Due to the use of weighting factor rounding differences from ± 1 persons may occur.

Table 12-7: Safety potential of the driver alertness measure and EU-27 extrapolation of casualties by 2025 and 2030 according to the accident location, kind of road user and injury severity

Table 12-7 shows the number of persons in GIDAS addressed by the measure and the calculated safety potential. The safety potential is the basis for the extrapolation of the absolute number by 2025 and 2030 (marked red). The absolute number is defined as the maximum possible number of addressed persons, assuming that there are no restrictions by the system or market. In the next step, the absolute number is adjusted to the results of the field tests.

According to the baseline, 44 % of drivers who received a warning stopped within 20 minutes. This percentage increases to 87 % by the treatment (with nudge). In order to be able to extrapolate the accident scenario for the treatment, we assume that 44 % (baseline) of the injured persons were addressed by the driver alert nudge and 56 % are equal to absolute number of injured people. Therefore, the absolute number is extrapolated to the accident scenario without driver alert nudge. This number of injured persons is then multiplied by the percentage of the treatment

(87 %). The result gives the number of injured persons who could be addressed by the treatment.

For the Y-factor we assume that each driver (100%) received the warning, but it is up to them if they take a break within the next 20 minutes or not. Depending on the other measures, about 25 accidents are double-addressed. These accidents are deducted by the Z-factor (Table 12-6). The boundary conditions of the three scenarios for market penetration are explained in the chapter 12.1.2 - Market penetration.

The results of the alertness treatment (nudge) estimate that a total number of 696 fatalities will be addressed in 2025 and 605 fatalities in 2030, if an immediate 100 % market penetration is assumed. In addition, more than 21,000 slightly and seriously injured persons could be addressed in 2030. The realistic estimation will probably be between the optimistic and pessimistic scenario.

Driver Alertness Feedback *-addressable casualties-*	Total		Optimistic scenario		Pessimistic scenario	
	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}
slightly injured	15,538	16,766	3,083	5,397	775	2,062
seriously injured	4,445	4,305	882	1,386	222	530
fatally injured	696	605	138	195	35	74

Table 12-8: Impact assessment of the driver alertness feedback by 2025 and 2030

In the optimistic scenario, 138 fatalities could be addressed in 2025 and 195 fatalities in 2030. Depending on the market penetration of vehicle assistance systems in Europe, the pessimistic scenario seems to be the more realistic scenario. Based on their assumptions, 35 fatalities would be addressed in 2025 and 74 fatalities in 2030. In addition, more than 2,500 slightly and seriously injured persons will be addressed in 2030.

Usage of safety ADAS to prevent close following

The ACC measure is designed to complement the adaptive cruise control systems in vehicles and should motivate the driver to use the system more often. The main objective of the ACC system and the ACC measure is to prevent rear-end accidents regardless of the accident location.

The filtering of the GIDAS database is based on rear-end crashes, whereby the EGO-vehicle had a front collision and the opponent had a rear-end collision. For the selection of rear-end collisions, only the first collisions of the EGO-vehicles are considered and both participants (EGO, opponent) must have driven in the same lane. Rear-end collisions which have occurred according to sudden physical disability or vehicle damage are excluded.

This selection considers all rear-end collisions that happened in the first conflict situation. If the filtering only bases on the main accident causation (e.g. insufficient safety distance) or only on the accident type, not all rear-end collisions will be covered.

EGO-vehicles are defined as passenger cars or light commercial vehicles with a Gross Vehicle Weight (GVW) of up to 3.5 t. Both vehicle categories usually base on the same platform and are mainly equipped with the same passive and active safety features. The opponents are defined as motorized two-track vehicles. Conflicts between EGO-vehicles and single-track vehicles (cyclists, PTWs) and pedestrians are excluded from filtering for the ACC measure.

Table 12-9 shows the number of persons in GIDAS addressed by the measure and the calculated safety potential. The safety potential is the basis for the extrapolation of the absolute number of addressed persons in 2025 and 2030.

In addition to the addressed occupants of the EGO-vehicle and their opponents, the measure can also address pedestrians, cyclists or motorized two-wheelers, although they were initially excluded from the filtering (as opponent in the EGO's first collision). However, VRU casualties can occur in subsequent collisions, e.g. when the vehicle in front is projected forwards into a pedestrian, cyclist or PTW. It is assumed that if the ACC measure prevents the first collision, all other collisions can be also avoided.

ACC Usage GIDAS 1999 - 2019* - relative weighted -			CITY (URBAN)						RURAL (w/o motorway)						MOTORWAY						TOTAL					
			ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$
			n	%	n	%	n	n	n	%	n	%	n	n	n	%	n	%	n	n	n	%	n	%	n	n
CASUALTIES	Car Occupants	slightly	12,470	52.2%	1,351	10.8%	32.529	29.336	8,332	34.9%	854	10.3%	20.580	19.108	3,105	13.0%	712	22.9%	23.367	27.762	23,907	100%	2,918	12.2%	76.476	76.206
		seriously	1,180	29.0%	76	6.5%	1.252	929	2,302	56.5%	72	3.1%	1.593	1.539	593	14.5%	124	20.9%	2.273	2.211	4.075	100%	272	6.7%	5.118	4.679
		fatally	38	16.4%	3	7.9%	126	100	154	66.5%	1	0.6%	33	27	39	17.1%	4	11.0%	116	110	231	100%	8	3.6%	275	238
	Goods Vehicle Occupants	slightly	97	20.0%					140	29.0%					247	51.0%	12	4.8%	966	1.527	485	100%	12	2.5%	966	1.527
		seriously	16	12.2%					32	24.5%	1	3.7%	110	100	84	63.3%	1	0.9%	41	61	132	100%	2	1.5%	151	161
		fatally	2	15.6%					2	15.0%					7	69.4%					10	100%				
	Motorised Two-Wheelers	slightly	3,110	77.6%					836	20.9%					60	1.5%					4,006	100%				
		seriously	783	56.5%					567	40.9%					35	2.6%					1,385	100%				
		fatally	22	28.2%					52	66.5%					4	5.3%					79	100%				
	Cyclists	slightly	8,178	94.4%	1	0.1%	10	13	488	5.6%	1	0.2%	82	120	0	0%					8,665	100%	2	0.1%	93	133
		seriously	1,429	87.6%					202	12.4%	2	1.2%	358	685	0	0%					1,631	100%	2	0.1%	358	685
		fatally	26	60.1%					17	38.9%					1	1.0%					43	100%				
	Pedestrians	slightly	2,449	95.8%	3	0.1%	120	116	101	3.9%					7	0.3%					2,557	100%	3	0.1%	120	116
		seriously	840	92.1%	1	0.1%	54	59	64	7.0%					8	0.9%					911	100%	1	0.1%	54	59
		fatally	45	70.5%					15	23.5%					4	6.0%					64	100%				
	Other	slightly	883	84.1%					142	13.5%	11	7.5%	148	86	25	2.3%	2	6.2%	30	17	1,049	100%	12	1.2%	178	104
		seriously	70	73.6%					24	24.7%					2	1.7%					96	100%				
		fatally	1	32.8%					2	53.1%					0	14.1%					3	100%				
	TOTAL	**slightly**	27,187	66.8%	1,355	5.0%	32.659	29.465	10,039	24.7%	866	8.6%	20.811	19.314	3,444	8.5%	726	21.1%	24.363	29.306	40,670	100%	2,946	7.2%	77.833	78.086
		seriously	4,318	52.5%	77	1.8%	1.306	988	3,191	38.8%	76	2.4%	2.061	2.323	722	8.8%	125	17.3%	2.314	2.272	8,230	100%	278	3.4%	5.681	5.583
		fatally	133	31.0%	3	2.2%	126	100	241	56.1%	1	0.4%	33	27	55	12.9%	4	7.8%	116	110	430	100%	8	1.9%	275	238

*Due to the use of weighting factor rounding differences from ± 1 persons may occur.

Table 12-9: Safety potential of the ACC measure and EU-27 extrapolation of casualties in 2025 and 2030 according to the accident location, kind of road user and injury severity

According to the baseline value, the ACC usage over the total driving time is on average 14.4 %. After the treatment by the ambient display nudge or by competitive leader board nudge, the percentage of ACC usage increases to 20.82 % and 30.67 % respectively.

For the calculation of the impact of this nudge it is assumed that the current number of injured persons is associated to the current frequency of ACC usage (baseline, 14.4 % of driving time). Then, the number of injured persons is multiplied by the changed percentage with nudge. The result is the number of injured persons who could be addressed by the nudge.

Depending on the other measures, about 64 ACC accidents are also addressed by other measures. These accidents are reduced by the Z-factor (Table 12-6). The boundary conditions of the three scenarios for market penetration are explained in the sub-chapter Market penetration.

The results of the impact assessment for the ACC - ambient display nudge (Table 12-10) estimate a total number of 66 fatalities that could be addressed in 2025 and 57 fatalities in 2030, if we assume a 100 % market penetration. In addition, nearly 20,000 slightly and seriously injured persons could be addressed in 2030.

ACC Usage - Ambient *-addressable casualties-*	Total		Optimistic scenario		Pessimistic scenario	
	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}
slightly injured	18,524	18,584	3,705	6,040	924	2,286
seriously injured	1,352	1,329	270	432	67	163
fatally injured	66	57	13	18	3	7

Table 12-10: Impact assessment of the ACC - ambient display nudge in 2025 and 2030

For the pessimistic and optimistic scenario of the ACC - ambient display nudge, three to thirteen fatalities and more than 950 to 3,900 slightly and seriously injured persons could be addressed in 2025. The numbers of addressable persons will increase in 2030. It is assumed that the measure will address seven to eighteen fatalities and nearly 2,450 - 6,500 slightly and seriously injured persons.

The results of the impact assessment of the ACC - competitive leader board nudge (Table 12-11) estimate a total number of 97 fatalities will be addressed in 2025 and 83 fatalities in 2030, if we assumed an immediate 100 % market penetration. In addition, more than 29,000 slightly and seriously injured persons could be addressed in 2030.

For the pessimistic and optimistic scenario of the ACC - competitive leader board nudge, five to nineteen fatalities and nearly 1,500 to 5,800 slightly and seriously injured persons could be addressed in 2025. The numbers of addressable persons will increase in 2030. It is assumed that the measure will address 10 to 27 fatalities and more than 3,500 to 9,500 slightly and seriously injured persons.

ACC Usage - Leader board -addressable casualties-	Total		Optimistic scenario		Pessimistic scenario	
	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}
slightly injured	27,294	27,383	5,459	8,899	1,361	3,368
seriously injured	1,992	1,958	398	636	99	241
fatally injured	97	83	19	27	5	10

Table 12-11: Impact assessment of the ACC - competitive leader board nudge in 2025 and 2030

The increase of the ACC usage (+11.0 % over total driving time) by the ACC - competitive leader board nudge compared to the ACC - ambient display nudge leads to an increase of the addressed persons by a factor of 1.5.

Attention to potential hazards in intersections

The nudge addressing potential hazards is designed to improve timely attention to a potential hazard at urban intersections. Passenger car drivers receive a nudge at non-signalized intersections, to direct their attention towards areas of the intersection where view obstructions would probably hide an approaching bicyclist.

The GIDAS database is filtered for all urban accidents at intersections. For the selection of relevant accidents, only conflict situations between M1/N1 vehicles (EGO) and cyclists are considered. In order to apply the potential effect of the speed reduction of this measure to the GIDAS database, the initial speeds of the EGO-vehicles have to be known.

The field test showed that the attention of some EGO-vehicle drivers was increased and some of them reduced their initial speed before entering the intersection. Distraction and speeding are two aspects that could cause conflicts between vehicles and cyclists. Consequently, the impact assessment considers both causes separately.

For the selection of the distraction accidents some assumptions have to be made as inattention is not directly coded as an accident causation in the GIDAS or police records. It is assumed that drivers who did not react (no braking, no steering) before the conflict situation were inattentive. For this kind of drivers, the attention measure could alert the driver of a hazard potential and encourage the driver to brake or to brake earlier. Also, all drivers are included who reacted (e.g. braking) in front of the intersection but initiated the braking sequence more than 40 m before the intersection. At this point, the measure could encourage the driver to reduce speed even more or to be more attentive.

Depending on the speed behaviour, the percentage of speed reduction derived from the results of the field test and applied to the GIDAS dataset. Therefore, the percentage of GIDAS accidents is calculated which could have been addressed by the speed reduction. An accident is addressable if the initial speed of the EGO-vehicle, multiplied by the percentage speed reduction, is equal to less than the avoidance speed. The avoidance speed is determined by accident reconstruction for each GIDAS accident.

Table 12-12 shows the safety potential of the attention treatment and the speed treatment of the EGO-vehicle drivers. It says that the attention nudge could have a larger effect than the speed nudge in 2025 and 2030. In the next step, the absolute numbers are adjusted to the results of the field tests.

Attention to potential hazards GIDAS 1999 - 2019* - relative weighted -			CITY (URBAN)					
			ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$
			n	%	n	%	n	n
CASUALTIES	Car Occupants	slightly	12,470	52.2%	9	0,1%	224	202
		seriously	1,180	29.0%				
		fatally	38	16.4%				
	Goods Vehicle Occupants	slightly	97	20.0%				
		seriously	16	12.2%				
		fatally	2	15.6%				
	Motorised Two-Wheelers	slightly	3,110	77.6%				
		seriously	783	56.5%				
		fatally	22	28.2%				
	Cyclists	slightly	8,178	94.4%	1.290	15,8%	29.362	36.265
		seriously	1,429	87.6%	204	14,3%	11.529	18.269
		fatally	26	60.1%	5	18,8%	240	251
	Pedestrians	slightly	2,449	95.8%				
		seriously	840	92.1%				
		fatally	45	70.5%				
	Other	slightly	883	84.1%	1	0,1%	4	2
		seriously	70	73.6%				
		fatally	1	32.8%				
	TOTAL	**slightly**	27,187	66.8%	1.300	4,8%	29.590	36.470
		seriously	4,318	52.5%	204	4,7%	11.529	18.269
		fatally	133	31.0%	5	3,6%	240	251

Speed to potential hazards GIDAS 1999 - 2019* - relative weighted -			CITY (URBAN)					
			ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$
			n	%	n	%	n	n
CASUALTIES	Car Occupants	slightly	12,470	52.2%	14	0,1%	347	313
		seriously	1,180	29.0%	1	0,1%	14	11
		fatally	38	16.4%				
	Goods Vehicle Occupants	slightly	97	20.0%				
		seriously	16	12.2%				
		fatally	2	15.6%				
	Motorised Two-Wheelers	slightly	3,110	77.6%				
		seriously	783	56.5%				
		fatally	22	28.2%				
	Cyclists	slightly	8,178	94.4%	2.643	32,3%	60.160	74.305
		seriously	1,429	87.6%	397	27,8%	22.434	35.549
		fatally	26	60.1%	7	28,2%	360	376
	Pedestrians	slightly	2,449	95.8%	1	0,1%	40	39
		seriously	840	92.1%				
		fatally	45	70.5%				
	Other	slightly	883	84.1%	1	0,1%	4	2
		seriously	70	73.6%				
		fatally	1	32.8%				
	TOTAL	**slightly**	27,187	66.8%	2.659	9,8%	60.552	74.660
		seriously	4,318	52.5%	398	9,2%	22.448	35.559
		fatally	133	31.0%	7	5,5%	360	376

*Due to the use of weighting factor rounding differences from ± 1 persons may occur.

Table 12-12: Safety potential of the attention nudge to potential hazards and EU-27 extrapolation of casualties in 2025 and 2030 according to attention (orange) and speed (blue), kind of road user and injury severity

The absolute numbers from Table 12-12 serve as basis for the impact assessment of the attention nudge. From the field test it is known, that the measure increased to attention of 10 out of 18 persons. This gives a benefit of 56 % for the further calculation. In parallel, the absolute number of addressable persons must be reduced by the double-addressed factor (97,4 %). Depending on the three scenarios, the addressable persons are shown in Table 13 according to injury severity for attention measures (orange). The percentage of people reacting to the measure (Y-factor) is assumed to be 100 %.

For the speed reduction it is assumed that 2 % of the initial speed is reduced by the attention measure. This percentage serves as basis to calculate the proportion of GIDAS accidents that could be addressed by a reduction of initial speed of 2 %. If the EGO-vehicle driver was addressed with the attention nudge, 9.4 % of the GIDAS accidents in the master dataset would have been addressed for the selected accident scenario. This value of 9.4 % is considered as benefit for the calculations.

Also, for the speed reduction, the number of absolutely addressable persons must be reduced by double-addressed accidents. Additionally, accidents are excluded that were already addressed by the attention nudge. These are approximately 25 % of the potential accidents for speed reduction. Depending on the three scenarios, the addressable persons by the speed reduction are shown in Table 12-13 (blue).

Potential hazard - Attention *-addressable casualties-*	Total		Optimistic scenario		Pessimistic scenario	
	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}
slightly injured	16,111	19,857	3,222	6,454	804	2,442
seriously injured	6,277	9,947	1,255	3,233	313	1,224
fatally injured	131	136	26	44	7	17
Potential hazard - Speed *-addressable casualties-*	Total		Optimistic scenario		Pessimistic scenario	
	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}
slightly injured	4,172	5,144	835	1,672	208	633
seriously injured	1,547	2,450	309	797	77	302
fatally injured	25	26	5	8	2	3
∑ Potential hazard *-addressable casualties-*	Total		Optimistic scenario		Pessimistic scenario	
	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}
slightly injured	20,283	25,001	4,057	8,126	1,012	3,075
seriously injured	7,824	12,397	1,564	4,030	390	1,526
fatally injured	156	162	31	52	9	20

Table 12-13: Impact assessment of the attention nudge to potential hazards by increasing the attention (orange), reducing the initial speed (blue) and the sum (grey) of addressable persons in 2025 and 2030

The sum (grey) of both impacts (increased attention and speed reduction) is the total number of addressable persons for the measure "potential hazards in intersections". The estimation says that 156 fatalities will be addressed in 2025 and 162 fatalities in 2030, if an immediate 100% market penetration is assumed. In addition, 28,000 slightly and seriously injured persons could be addressed in 2025 and up to 37,000 in 2030.

The most probable scenario will be between the optimistic and the pessimistic scenario. However, if the measure can be applied by a smartphone app, the optimistic assessment would be more realistic than the pessimistic. In-vehicle safety systems will enter the market slower than app-based measures.

In the optimistic scenario, 31 fatalities could be addressed in 2025 and 52 fatalities in 2030. In addition, 5,500 slightly and seriously injured persons could be addressed in 2025 and up to 12,000 in 2030. Compared to the optimistic scenario, the pessimistic scenario would address on average 74 % fewer people in 2025 and 62 % fewer people in 2030.

12.2.2 Coaching

The aim of the coaching measures is to cement a driver's choice of the safer behaviour option by providing coaching feedback. In the MeBeSafe project the following coaching schemes have been developed:

- **HGV driver behavioural change through online coaching** - Coach HGV drivers to cement the better driving skills
- **Behavioural change through online private driver coaching** - Coach the non-ACC users to become potential ACC users

If the coaching schemes would be launched in the EU with a market penetration of 100 % and the best boundary conditions, it is expected that up to 675 fatalities in 2025 and about 750 fatalities in 2030 could be addressed. In addition, 101,000 slightly and seriously injured persons could be addressed in 2025 and up to 122,000 persons in 2030. Further details on the coaching measures and the impact assessments are describe in the following sub-chapters.

It is assumed that the results of the optimistic scenario from the HGV coaching with 75% benefit and the pessimistic scenario from the ACC - competitive leader board with coaching scheme are the more realistic estimations. The sum of each coaching impact assessment indicates that 92 fatalities could be addressed in 2025 and 182 fatalities in 2030. In addition, 7,110 slightly and seriously injured persons could be addressed in 2025 and up to 18,100 persons in 2030. Further details on the coaching measures and the impact assessments are described in the following sub-chapters.

HGV driver behavioural change through online coaching

For the impact assessment of the HGV driver coaching measure, all HGV drivers from the GIDAS database are selected, who were either the main accident causer or have at least contributed to the accident without being the main causer. In GIDAS, up to three accident causes can be coded per participant.

HGV are defined in the coaching measure as commercial vehicle with a GVW above 3,5 tonnes and selected from the database accordingly. Finally, this gives 3,192 HGV drivers with at least one coded accident cause.

Table 12-14 shows the safety potential of HGV driver coaching in GIDAS and the extrapolated number of addressable persons (absolute number) for the EU in 2025 and 2030. The absolute numbers serve as basis for the adjustment to the mentioned boundary conditions.

Coaching HGV drivers GIDAS 1999 - 2019* - relative weighted -			CITY (URBAN)						RURAL (w/o motorway)						MOTORWAY						TOTAL					
			ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$
			n	%	n	%	n	n	n	%	n	%	n	n	n	%	n	%	n	n	n	%	n	%	n	n
CASUALTIES	Car Occupants	slightly	12,470	52.2%	1,047	8.4%	25,197	22,724	8,332	34.9%	681	8.2%	16,421	15,247	3,105	13.0%	585	18.8%	19,197	22,808	23,907	100%	2,313	9.7%	60,815	60,778
		seriously	1,180	29.0%	65	5.5%	1,068	793	2,302	56.5%	161	7.0%	3,549	3,429	593	14.5%	98	16.5%	1,793	1,744	4.075	100%	324	7.9%	6,411	5,966
		fatally	38	16.4%	5	12.9%	207	164	154	66.5%	11	7.3%	402	332	39	17.1%	14	35.4%	372	354	231	100%	30	13.0%	981	851
	Goods Vehicle Occupants	slightly	97	20.0%	78	80.7%	11,024	10,300	140	29.0%	116	82.8%	11,404	10,551	247	51.0%	227	91.9%	18,400	29,084	485	100%	422	87.0%	40,828	49,935
		seriously	16	12.2%	13	82.0%	968	814	32	24.5%	29	89.0%	2,661	2,426	84	63.3%	82	98.6%	4,411	6,570	132	100%	124	94.2%	8,041	9,810
		fatally	2	15.6%	2	100%	111	84	2	15.0%	1	66.7%	285	237	7	69.4%	7	100%	1,108	1,974	10	100%	10	95.0%	1,504	2,295
	Motorised Two-Wheelers	slightly	3,110	77.6%	94	3.0%	3,649	3,361	836	20.9%	29	3.4%	911	859	60	1.5%	2	2.9%	410	691	4,006	100%	124	3.1%	4,970	4,912
		seriously	783	56.5%	37	4.8%	1,184	1,028	567	40.9%	20	3.5%	1,125	1,372	35	2.6%	2	6.5%	206	275	1,385	100%	60	4.3%	2.515	2,676
		fatally	22	28.2%	2	6.8%	78	62	52	66.5%	4	7.5%	162	146	4	5.3%	1	20.8%	74	92	79	100%	6	8.0%	314	299
	Cyclists	slightly	8,178	94.4%	424	5.2%	9,655	11,925	488	5.6%	10	2.0%	664	968	0	0%					8,665	100%	434	5.0%	10,319	12,893
		seriously	1,429	87.6%	67	4.7%	3,770	5,974	202	12.4%	4	2.1%	637	1,218	0	0%					1,631	100%	71	4.3%	4,407	7,192
		fatally	26	60.1%	5	19.5%	248	259	17	38.9%	2	11.7%	88	82	1	1.0%					43	100%	7	16.3%	336	341
	Pedestrians	slightly	2,449	95.8%	144	5.9%	5,800	5,630	101	3.9%	3	3.2%	183	178	7	0.3%	4	60.3%	146	149	2,557	100%	151	5.9%	6,129	5,957
		seriously	840	92.1%	67	7.9%	3,362	3,677	64	7.0%	8	12.3%	448	461	8	0.9%	3	36.0%	167	254	911	100%	77	8.5%	3,976	4,393
		fatally	45	70.5%	10	23.0%	742	677	15	23.5%	4	24.1%	205	165	4	6.0%	1	33.7%	165	237	64	100%	15	23.9%	1,112	1,079
	Other	slightly	883	84.1%	99	11.2%	372	201	142	13.5%	22	15.8%	312	182	25	2.3%	9	37.7%	179	103	1,049	100%	131	12.5%	863	486
		seriously	70	73.6%	8	11.7%	79	45	24	24.7%	6	25.2%	148	89	2	1.7%	1	46.9%	20	10	96	100%	15	15.6%	247	144
		fatally	1	32.8%					2	53.1%					0	14.1%					3	100%				
	TOTAL	slightly	27,187	66.8%	1,886	6.9%	55,697	54,141	10,039	24.7%	862	8.6%	29,895	27,985	3,444	8.5%	828	24.0%	38,331	52,835	40,670	100%	3,576	8.8%	123,924	134,961
		seriously	4,318	52.5%	257	6.0%	10,431	12,332	3,191	38.8%	228	7.1%	8,568	8,995	722	8.8%	186	25.8%	6,598	8,854	8,230	100%	671	8.2%	25,598	30,181
		fatally	133	31.0%	23	17.5%	1,385	1,246	241	56.1%	22	9.0%	1,142	962	55	12.9%	23	41.9%	1,720	2,657	430	100%	68	15.9%	4,247	4,865

*Due to the use of weighting factor rounding differences from ± 1 persons may occur.

Table 12-14: Safety potential of the HGV driver coaching and EU-27 extrapolation of casualties in 2025 and 2030 according to the accident location, kind of road user and injury severity

In order to determine a potential effect of the HGV coaching measure, the group of all HGV drivers with at least one accident cause is adjusted to the boundary conditions of the measure. Due to technical problems of the application and the corona crisis, the number of HGV drivers and trips in the field test campaign was too small for a robust and meaningful impact assessment of the driver behaviour according to smoothness, harsh braking and harsh acceleration. Consequently, these three types of behaviour could not be evaluated in a dedicated impact assessment, but instead, the general effect of HGV driver coaching is evaluated.

Due to the fact that not all accident causes can be addressed by coaching, the group of HGV drivers is adjusted by the following boundary conditions. It is assumed that accidents caused by limited ability to drive (e.g. alcohol, intoxicating substances), speeding, technical or maintenance faults and other accident causes without driver influence (e.g. weather conditions, road conditions) are excluded. Accidents due to fatigue are taken into account in coaching. Targeted coaching has the potential for avoiding accidents due to fatigue. After filtering, 73,62 % of HGV drivers are generally addressable by the coaching scheme.

In addition, the field test samples show that not every HGV driver has to be coached. In the test campaign, five out of 29 HGV drivers show potential for coaching and were coached. Thus, the assumed share of coachable persons (Y-factor) for the HGV driver coaching is 17 %.

However, it seems not meaningful to calculate the impact on the basis of five coached HGV drivers. Accordingly, an additional (theoretical) benefit variation is implemented to show the effect of a benefit (X-factor) of 25 % and 75 %. The benefit describes the percentage of HGW drivers who show a safer behaviour after the coaching sessions.

Like for the other nudging measures, the dataset for the HGV coaching also has to be multiplied by a certain percentage (96.33 %, Z-factor) to exclude double-addressed accidents. The boundary conditions of the three scenarios for the market penetration are explained in the sub-chapter **Market penetration**.

The results of the impact assessment for the HGV driver coaching is shown in Table 12-15. The calculation of the total number estimates that 130 fatalities will be addressed in 2025 and 149 fatalities in 2030, if a benefit of 25 % is assumed. With a benefit of 75 %, the estimation of the total number increases by a factor of three. From Deliverable 5.4 it is known that the majority of drivers evaluated the concept behind the app and the coaching approach very positively, so the 75 % benefit seems more realistic.

Coaching HGV drivers *-addressable casualties-*	Total				Optimistic scenario				Pessimistic scenario			
	EU_{2025}		EU_{2030}		EU_{2025}		EU_{2030}		EU_{2025}		EU_{2030}	
	X=25%	X=75%	X=25%	X=75%	X=25%	X=75%	X=25%	X=75%	X=25%	X=75%	X=25%	X=75%
slightly injured	3,788	11,364	4,126	12,377	758	2,273	1,341	4,022	189	567	507	1,522
seriously injured	782	2,347	923	2,768	156	469	300	900	39	117	113	340
fatally injured	130	389	149	446	26	78	48	145	6	19	18	55

Table 12-15: Impact assessment of the HGV coaching with a variation of the benefit value X in 2025 and 2030

In the optimistic scenario with a benefit of 75 %, 78 fatalities could be addressed in 2025 and 145 fatalities in 2030. Additionally, up to 2,700 slightly or seriously injured persons are addressed in 2025 and more than 4,900 injured persons in 2030.

It is assumed that the optimistic scenario is more realistic, because the market penetration of smartphone applications with a system for tracking the truck driver behaviour and an online coaching scheme tends to be faster than In-vehicle measures.

Behavioural change through online private driver coaching

The behavioural change through online driver coaching has the intention to motivate ACC non-users to become ACC user. Previous analyses showed that ACC-oriented coaching would have the largest effect on drivers who do not use ACC at all.

The baseline values for the impact assessments are the results of the ACC measure from 12.2.1 - In-vehicle measures. For 2020, the results of the ACC - ambient display nudge shows that 20.82 % of participants use ACC. According to the ACC - competitive leader board nudge, the percentage of ACC user increase to 30.67 %. These figures of ACC users is used to calculate the percentage of ACC non-users.

From the field test setup, it was assumed that 30 % of ACC non-users could benefit from ACC coaching. For the impact assessment, the percentage of coachable ACC non-users was adopted (Y-factor). Furthermore, it is assumed that 60 % of the coached ACC non-users become ACC-users (X-factor).

Figure 12-2 shows the assumed distributions of ACC usage due to the two nudges (ACC - ambient display nudge, ACC - competitive leader board nudge) for the period between 2020 and 2030, if all ACC non-users would be coached.

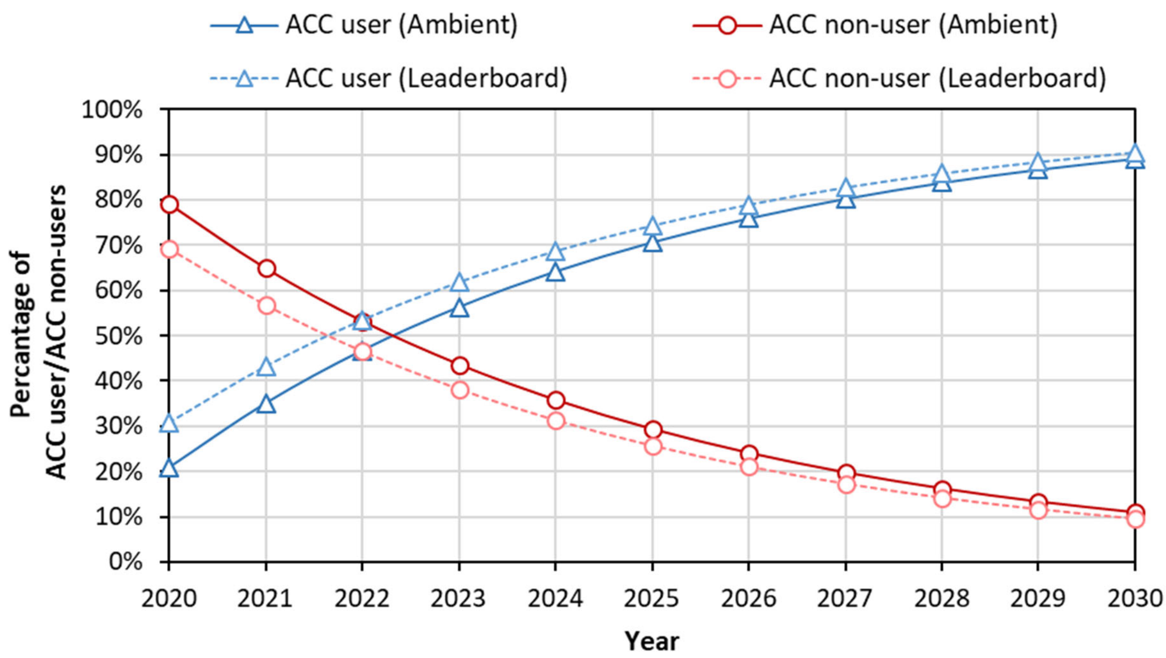

Figure 12-2: Share of ACC users (blue) and ACC non-users (red) according to ACC-ambient display nudge (straight) and ACC-competitive leader board nudge (dashed) between 2020 and 2030

The prerequisite for this estimation is an installed ACC in the vehicles. The assumption for the ACC – ambient display nudge and online coaching is that 70 % of drivers will use ACC in 2025 and 89 % of in 2030. For the ACC - competitive leader board nudge and coaching the estimation says that 75 % of drivers will use ACC in 2025 and 90% in 2030, respectively.

The calculation of the impact assessment for ACC coaching is based on the impact assessment for the ACC In-vehicle measure (12.2.1 - In-vehicle measures). The difference between the impact assessment for the ACC In-vehicle measure and ACC coaching is that the benefit value for the ACC In-vehicle nudge remains constant over the period from 2020 to 2030. In contrast, the benefit for ACC coaching increases over time.

Figure 12-2 serves as basis for the ACC usage rate (benefits) of the ACC - ambient display nudge and ACC - competitive leader board in 2025 and 2030. All other influencing factors are the same as for the ACC In-vehicle impact assessment.

The results of the impact assessment for the ACC coaching scheme is shown in Table 12-16. The ACC – ambient display nudge with coaching will address a total number of 240 fatalities in 2025 and 262 fatalities in 2030. In contrast, the ACC - competitive leader board nudge with coaching could address 289 fatalities in 2025 and 304 fatalities in 2030. Again, a market penetration of 100 % has been assumed here.

ACC Coaching - Ambient *-addressable casualties-*	Total		Optimistic scenario		Pessimistic scenario	
	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}
slightly injured	67,950	85,996	13,590	27,949	3,389	10,578
seriously injured	4,959	6,149	992	1,998	247	756
fatally injured	240	262	48	85	12	32
ACC Coaching - Leader board *-addressable casualties-*	Total		Optimistic scenario		Pessimistic scenario	
	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}
slightly injured	81,615	99,706	16,323	32,404	4,071	12,264
seriously injured	5,957	7,129	1,191	2,317	297	877
fatally injured	289	304	58	99	14	37

Table 12-16: Impact assessment of the ACC - ambient display nudge and the ACC - competitive leader board nudge in 2025 and 2030

For the optimistic scenario of the ACC - ambient display nudge, 48 fatalities and up to 14,500 slightly and seriously injured persons could be addressed in 2025. The numbers of addressable persons are assumed to increase in 2030. It is assumed that the measure will address 85 fatalities and nearly 30,000 slightly and seriously injured persons.

The ACC - competitive leader board nudge could address 58 fatalities and more than 17,500 slightly and seriously injured persons in the optimistic scenario in 2025. In 2030 it is assumed that the measure will address 99 fatalities and nearly 35,000 slightly and seriously injured persons.

Here, it is assumed that the pessimistic scenario is the more realistic one. In this scenario, the ACC - ambient display nudge could address 12 fatalities and more than 3,600 slightly and seriously injured persons in 2025. In 2030, the measure will address 32 fatalities and more than 18,000 slightly and seriously injured persons.

For the pessimistic scenario of the ACC - competitive leader board nudge, 14 (37) fatalities and more than 4,300 (13,100) slightly and seriously injured persons could be addressed in 2025 (2030).

If the ACC coaching can also be offered for commercial vehicles, the number of addressed persons could be increased by a factor of five.

12.2.3 Infrastructure measures

The aim of infrastructure nudging measures is to motivate drivers of motorized vehicles and cyclists to reduce their initial speed in front of potential accident locations and to increase their attention. The measures are mainly implemented by visual measures, which differ depending to the area of application. The following infrastructure measures have been developed in the MeBeSafe project:

- **Safe speed/trajectory on interurban roads** - Nudge speeding drivers of motorized vehicles to reduce speed in front of hazardous motorway exits, leading to a safer trajectory on the ramp
- **Cyclists' speed reduction (Sweden)** - Nudge cyclists to reduce speed and to increase attention in front of hazardous intersections
- **Cyclists' speed reduction (Netherlands)** - Nudge cyclists to reduce speed and to increase attention for the priority (right of way) at the intersection

The results of the field test indicated that the Dutch cyclist nudge was not able to fully influence cyclist speeds. [Ljung Aust, et al. (2020)] The difference in speed distribution with and without nudge is not statistically significant. Consequently, the impact assessment for the Dutch cyclist nudge is not carried out and no addressed persons are included for the overall summary of the infrastructure measures.

If the other infrastructure measures are launched in the EU-27 with an installation rate of 100 % for all hazardous locations, it could be expected that up to 279 fatalities in 2025 and 249 fatalities in 2030 will be addressed. In addition, 14,746 slightly and seriously injured persons could be addressed in 2025 and up to 17,770 persons in 2030.

The difficulty in assessing infrastructure measures is that no information on installation rates is available on European level. For this purpose, it is assumed that the pessimistic scenario is the most realistic scenario.

The sum of each infrastructure impact assessment indicate that 28 fatalities could be addressed in 2025 and 49 fatalities in 2030. In addition, 1,474 slightly and seriously injured persons could be addressed in 2025 and up to 3,553 persons in 2030. Further details on the infrastructure measures and the impact assessments are described in the following sub-chapters.

For the impact assessment of the infrastructure measures, which is also based on the GIDAS database, it should be considered that the traffic and accident situation (especially for cyclists) in Germany differs from the situation in Sweden and the Netherlands. Generally, cyclist traffic varies substantially between the EU-27 countries (Special Eurobarometer 422a, 2014). It is assumed that the impact in countries with a higher rate of bicycle use (e.g. the Netherlands, Sweden, Denmark) has a higher impact on accidents than in Eastern Europe. However, there is a lack of reliable accident data for the countries to confirm this assumption.

Safe speed/trajectory on interurban roads

The measure for safe speed and trajectory on interurban roads was tested on an exit lane in Eindhoven in the Netherlands. The aim was to identify drivers with a speed of at least 10 % above the speed limit (which decreases from 70 km/h to 50 km/h, see chapter 9.2) and to encourage them by a visual nudge to reduce their speed and increase their attention. The speed reduction and increased attention also implies that drivers take a safer trajectory on the following exit ramp.

For the impact assessment, only accidents were considered. In general, the measure aims to preserve a safer driver behaviour. However, safe driving behaviour is difficult to assess. For this reason, accidents are considered as result of a cascade of critical events. A critical situation can be triggered by speeding, which the measure aims to address by a nudge.

For the analysis, "speeding accident" was defined for all accidents where at least one accident cause was coded as "inappropriate speed" or the driver was at least 5 km/h faster than the speed limit.

In the first step of the impact assessment, the relevant accidents have to be identified from the database. National statistics provide limited information on the exact localization of accidents and the used lanes. Consequently, it is difficult to deduce from national statistics whether the accidents happened on a motorway exit or not.

The identification of relevant accidents from GIDAS is also difficult. Accidents in motorway exits are not directly coded via separate parameters. Some of the GIDAS accidents in motorway exits can be easily identified using the accident type "123" (Figure 12-3). This type of accident describes a driving accident that occurred when turning into an exit lane (Ortlepp, 2016). However, this accident type does not include all accidents in GIDAS that happened on a motorway exit or ramp, so additional queries are necessary.

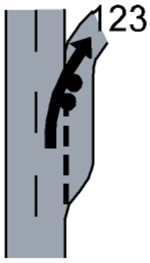

Figure 12-3: Type of accident 123 - Turning into an exit lane

As there is an extensive set of photographs available for each GIDAS accident, an additional case-by-case analysis was carried out to find actually addressed cases. Therefore, several filters are applied to the GIDAS database (motorway accidents in which at least one participant was speeding) and the GPS coordinates were used to exclude all accidents that did not occur at motorway junctions. Finally, the remaining speeding accidents and accidents without GPS coordinates were analysed case by case to identify accidents on exit lanes or ramps. The single case analysis identified 116 actual accidents in the GIDAS database (unweighted), resulting in 147 weighted accidents.

The number of motorway accidents by kind of road user and injury severity is shown in Table 12-17. The safety potential is calculated in comparison to all weighted GIDAS accidents and is used for the extrapolation to the EU level in 2025 and 2030. The absolute numbers serve as basis for the adjustment to the boundary conditions of the field test.

Safe speed/trajectory on motorway exits GIDAS 1999 - 2019* - relative weighted -			CITY (URBAN)						RURAL (w/o motorway)						MOTORWAY						TOTAL					
			ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$
			n	%	n	%	n	n	n	%	n	%	n	n	n	%	n	%	n	n	n	%	n	%	n	n
CASUALTIES	Car Occupants	slightly	12,470	52.2%					8,332	34.9%					3,105	13.0%	104	3.4%	3,421	4,065	23,907	100%	104	3.4%	3,421	4,065
		seriously	1,180	29.0%					2,302	56.5%					593	14.5%	25	4.1%	450	437	4.075	100%	25	4.1%	450	437
		fatally	38	16.4%					154	66.5%					39	17.1%	1	2.0%	21	20	231	100%	1	2.0%	21	20
	Goods Vehicle Occupants	slightly	97	20.0%					140	29.0%					247	51.0%	1	0.3%	57	90	485	100%	1	0.3%	57	90
		seriously	16	12.2%					32	24.5%					84	63.3%	3	3.4%	154	229	132	100%	3	3.4%	154	229
		fatally	2	15.6%					2	15.0%					7	69.4%					10	100%				
	Motorised Two-Wheelers	slightly	3,110	77.6%					836	20.9%					60	1.5%	6	10.5%	1,485	2,504	4,006	100%	6	10.5%	1,485	2,504
		seriously	783	56.5%					567	40.9%					35	2.6%	6	15.9%	502	672	1,385	100%	6	15.9%	502	672
		fatally	22	28.2%					52	66.5%					4	5.3%	1	29.2%	105	129	79	100%	1	29.2%	105	129
	Cyclists	slightly	8,178	94.4%					488	5.6%					0	0%					8,665	100%				
		seriously	1,429	87.6%					202	12.4%					0	0%					1,631	100%				
		fatally	26	60.1%					17	38.9%					1	1.0%	1	100%	13	17	43	100%	1	100%	13	17
	Pedestrians	slightly	2,449	95.8%					101	3.9%					7	0.3%					2,557	100%				
		seriously	840	92.1%					64	7.0%					8	0.9%					911	100%				
		fatally	45	70.5%					15	23.5%					4	6.0%					64	100%				
	Other	slightly	883	84.1%					142	13.5%					25	2.3%					1,049	100%				
		seriously	70	73.6%					24	24.7%					2	1.7%					96	100%				
		fatally	1	32.8%					2	53.1%					0	14.1%					3	100%				
	TOTAL	slightly	27,187	66.8%					10,039	24.7%					3,444	8.5%	111	3.2%	4,963	6,658	40,670	100%	111	3.2%	4,963	6,658
		seriously	4,318	52.5%					3,191	38.8%					722	8.8%	33	4.6%	1,106	1,338	8,230	100%	33	4.6%	1,106	1,338
		fatally	133	31.0%					241	56.1%					55	12.9%	3	4.4%	138	166	430	100%	3	4.4%	138	166

*Due to the use of weighting factor rounding differences from ± 1 persons may occur.

Table 12-17: Safety potential of the speed/trajectory measure on motorway exits and EU-27 extrapolation of casualties in 2025 and 2030 according to the accident location, kind of road user and injury severity

The field test showed that the nudging measure reduces the initial speed by up to 3.0 km/h for vehicles going between 80 and 85 km/h. Vehicles with a higher initial speed between 95 and 100 km/h even slowed down by 4.6 km/h (4.9%) on average.

For the calculation of the related benefit, the initial speed distribution of GIDAS accidents on motorway exit lanes is shown in Figure 12-4.

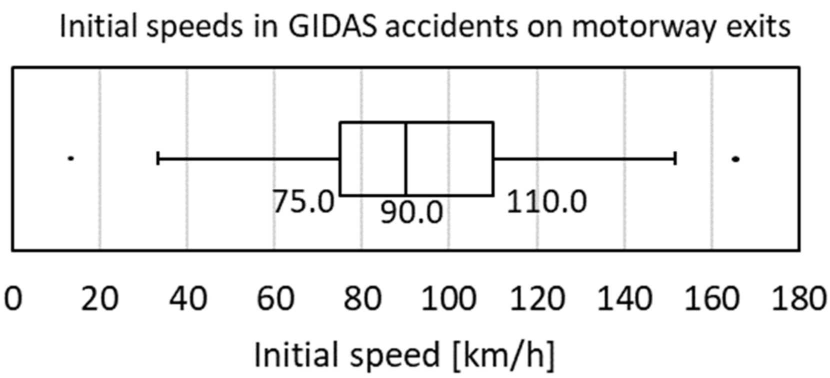

Figure 12-4: Box plot of the initial speed in accidents on motorway exits (GIDAS)

Half of all considered accidents occurred at initial speeds between 75 and 110 km/h. The median value is 90 km/h. Thus, an average speed reduction of 4.9 % is chosen for the impact assessment because this fits the indicated test range quite well.

This speed reduction of 4.9 % serves as basis for calculating the proportion of GIDAS accidents that could have been avoided by the nudge's speed reduction. Therefore, an accident is defined as addressable if the initial speed multiplied by the percentage of speed reduction is equal or less than the coded avoidance speed from the accident reconstruction. If the measure is installed in all relevant GIDAS accidents on motorway exit lanes or ramps, 20.4 % of accidents could have been avoided. The value of 20.4 % is considered as benefit (X-factor) for the impact assessment.

Due to the fact that the measure only addresses speeding vehicles with a headway of at least 90 m to the leading vehicle, 70 % of addressable drivers are nudged (Y-factor). Again, the chosen dataset for the measure has to be multiplied by a percentage of 99.90 % (Z-factor) to excluded double-addressed accidents (which are very few as the other nudges focus on completely other accident situations). The results of the impact assessment according to the three market penetration scenarios (sub-chapter Market penetration) are shown in Table 12-18.

Safe speed/trajectory on motorway exits *-addressable casualties-*	Total		Optimistic scenario		Pessimistic scenario	
	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}
slightly injured	708	950	177	475	71	190
seriously injured	158	191	39	95	16	38
fatally injured	20	24	5	12	2	5

Table 12-18: Impact assessment of the speed/trajectory measure on motorway exits in 2025 and 2030

The calculation estimates that 20 fatalities will be addressed in 2025 and 24 fatalities in 2030, if 100 % of motorway exits are equipped with the nudge. The adjustment of the total number to the optimistic market penetration scenario would result in five fatalities in 2025 and twelve fatalities in 2030. For infrastructure measures, the pessimistic scenario leads to a more realistic impact assessment, where two fatalities will be addressed in 2025 and five in 2030. Additionally, 87 (228) slightly or seriously injured persons are addressed in 2025 (2030).

The aim of the measure is to treat speeding and trajectories at location where these properties can lead to problems (e.g. unstable driving situation, loss of control of vehicles, accidents). The measure was tested at a motorway exit and the impact assessment calculated the impact of the nudge for this location. But in principle it is also conceivable that this measure can be used at locations where speeding or critical trajectories could also be problematic.

In addition to the tested location on a motorway exit, the impact assessment is extended by all relevant accidents in curves on interurban roads (incl. rural roads and motorways), where speeding was a problem. For this purpose, all accidents were filtered out of GIDAS that occurred on motorways and rural roads (i.e. the following GIDAS parameters for road classifications were used: motorway, federal-, state and district highways) where the accident was either caused by the driver´s losing control of his vehicle in a curve or accidents happened because of a deceleration lane. The last named filter also includes the accident scenario on motorway exits. The filtering of the GIDAS database according to the criteria identified 977 accidents (unweighted), resulting in 983 weighted accidents. The number of accidents by accident location (urban, rural, motorway), kind of road user and injury severity is shown in Table 12-19. It should be noted that some accidents in curves on interurban roads can also have happened in urban areas where for example a federal highway passes through a village.

Safe speed/trajectory on interurban roads GIDAS 1999 - 2019* - relative weighted -			CITY (URBAN)						RURAL (w/o motorway)						MOTORWAY						TOTAL					
			ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$
			n	%	n	%	n	n	n	%	n	%	n	n	n	%	n	%	n	n	n	%	n	%	n	n
CASUALTIES	Car Occupants	slightly	12,470	52.2%	225	1.8%	5.409	4.878	8,332	34.9%	508	6.1%	12,235	11,360	3,105	13.0%	118	3.8%	3,874	4,603	23,907	100%	851	3.6%	21,518	20,841
		seriously	1,180	29.0%	76	6.4%	1.241	921	2,302	56.5%	224	9.7%	4,949	4,782	593	14.5%	33	5.6%	606	589	4.075	100%	333	8.2%	6,796	6,292
		fatally	38	16.4%	3	7.8%	125	99	154	66.5%	26	16.8%	921	762	39	17.1%	2	4.0%	42	40	231	100%	30	13.1%	1,089	902
	Goods Vehicle Occupants	slightly	97	20.0%	11	11.0%	1.496	1.398	140	29.0%	8	5.4%	737	682	247	51.0%	1	0.3%	57	90	485	100%	19	3.9%	2,291	2,170
		seriously	16	12.2%					32	24.5%	4	11.3%	338	308	84	63.3%	3	3.4%	154	229	132	100%	7	4.9%	491	537
		fatally	2	15.6%					2	15.0%	1	33.3%	143	118	7	69.4%					10	100%	1	5.0%	143	118
	Motorised Two-Wheelers	slightly	3,110	77.6%	24	0.8%	932	859	836	20.9%	34	4.1%	1,090	1,028	60	1.5%	6	10.5%	1,485	2,504	4,006	100%	65	1.6%	3,508	4,391
		seriously	783	56.5%	15	1.9%	477	414	567	40.9%	34	6.0%	1,903	2,321	35	2.6%	6	15.9%	502	672	1,385	100%	54	3.9%	2,882	3,407
		fatally	22	28.2%	2	10.6%	122	96	52	66.5%	3	5.9%	127	114	4	5.3%	1	29.2%	105	129	79	100%	7	8.5%	353	340
	Cyclists	slightly	8,178	94.4%	1	0.0%	24	30	488	5.6%					0	0%					8,665	100%	1	0.0%	24	30
		seriously	1,429	87.6%					202	12.4%					0	0%					1,631	100%				
		fatally	26	60.1%					17	38.9%					1	1.0%	1	100%	13	17	43	100%	1	1.0%	13	17
	Pedestrians	slightly	2,449	95.8%	1	0.0%	43	42	101	3.9%					7	0.3%					2,557	100%	1	0.0%	43	42
		seriously	840	92.1%					64	7.0%					8	0.9%					911	100%				
		fatally	45	70.5%	1	1.3%	42	39	15	23.5%					4	6.0%					64	100%	1	0.9%	42	39
	Other	slightly	883	84.1%					142	13.5%	2	1.1%	22	13	25	2.3%					1,049	100%	2	0.1%	22	13
		seriously	70	73.6%					24	24.7%	1	3.3%	20	12	2	1.7%					96	100%	1	0.8%	20	12
		fatally	1	32.8%					2	53.1%					0	14.1%					3	100%				
	TOTAL	slightly	27,187	66.8%	261	1.0%	7,905	7,206	10,039	24.7%	551	5.5%	14,085	13,083	3,444	8.5%	125	3.6%	5,416	7,196	40,670	100%	938	2.3%	27,405	27,486
		seriously	4,318	52.5%	91	2.1%	1,718	1,335	3,191	38.8%	262	8.2%	7,210	7,422	722	8.8%	41	5.7%	1,262	1,490	8,230	100%	395	4.8%	10,190	10,247
		fatally	133	31.0%	6	4.4%	289	234	241	56.1%	29	12.2%	1,191	995	55	12.9%	3	5.8%	160	186	430	100%	38	9.0%	1,639	1,415

*Due to the use of weighting factor rounding differences from ± 1 persons may occur.

Table 12-19: Safety potential of the speed/trajectory measure on interurban roads and EU-27 extrapolation of casualties in 2025 and 2030 according to the accident location, kind of road user and injury severity

The absolute numbers serve (red box) as basis for the adjustment to the boundary conditions of the field test, which also apply to the extended impact assessment of the nudge. For a better comparison of the two impact assessments, the assumptions for market penetration and non double-addressed factor remain the same.

The calculation with the extended dataset estimates that 234 fatalities will be addressed in 2025 and 202 fatalities in 2030, if 100 % of the inter-urban locations are equipped with the nudge. The adjustment of the total number to the optimistic market penetration scenario would result in 58 fatalities in 2025 and 101 fatalities in 2030. For infrastructure measures, the pessimistic scenario leads to a more realistic impact assessment, where 23 fatalities will be addressed in 2025 and 40 in 2030. Additionally, 536 (1,076) slightly or seriously injured persons are addressed in 2025 (2030).

Safe speed/trajectory on interurban roads -addressable casualties-	Total		Optimistic scenario		Pessimistic scenario	
	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}
slightly injured	3,910	3,921	977	1,961	391	784
seriously injured	1,454	1,462	363	731	145	292
fatally injured	234	202	58	101	23	40

Table 12-20: Impact assessment of the speed/trajectory measure on interurban roads in 2025 and 2030

The extension of the dataset for interurban roads show that accidents on motorway exits represent 11,8% of the accident scenario, resulting in 16,3% for the weighted accidents scenario. If the results from the field test are applied to dangerous road exits and critical curves on interurban roads (including highways and country roads), where loss of control in combination with speeding dominates, nine to twelve times higher fatalities could be addressed. The numbers of addressed slightly and severely injured persons would be four to nine times higher.

Cyclists' speed reduction - Sweden

The cyclists' speed reduction measure in Sweden was implemented at two test sites in Gothenburg. The intention of the two measures is to increase the attention of the cyclists and to reduce their initial speeds in front of an intersection where serious bicycle accidents occurred in the past. The main objective of the field trial is to analyse the speed behaviour before and after the implementation of the nudging measure.

For the impact assessment, the GIDAS database is filtered for urban accidents that occurred at junctions, crossings, roundabouts or property exits where cyclists had a conflict with another road user (incl. pedestrians). Driving (loss of control) accidents of cyclists are excluded.

Table 12-21 shows the number of (weighted) GIDAS accidents between cyclists and other road users at junctions, crossings, roundabouts or property exits. The safety potential is calculated in comparison to all weighted GIDAS accidents.

Cyclists' speed reduction **Sweden** GIDAS 1999 - 2019* - relative weighted -			CITY (URBAN)						RURAL (w/o motorway)					
			ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$
			n	%	n	%	n	n	n	%	n	%	n	n
CASUALTIES	Car Occupants	slightly	12,470	52.2%	30	0.2%	713	643	8,332	34.9%				
		seriously	1,180	29.0%	1	0.1%	14	11	2,302	56.5%				
		fatally	38	16.4%					154	66.5%				
	Goods Vehicle Occupants	slightly	97	20.0%	1	0.6%	77	72	140	29.0%				
		seriously	16	12.2%					32	24.5%				
		fatally	2	15.6%					2	15.0%				
	Motorised Two-Wheelers	slightly	3,110	77.6%	23	0.7%	876	807	836	20.9%				
		seriously	783	56.5%	3	0.4%	96	83	567	40.9%				
		fatally	22	28.2%					52	66.5%				
	Cyclists	slightly	8,178	94.4%	4,808	58.8%	109,435	135,165	488	5.6%				
		seriously	1,429	87.6%	711	49.7%	40,185	63,677	202	12.4%				
		fatally	26	60.1%	15	57.6%	735	767	17	38.9%				
	Pedestrians	slightly	2,449	95.8%	33	1.3%	1,331	1,293	101	3.9%				
		seriously	840	92.1%	7	0.8%	346	379	64	7.0%				
		fatally	45	70.5%					15	23.5%				
	Other	slightly	883	84.1%	2	0.3%	9	5	142	13.5%				
		seriously	70	73.6%					24	24.7%				
		fatally	1	32.8%					2	53.1%				
	TOTAL	**slightly**	27,187	66.8%	4,897	18.0%	112,442	137,985	10,039	24.7%				
		seriously	4,318	52.5%	721	16.7%	40,641	64,150	3,191	38.8%				
		fatally	133	31.0%	15	11.1%	735	767	241	56.1%				

Cyclists' speed reduction **Sweden** GIDAS 1999 - 2019* - relative weighted -			MOTORWAY						TOTAL					
			ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$
			n	%	n	%	n	n	n	%	n	%	n	n
CASUALTIES	Car Occupants	slightly	3,105	13.0%					23,907	100%	30	0.2%	713	643
		seriously	593	14.5%					4.075	100%	1	0.1%	14	11
		fatally	39	17.1%					231	100%				
	Goods Vehicle Occupants	slightly	247	51.0%					485	100%	1	0.6%	77	72
		seriously	84	63.3%					132	100%				
		fatally	7	69.4%					10	100%				
	Motorised Two-Wheelers	slightly	60	1.5%					4,006	100%	23	0.7%	876	807
		seriously	35	2.6%					1,385	100%	3	0.4%	96	83
		fatally	4	5.3%					79	100%				
	Cyclists	slightly	0	0%					8,665	100%	4,808	58.8%	109,435	135,165
		seriously	0	0%					1,631	100%	711	49.7%	40,185	63,677
		fatally	1	1.0%					43	100%	15	57.6%	735	767
	Pedestrians	slightly	7	0.3%					2,557	100%	33	1.3%	1,331	1,293
		seriously	8	0.9%					911	100%	7	0.8%	346	379
		fatally	4	6.0%					64	100%				
	Other	slightly	25	2.3%					1,049	100%	2	0.3%	9	5
		seriously	2	1.7%					96	100%				
		fatally	0	14.1%					3	100%				
	TOTAL	**slightly**	3,444	8.5%					40,670	100%	4,897	18.0%	112,442	137,985
		seriously	722	8.8%					8,230	100%	721	16.7%	40,641	64,150
		fatally	55	12.9%					430	100%	15	11.1%	735	767

*Due to the use of weighting factor rounding differences from ± 1 persons may occur.

Table 12-21: Safety potential of cyclists' speed reduction measure in Sweden and EU-27 extrapolation of casualties in 2025 and 2030 according to the accident location, kind of road user and injury severity

The percentage of the safety potential is used to extrapolate the numbers of addressable persons (absolute number) for the EU-27 in 2025 and 2030. The absolute numbers serve as basis for the adjustment to the boundary conditions.

The field test showed that the measure on the one test site reduced the initial speed of cyclists by 0.7 km/h on average. Compared to the average baseline speed of 23.4 km/h, the speed reduction is 3 %. This percentage serves as basis for calculating the number of accidents that could be avoided by a reduction of initial speed by 3 %. As a result, 8.6 % of the relevant GIDAS accidents in the master dataset could have been addressed and this value is considered as benefit (X-factor) for the impact assessment.

For the addressed cyclists by the measure (Y-factor), the optimal value from the field test of 72 % is assumed. Then, the dataset for the measure is again multiplied by the specific percentage (98.97 %, Z-factor) to excluded double-addressed accidents. The results of the impact assessment according to the three market penetration scenarios (sub-chapter **Market penetration**) are shown in Table 12-22.

Cyclists' speed reduction ***Sweden*** *-addressable casualties-*	Total		Optimistic scenario		Pessimistic scenario	
	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}	EU_{2025}	EU_{2030}
slightly injured	6,891	8,456	1,723	4,228	689	1,691
seriously injured	2,491	3,931	623	1,966	249	786
fatally injured	45	47	11	23	5	9

Table 12-22: Impact assessment of cyclists' speed reduction measure in Sweden in 2025 and 2030

The calculation of the total number says that 45 fatalities will be addressed in 2025 and 47 fatalities in 2030, if 100 % of intersections would be equipped with the nudge. In the optimistic scenario eleven (23) fatalities are addressable in 2025 (2030).

For infrastructure measures, the pessimistic scenario leads to a more realistic impact assessment, where five fatalities will be addressed in 2025 and nine fatalities in 2030. Additionally, more than 930 slightly or seriously injured persons are addressed in 2025 and up to 2,400 injured persons in 2030.

Cyclists' speed reduction - Netherlands

The cyclists' speed reduction measure in the Netherlands was implemented on one test site in Eindhoven (NL), where only cyclists, moped riders and pedestrians are allowed to drive or to walk. The nudge aims to increase the driver's attention to the priority (right of way) at the intersection. Therefore, the speed and safety changes by the nudging measure are evaluated. The location was selected because of many cyclist-cyclist and cyclist-pedestrian interactions, which represents a safety concern. The main objective of the field trial is to analyse the speed behaviour before and after the application of the nudging measure.

The GIDAS database is again filtered for all urban accidents that have occurred at junctions, crossings, roundabouts or property exits with conflict situations between cyclists/moped riders and cyclists, pedestrians or moped riders.

In contrast to the Swedish treatment, conflict situations between cyclists and passenger cars, PTWs or HGVs are excluded. Furthermore, the master dataset also excludes driving accidents of cyclists.

Table 12-23 shows the number of relative weighted GIDAS accidents for the mentioned conflict situations.

Cyclists’ speed reduction *Netherlands* GIDAS 1999 - 2019* - relative weighted -			CITY (URBAN)						RURAL (w/o motorway)						MOTORWAY						TOTAL					
			ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$	ALL (GIDAS)		SAFTEY POTENTIAL		$EU_{SP,2025}$	$EU_{SP,2030}$
			n	%	n	%	n	n	n	%	n	%	n	n	n	%	n	%	n	n	n	%	n	%	n	n
CASUALTIES	Car Occupants	slightly	12,470	52.2%					8,332	34.9%					3,105	13.0%					23,907	100%				
		seriously	1,180	29.0%					2,302	56.5%					593	14.5%					4.075	100%				
		fatally	38	16.4%					154	66.5%					39	17.1%					231	100%				
	Goods Vehicle Occupants	slightly	97	20.0%					140	29.0%					247	51.0%					485	100%				
		seriously	16	12.2%					32	24.5%					84	63.3%					132	100%				
		fatally	2	15.6%					2	15.0%					7	69.4%					10	100%				
	Motorised Two-Wheelers	slightly	3,110	77.6%	68	2.2%	2,650	2,442	836	20.9%					60	1.5%					4,006	100%	68	2.2%	2,650	2,442
		seriously	783	56.5%	13	1.6%	409	356	567	40.9%					35	2.6%					1,385	100%	13	1.6%	409	356
		fatally	22	28.2%					52	66.5%					4	5.3%					79	100%				
	Cyclists	slightly	8,178	94.4%	901	11.0%	20,511	25,333	488	5.6%					0	0%					8,665	100%	901	11.0%	20,511	25,333
		seriously	1,429	87.6%	120	8.4%	6,783	10,748	202	12.4%					0	0%					1,631	100%	120	8.4%	6,783	10,748
		fatally	26	60.1%	1	3.9%	49	52	17	38.9%					1	1.0%					43	100%	1	3.9%	49	52
	Pedestrians	slightly	2,449	95.8%	290	11.8%	11,722	11,378	101	3.9%					7	0.3%					2,557	100%	290	11.8%	11,722	11,378
		seriously	840	92.1%	50	6.0%	2,518	2,755	64	7.0%					8	0.9%					911	100%	50	6.0%	2,518	2,755
		fatally	45	70.5%	1	2.2%	72	66	15	23.5%					4	6.0%					64	100%	1	2.2%	72	66
	Other	slightly	883	84.1%					142	13.5%					25	2.3%					1,049	100%				
		seriously	70	73.6%					24	24.7%					2	1.7%					96	100%				
		fatally	1	32.8%					2	53.1%					0	14.1%					3	100%				
	TOTAL	**slightly**	27,187	66.8%	1260	4.6%	34,883	39,153	10,039	24.7%					3,444	8.5%					40,670	100%	1260	4.6%	**34,883**	**39,153**
		seriously	4,318	52.5%	183	4.2%	9,711	13,859	3,191	38.8%					722	8.8%					8,230	100%	183	4.2%	**9,711**	**13,859**
		fatally	133	31.0%	2	1.5%	121	117	241	56.1%					55	12.9%					430	100%	2	1.5%	**121**	**117**

*Due to the use of weighting factor rounding differences from ± 1 persons may occur.

Table 12-23: Safety potential of cyclists’ speed reduction measure in the Netherlands and EU extrapolation of casualties in 2025 and 2030 according to the accident location, kind of road user and injury severity

The safety potential is calculated in comparison to all weighted GIDAS accidents. The percentage of the safety potential is used to extrapolate the numbers of maximum addressable persons (absolute number) for the EU in 2025 and 2030. The absolute numbers serve as basis for the adjustment to the boundary conditions of the nudge.

The results of the field test indicated that the Dutch cyclist nudge was not able to significantly influence cyclist speeds. Consequently, there was no effect on cyclists/moped riders and the impact assessment for the Dutch cyclist nudge was therefore not carried out. For the overall summary and the calculation for economic costs, no addressed persons are included in the calculations.

12.3 Overall summary

The method of the Euro NCAP Advanced is applied to estimate the number of addressed persons in road traffic accidents for the EU-27 by MeBeSafe measures depending on the user acceptance and several market penetration scenarios.

The total number of addressed persons is based on a 100 % market penetration in 2025 and 2030 (Figure 12-5). According to the market penetration scenario, the MeBeSafe measures could address approximately 1,874 fatalities in 2025 and 1,824 fatally injured persons in 2030. In relation to all fatally injured persons in all road traffic accidents, the MeBeSafe measures achieve a relative share of 9.1 % in 2025 and 9.5 % in 2030 in the group of fatally injured persons.

Additionally, the MeBeSafe measures could address 193,046 seriously and slightly injured persons in 2025 and 227,570 persons in 2030. The relative share in the group of seriously and slightly injured persons is 13.3 % in 2025 and 14.5 % in 2030.

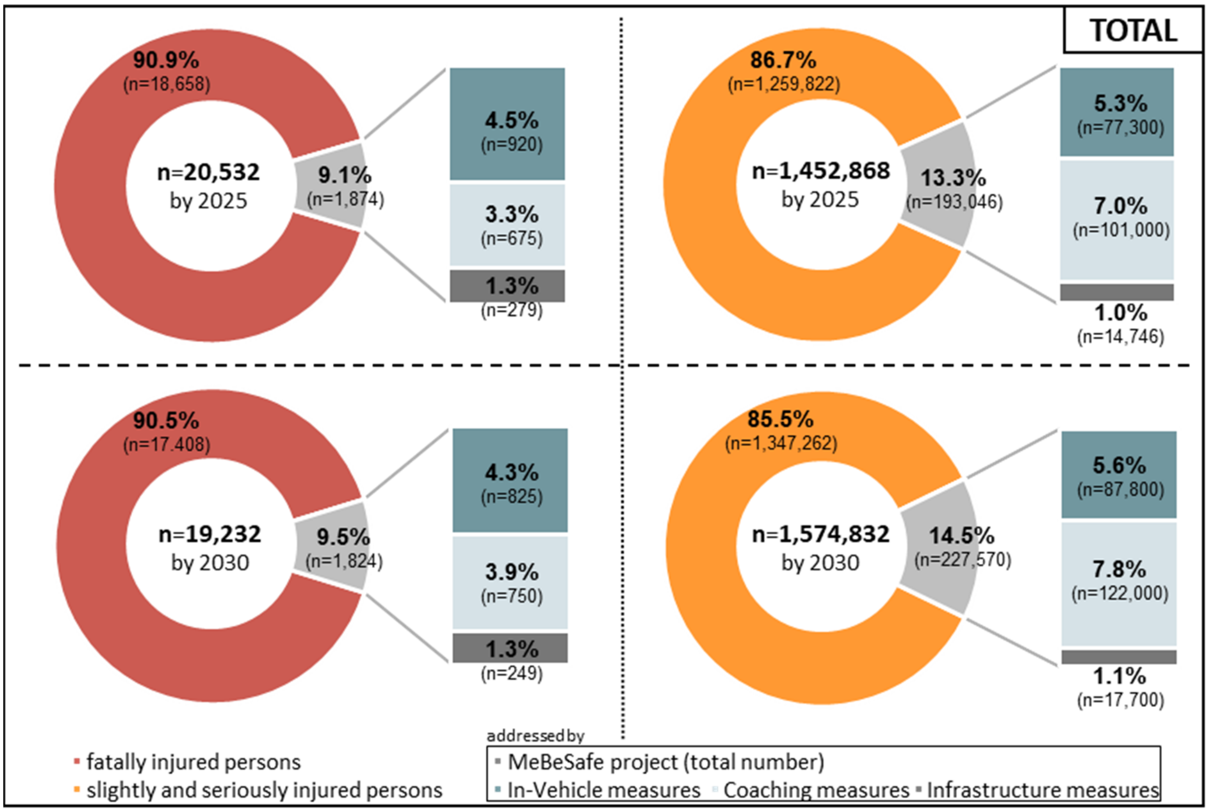

Figure 12-5: Impact assessment according to the total estimation of the MeBeSafe project to the EU-27 for fatally injured persons (left) and slightly/seriously injured persons (right) in 2025 and 2030

The realistic number of addressed persons is based on the most plausible market penetration scenarios of each MeBeSafe measure. The most realistic scenarios are described in 12.2 - Impact assessment. The sum of the most realistic scenarios of each measure address 0.7 % of all fatally injured persons. That corresponds to 189 fatalities (0.9 %) in 2025 and 366 fatalities (1.9 %) in 2030 (Figure 12-6).

These scenarios could additionally address 16,584 seriously and slightly injured persons (1.2 %) in 2025 and 40,053 persons (2.5 %) in 2030.

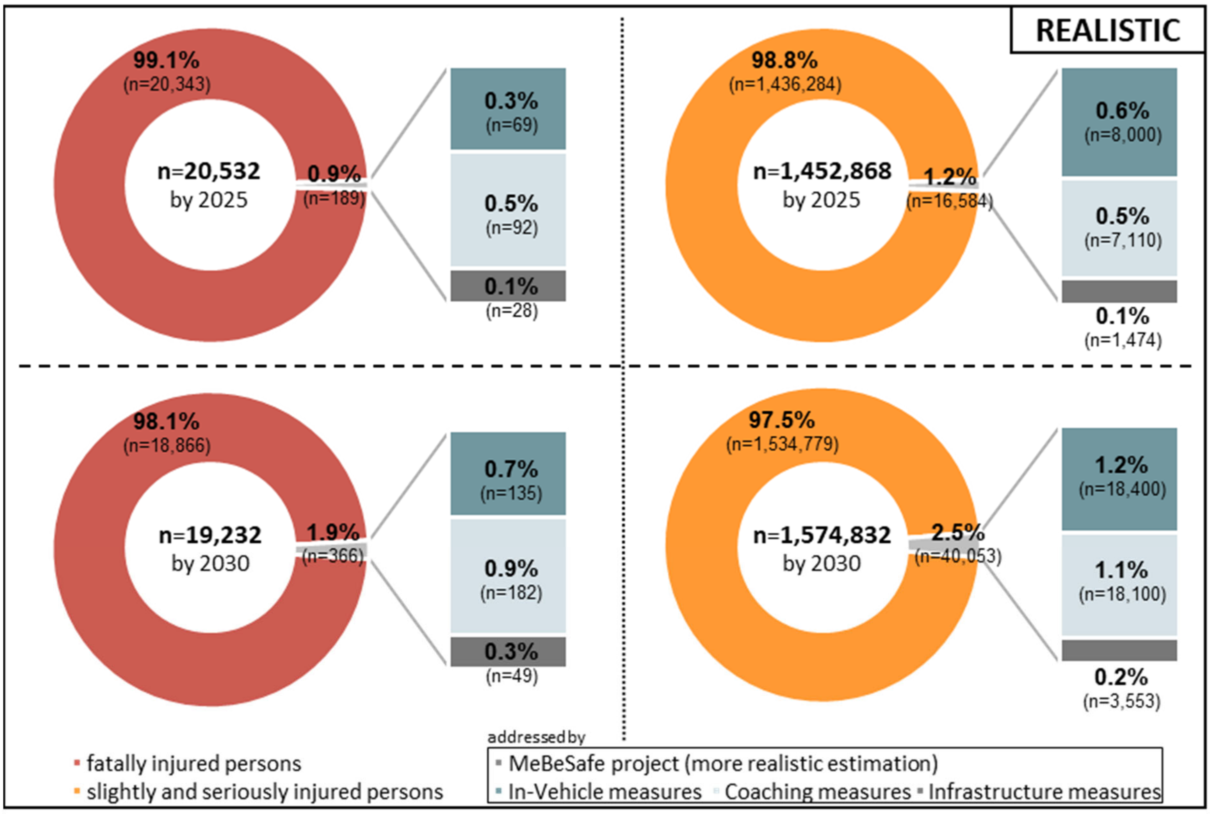

Figure 12-6: Impact assessment according to the realistic estimation of the MeBeSafe project to the EU-27 for fatally injured persons (left) and slightly/seriously injured persons (right) in 2025 and 2030

12.4 Economic impact

The economic impact is a cost estimation on the basis of the addressed casualties to quantify the potential financial savings for the EU-27 from the MeBeSafe project in 2025 and 2030.

Socio-economic costs of road traffic accidents in the EU-27 represent 1.8 % of the Gross Domestic Product (GDP). These costs include healthcare costs for the management and treatment of injuries, administration costs of liability settlements, damage to public goods, and loss of output from those injured or killed.

Table 12-24 gives an overview of all standard values depending on the cost components and the injury severity. The values base on the “SafetyCube” project co-founded by the Horizon 2020 Framework Program of the European Union (Wijnen, 2017).

2017	slightly injured persons	seriously injured persons	fatally injured persons
Medical cost	€1,439	€16,719	€5,430
Production loss	€2,669	€43,627	€655,376
Human costs	€15,597	€230,385	€1,587,001
Property costs	€5,317	€7,622	€11,555
Administrative costs	€1,876	€4,364	€6,346
other costs	€519	€413	€3,638
Total (unit) costs	**€27,417**	**€303,130**	**€ 2,269,346**

Table 12-24: Standard values for medical cost components and unit costs for the year 2017 (Wijnen, 2017)

Based on Table 12-24, the estimation of the medical cost components are calculated with a growth rate of 1.8 % per year until 2025 and 2030. It is assumed that the medical cost components increase to €31.6k for slightly, to €350k for seriously and to €2.6M for fatally injured persons in 2025. For the estimation in 2030 it is expected that the costs increase to €34.5k for a slightly injured person, €382k for a seriously injured person, and €2.8 million for a fatally injured person (Table 12-25).

	2025	2030
slightly injured persons	€31,623	€34,573
seriously injured persons	€349,632	€382,252
fatally injured person	€2,617,477	€2,861,685
Total (unit) costs	**€2,998,732**	**€3,278,511**

Table 12-25: Extrapolation of the cost components of medical costs by injury severity until 2025 and 2030

These values are multiplied with the addressed persons of the MeBeSafe project in 2025 and 2030 according to the total number and the realistic scenario.

Note that these estimates do not include savings due to the enhanced productivity of those who would be delayed (but not injured) by the accidents avoided due to the MeBeSafe results.

It is estimated that the measures developed in the MeBeSafe project could potentially address socio-economic costs of €19.5 billion in 2025 and €24.9 billion in 2030. The realistic estimation would be smaller by a factor of around 10. Based on the realistic market penetration scenario, it is assumed that €2.0 billion could be saved in 2025 and €2.2 billion in 2030 (Figure 12-7).

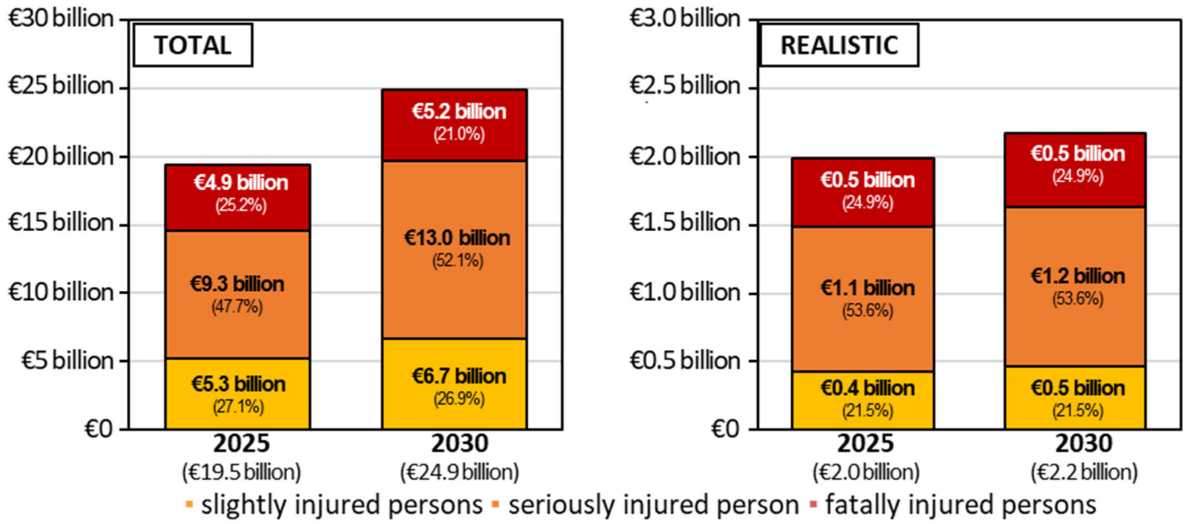

Figure 12-7: Economic cost estimation according to the accident reduction for the total number (left) and realistic estimation (right) in 2025 and 2030 by the MeBeSafe project

Independent from the market penetration scenarios or the predicted year the half of the economic costs are caused by seriously injured persons. A quarter of the costs are accounted for by the slightly injured and the fatally injured persons.

Safety measures in vehicles usually result in higher market prices. However, the proposed In-vehicle measures make use of components that are already present in the vehicle for other purposes and will probably not result in higher costs.

The assumption that all EU-based OEMs account for 10 % of the global vehicle production in 2025/2030 and the MeBeSafe measures will be available in 50 % of new vehicles sold world-wide by the MeBeSafe partner OEMs (BMW, Fiat, Volvo) with a market share of 15 % and in 20 % of new vehicles of other OEMs with a market share of 85 % (estimate global market 100M) will result in 2.45 million vehicles per year that will be equipped with the MeBeSafe nudging measures.

When assuming that the extra price supplement for cars equipped with these measures is between €100 and €200, this translates to an extra turnover for European OEMs of €245 million to €490 million per year.

13 Evaluation of the MeBeSafe measures

During the field trials, there were a number of lessons learned that if adhered to will make the nudge/coaching measure better when implemented next time around. These learnings are described below.

13.1 Evaluation of 01 - Driver alertness feedback

For driver alertness feedback, the nudging concept consisted of providing the driver with an additional incentive to stop and take a break when the Driver Alert system indicates that a break would be beneficial, i.e. when high levels of drowsiness are detected.

Offering this incentive worked really well, all things considered. Interestingly, one important lesson learned during development of this nudging concept was that while the value of the reward naturally has a large influence on a particular driver's propensity to take the recommended break, the way in which the reward is presented also has a large impact. Keeping the precise nature of the reward hidden until the driver actually stops was found to act as substantial additional motivation to take the break.

A precise explanation of exactly why triggering drivers' curiosity acts as additional motivation to stop will have to wait until further research has been conducted. However, it is not unreasonable to assume that triggering curiosity may have the same type of influence on drivers' state as being offered something for free. Both result in near instantaneous, positive emotions. Creating such emotions in the driver us likely a key requirement if one wants to be able to break through what drivers sometimes refer to as the "wall of tiredness" when driving really drowsy.

In future development of concepts that rely on offering incentives to increase compliance with a recommended behaviour, it is therefore suggested that one pays as much attention to the way in which the incentive is delivered, as to the nature of the incentive itself. Both can impact the way drivers respond, and with an adequate delivery method, the impact of the incentive itself can be increased.

13.2 Evaluation of O2 - Usage of safety ADAS to prevent close following

A very interesting aspect of the Field Trial for O2 – usage of safety ADAS to prevent close following was that time and resources allowed for two rather than just one nudging concept to be studied in the field trial. When deploying nudging concepts of this kind, an obvious question to ask is of course whether drivers will be affected in the same way by different concepts, or if some nudges are more effective than others.

As could be seen in the results section for O2 where the effects of the two nudges were compared on a per-driver basis (see Figure 5-5), the answer seems to be that the two nudging concepts had different effects on most of the drivers; only a few drivers showed a similar change in ACC usage under treatment phases in the field trial. Furthermore, the effects were not uniformly biased in any particular direction. Some drivers responded better to the Ambient Display nudge while others responded best to the Competitive Leader Board nudge. Finally, some drivers were also negatively affected in the sense that their ACC usage decreased in the treatment phases.

This provides several interesting learnings for the future. First, if one wants to create a particular type of change in a large driver population by nudging, it is clear that quite a bit of experimentation will be needed to find the right concepts. Second, the final design should likely include more than one nudging concept or style if it is to be effective across the whole population; it is unlikely that there exists a one-size-fits-all design that will appeal to all users equally. Third, it is important to provide for some form of monitoring mechanism that can be used to detect which users are negatively affected by the nudge, in order to either stop nudging them or switch to a different concept.

13.3 Evaluation of O3 - In-vehicle nudging solution to direct driver attention to possible hazards

The in-vehicle nudging solution to direct the attention of drivers to areas with possible hazards, consists of an HMI (as a HUD) connected to a model for the estimation of the possible hazard. This solution was developed in order to only nudge the driver in case of an increased hazard level above a pre-defined threshold. We distinguish between a **static hazard**, e.g. posed because of a location being busy and confusing close to a school or because of view-blocking obstructions and a **dynamic hazard**, which refers to another road user (in view of the driver) whose path possibly interferes with the path of the ego-vehicle. The in-vehicle nudge has specifically been developed to draw the driver's attention to potentially hazardous interactions with cyclists.

The nudging system is an addition to already common cyclist-AEB (autonomous emergency braking) systems that (harshly) warns drivers in case of an imminent encounter with a cyclist, and in absence of a driver response slams the brakes autonomously to avoid or mitigate a collision with a cyclist. An AEB system comes in operation approximately less than 2 seconds prior to a collision and it operates only in case of a high degree of certainty that the collision is about to happen. The in-vehicle nudging solution has a different horizon of operation. It provides information in a subtle way to the driver, starting some 6 seconds before the vehicle actually enters the predicted hazardous zone. As the nudge is non-intrusive and subtle, there is no need for the escalation of the HMI to have a high degree of certainty that the hazard is actually present. False positive escalations are far less of an issue for nudging than for AEB. It is for this reason that no integration between the nudging system and existing AEB systems has been strived for in the MeBeSafe project.

13.3.1 GPS-staged HMI escalation

Though a complete Proof-of-Concept system incl. the different components has been developed in MeBeSafe, the field-operational-test has been performed on the basis of a staged HMI only: the HMI was programmed to escalate at each of the 74 intersections on a pre-defined route through the inner city of Eindhoven based on an accurate GPS signal. The reason for running the FOT in this way is to come to repeatable tests, in which each naïve participant in the test is exposed to the same inputs. Despite the fact that the HMI escalated 74 times within the hour (on average once every 45 s), participants mentioned to experience the HMI as pleasant, relaxing and safe, and the majority (74%) would leave the HMI on in case such a system would be installed in their own vehicle. There is no evidence at this stage that there is a need to reduce the number of escalations with time. Nevertheless, the project has identified two possibilities to inhibit escalation:

- Using input from the static hazard model: only escalate the HMI in case the hazard estimate exceeds a certain pre-defined minimum level.
- Making use of a metric of the driver level of attention: only escalate the HMI in case the level of attention by the driver is below a pre-defined limit. Such a metric could be for instance the time spend by the driver to gaze in the direction of the potential hazard.

13.3.2 HMI escalation using a static hazard model

A refinement of in-vehicle nudging solution is found in using information from the static hazard model. The static hazard model identifies those intersections that pose an increased hazard level, e.g. because of the presence of a school, view-blocking obstructions, busy traffic (possibly during specific periods in the day), or a combination thereof. Independent input variables to the static hazard model are the GPS-position of the ego-vehicle and the time of day. Refinements are possible considering the day of the week (Sunday morning 8:30 am is usually less busy than Tuesday morning 8:30 am), or even the date to consider specific holidays.

Such an extension to the nudging solution is expected to reduce the number of 'false positive' HMI escalations. It must be noted that the high number of escalations of the HMI did not seem an issue for the participants in the reasonably short FOT. It needs to be investigated how the effectiveness of nudging is influenced in a longer FOT or Naturalistic Driving Study (NDS). Dependencies are expected from:

- Learning effects and experiences with the HMI by the users.
- False positive or incongruent HMI escalations, e.g. HMI escalation in a reasonably open area with no cyclists around.
- The number of escalations (true and false) per hour.

13.3.3 Integration with dynamic hazard model

A further upgrade of the nudging solution to direct the attention of drivers towards potentially hazardous situations comes from a coupling to the potential hazards that are in view of the driver; in this context, we refer to these as dynamic hazards. Within the MeBeSafe project, Cygnify has developed a cyclist prediction model, which provides inputs to a dynamic hazard model. Predictions are provided regarding the most probable manoeuvres that cyclists in view of the vehicle-under-test might intent to follow in the upcoming seconds. In case of a rise of the probability that the intended path of the vehicle-under-test intersects with the predicted trajectory of the cyclist in the upcoming seconds (5 to 6 sec.), a nudge is issued to the driver.

Current state-of-the-art AEB-systems only warn the driver and/or initiate an emergency braking actions in case a collision (with e.g. a cyclist) is imminent and the probability that the collision is unavoidable is very close to 100 %, in order to prevent any false positive responses of the system. Therefore, the time-to-collision (TTC) at which such AEB system acts usually is smaller than 2 sec. This is due to the fact that current systems have difficulty to anticipate on cyclist behaviour. The cyclist prediction model developed by Cygnify makes use of subtle clues in the cyclist's posture or moves, so that the behaviour of cyclists in the vicinity of the vehicle is more predictable for the upcoming seconds, so that any system on-board the vehicle, including an AEB-system, is better capable of anticipating to the manoeuvres of cyclists. Such cyclist prediction model is expected to be essential in the integration of a nudging system with an AEB system, where for larger TTC the driver is being nudged, and the system is capable of escalating a nudge seamlessly to a warning, and even an emergency braking action in case the driver does not handle the situation adequately to avoid a collision. The integration of nudging and AEB was however outside the scope of the current project.

13.3.4 HMI inhibition using a driver direction of attention model

Another innovation in passenger cars considers the driver drowsiness detection and, related to that, the detection of the level of attention of drivers. Less common momentarily is the in-vehicle detection of the direction of attention of drivers. In the MeBeSafe project, cameras were directed towards the driver during the FOT. From the images generated with these cameras, the time dependent direction of attention of the drivers was determined a posteriori by making use of machine learning techniques. It is expected that in the coming years, such techniques will become an integrated part of passengers to more precisely provide feedback to the human driver in collaboration with different kinds of driver support and automated driving systems. Such driver monitoring techniques are especially important in determining the readiness of a driver for taking over from an automated driving system in case the vehicle tends to manoeuvre outside the operational design domain of such automated driving system.

Input from a monitoring system that determines the direction of attention of a human driver in real time can also be used to inhibit nudges and warnings towards the driver, in case the driver is paying sufficient attention in the direction of an upcoming potentially hazardous situation. For determining the maximum benefit of such system, the requirements for nudging and/or warning inhibition need to be studied, e.g. in driver tests on a large scale. Such tests will provide important information regarding constraints and requirements for driver monitoring systems.

13.4 Evaluation of O4 - Behavioural change through online private driver coaching

While the field trial had to be cancelled for reasons described above in section 7.2, the results from the pilot tests (see deliverable D4.5) still provided a number of significant insights. To begin with, the test persons in general ranked the usefulness of the *Interactive Quick-guide* as high (avg 4.4 on a 1 to 5 scale), and several stated that they learned about car functions they would not otherwise have known about. This indicates that providing this type of coaching would be helpful to many users. Also, many participants wished that such a feature would be available at all times in the car, so they could learn about functions at some later time (i.e. after bringing the car home from the dealer). This indicates a genuine interest in the function themselves, where the hindrance for usage seems to be a lack of easily accessible how-to instructions.

Perhaps most importantly here, when looking specifically at the users who could be characterized as non-users with low interest in new car technology, several explicitly stated that they would never have tried to use the functions if they had not been prompted by the *Interactive Quick guide*. Thus, the app-based coaching was highly successful, in the sense that a first-time usage of ADAS was achieved for a number of individuals who otherwise would not have tried to activate these functions.

On the other hand, several test persons reported that the testing felt scary, even with a test leader in the vehicle, and they had many questions on capabilities and limitations of the functions. It is therefore not certain that they actually would have followed through with activation if the test leader not been present.

There were also two types of interaction problems with the *Interactive Quick guide* that provide key insights for the future. One was purely technical in nature, in the sense that users these days have come to expect the same type of natural language interaction as offered by e.g. Apple and Google when doing voice interaction. It follows that any system performing at a lower level than that will lead to frustration and/or aborted interactions. For example, one participant asked the car "Hey, what's does safe distance mean?" and got no reply. Future applications of the *Interactive Quick-guide* type therefore need to have access to a powerful natural speech engine if interactions are to run smoothly.

The other category of interaction problems was not technical, but rather followed particular user groups. While drivers with an expressed interested in car technology had no problems following the instructions given, many previous non-ADAS users had large problems completing ADAS activation. One interpretation of this result is that non-users with limited interest in advanced car technology lack motivation to try to understand what the guide is asking them to do, and hence get stuck in places where a motivated user does not experience any issues. It follows that the interaction models for this type of guides (i.e. how the dialogue is structured and how other information is presented) must be developed for, and tested on, what could be called "reluctant users" if one wants to be sure that they will be effective.

13.5 Evaluation 05: HGV driver behaviour coaching

The driver behaviour intervention developed for truck drivers in WP4 has two distinct parts; online coaching (the app DriveMate) and offline coaching (peer-to-peer coaching). Each part carries with it various shortcomings as well as possibilities for development. The goals for the suggestions on improvement made here are in line with the general goal of WP4 of creating an app which is easy to use (few functions) but which contains many different features for invoking various psychological mechanisms for behaviour change.

This evaluation consists of the two main parts related to the app and the coaching. However, improvements of the coaching are often dependent upon development of features in the app, and these two things are therefore not really separate, although they are presented under different headings.

13.5.1 Improvement and Evaluation of MeBeSafe coaching

Although the field trials undertaken of the coaching system have mainly been restricted to the DriveMate app (as the technical shortcomings have delayed the testing of the actual coaching), there are still a number of possible improvements which can be suggested for the offline coaching. These are of the two categories of planned but not implemented features and implemented features which need revision.

13.5.2 Implemented features

Video

The video feature of DriveMate has the ultimate aim of providing material for coaching discussions. It is thus not a measure of driving behaviour, but a pedagogical tool. It is also not a feature which is restricted to the app, although it is dependent upon the video playing capability.

Capability of playing video has been implemented in DriveMate version 2 (V2), but the content displayed is not of the types which were originally planned, but a light-weight version of this. Currently, only videos which are publicly available are shown. The original plan was for videos to be culled from several sources; the drivers' own recordings, automatic recordings by DriveMate and sequences identified from external sources (first of all the UDRIVE database[7]). These different sources require different types of technical development.

Currently, an incident recording function is included in the app, and development of this (as described below under 'Further development of DriveMate') would enable videos of traffic situations recorded by the drivers to be shown to them as part of their coaching. This feature could have two levels; private videos, which are only shown to the driver who recorded them, and public ones, where the driver allows DriveMate to show his videos to all drivers. The development needed for this is video recording, either directly by the app using the phone camera, or by setting up an external camera. The sorting of these recordings would be made by the drivers.

The DriveMate app could be set to record video when braking and acceleration events are recorded, as is done by the current settings. However, preliminary work with the UDRIVE database shows that such a simple algorithm (mainly using only the level of speed change as the trigger) yields recordings which are not very interesting from a pedagogical perspective (mostly traffic lights turning red). Research would be needed to develop an algorithm which identifies events which are actually dangerous, or unusual, in some way and which can be used for instruction.

This kind of algorithm could also be used for identifying interesting events from external sources such as the UDRIVE dataset. The algorithm as such could use information about speed and acceleration, but possibly also video analysis, although this cannot be implemented upon a phone, but would be an additional backend analysis. The technical aspects of this will be further described under the heading Automatic event recording.

[7] In the UDRIVE project (Van Nes et al., 2018), a fleet of trucks from four Dutch transport companies has been equipped with multiple video cameras and sensors, through which continuous driving data (e.g., acceleration, local speed limits) has been collected. The UDRIVE database is available for further research.

13.5.3 Not implemented features

Positive feedback

One major problem with all known telematic feedback systems is that they can only identify instances of possible risk (e.g. a harsh brake), while good driving is only the absence of such events. People, however, usually react better to positive feedback than negative feedback (Fong, Patall, Vasquez & Stautberg, 2019). In MeBeSafe, it was therefore planned to use positive instances as feedback in the app, i.e. examples of good driving. However, identifying such instances are very difficult, as they need to be found when circumstances of traffic are challenging but behaviour is uneventful.

Although the research needed to develop algorithms for this end was never undertaken (due to lack of data), it is believed that it is possible to do this. The solution would be similar to the one suggested for the risky events detection; using Cygnify video analysis software applied to footage from DriveMate. However, some additional data sources would probably be needed, especially a road database.

Using this technique, it would be possible to send examples of good driving behaviour to the drivers, with a message explaining why they have done well.

Main coach

Although it has not been possible to get any substantial feedback from the drivers of Litra and Bertschi concerning how they experience the app and coaching, this fact in itself indicates that truck drivers are a population of people who do not readily respond to questionnaires or e-mailed questions. It can also be suspected that they might have difficulties in implementing coaching as planned, as this necessitates reading some text and conducting an interaction which is unusual for them.

The solution for these two problems would be to keep in personal contact with the drivers, meeting them from time to time to discuss the issues and encourage them in their coaching. This might include taking part in and guiding the first coaching session, so as to get the process started. This function would be a sort of main coach, who would lead the implementation of the MeBeSafe system and monitor the drivers' progress.

Targeted feedback and coaching (profiling)

One possibility for improving upon coaching is to tailor the information given to the individual driver after his own behaviour. A simple example would be speed and speeding, which are easy to measure and understand. Its usefulness for coaching traffic safety at the level of the individual, however, is doubtful. Although speed may be indicated as a factor in crashes, and mean speed of roads has an effect on number of crashes, its predictive power when used to indicate risk between drivers is very small, and probably smaller than for many other predictors (Burns & Wilde, 1995; Lefeve, 1956; Munden, 1967; Quimby, Maycock, Palmer & Buttress, 1999; Wasielewski, 1984; af Wåhlberg, 2006; 2009).

Individualising the information in the app would therefore take a major effort of both programming and research into driver behaviour.

Complexity of the driving environment

One of the basic problems of almost all In Vehicle Monitoring Systems (IVMS) is that they measure pure behaviour of the driver, without any reference to the driving environment. They are therefore often viewed as not fully relevant by the drivers, because the determinants of the values are often outside of their control anyway. In most systems, good results can be shown on rural roads, and bad ones in urban areas, almost regardless of how well the driver has actually performed.

In MeBeSafe it was therefore discussed how it would be possible to measure the difficulty of navigating different roads, a feature of the environment which was called complexity. If this could be quantified in a meaningful way, and implemented in the app or backend, it could be used to control for the effect of the environment, and to reveal how well the drivers actually perform, given the circumstances. In effect, this would make driving on rural and urban roads comparable. Due to lack of data on which to develop the concept, and technical restraints, this feature was not implemented, apart from differences in cut-off values for harsh braking and acceleration dependent upon speed.

The solution to the complexity problem for DriveMate would lie in the use of the video capability described elsewhere in this text, and Cygnify's video analysis software, but would require a major research effort.

13.5.4 Evaluation of peer-to-peer coaching of MeBeSafe

As mentioned, the field trials have so far not really covered the coaching parts, due to the technical difficulties with the app. It is therefore not possible to refer to any empirical results for evaluation of the coaching. The general attitude of the drivers has been positive, however, at meetings held with the participating companies.

The peer-to-peer coaching system has been developed to draw its power from several different psychological mechanisms and techniques. It should therefore be fairly resilient to individual resistance to change; if coaching does not alter the drivers' behaviour, maybe feedback will, or social pressure, or competition.

13.5.5 Improvement and Evaluation of DriveMate V2

V2 of DriveMate consists of the software as run on the phones, back office handling of data by Cygnify and Shell, and a database for the driver behaviour and app use data.

The delivery of onboarding sessions was set to be once a day, but many drivers reported that they did not receive any new sessions. This could possibly be due to lack of space and computing power at the server, but the problem needs to be addressed anyway.

Some sort of connection error causes some trip files to contain very few data points, despite the trips being of long duration. This sometimes causes the feedback values to be very high (>1). The problem is currently handled by Cygnify, where trips with a ratio of data points to distance which are less than 0.4 are returned with a value of 0. A better solution would be to delete these trips (and return the message of 'Not enough data' to the drivers), but this would require changes to the app itself. The return of values of zero from Cygnify to the database also causes it to enter values of 'Not calculated yet' into the data.

The creation of double trips was a problem in V2, which was solved in the database by an automatic delete function. It was assumed to be due to a delay in response from the database, which prompted DriveMate to re-send the data. This problem could be solved in some different ways, for example by extending the wait period before re-sending data.

13.5.6 Further development of DriveMate

Overview

DriveMate V2 is a working tool for measurement of driver behaviour and delivery of coaching and the information needed for this. However, the basic setup of the app was designed with many more intended functions which would support the main functions. These planned but not implemented functions will be shortly described here.

Improved delivery of coaching sessions

The algorithm for delivery of onboarding and coaching sessions would need some further development, as there have been some indications that there is still some sort of bug in the code, which makes delivery unreliable. Furthermore, the algorithm currently runs separately for each driver, which means that the prompt for a coaching session might appear at very different times for the two people in a pair. A function should therefore be added which makes it possible for the drivers to be connected in pairs within the app framework. This coupling can then be added to the coaching prompt delivery algorithm, so that both drivers get the prompt at the same exact time.

The onboarding algorithm settings should also be made available to the main coach, so that the values could be adjusted for each company without need of a dedicated programmer.

Manual incident recording

The current recording function consists of a button displayed upon the screen when trips are recorded, which can be pressed (actually the whole screen is sensitive to touch) to indicate that an event has happened. This saves the GPS position and starts a voice memo function. Afterwards, the drivers can see a Google Streetview of this position and listen to the memo. The intended use is for drivers to be able to gather material for their coaching sessions.

A more advanced dash cam feature was originally planned, where about a minute of video from before the pressing of the button was to be recorded. This would be a much more powerful coaching tool than the current setup.

The technical development needed to enable this would be continuous video recording (and deleting) capability of the app, connection to the record button and the video displaying feature etc.

Automatic event recording

As described under the heading Video, identifying and recording traffic events for coaching is one of the possible developments of DriveMate. There are some technical problems involved with this, which will be shortly discussed here.

There are three main problems involved; the difficulty of correctly identifying events, the limited processing capability of phones, and the limited data transmission capability of phones. As video footage is rather costly in terms of bytes, an event recording system needs to be very exact, or it will flood the system with useless data.

The suggested solution for this problem is a two-stage system, where events are first identified from kinematic profiles, using an algorithm developed using the UDRIVE data. Video footage from these events is then sent for backend analysis. If transmission capability is limited during trip recording, this can be delayed until after the trip is finished. Video footage of events are then analysed using Cygnify's video analysis software, and the most interesting events are added to the video list of the driver from which it was recorded. The driver can thereafter make this video available to other drivers.

Discussion forum and chat

One possibility for DriveMate would be the inclusion of a forum section, where drivers could discuss issues about their work and driving. This would enable more information to be shared between drivers, and increase their interaction with the app. However, a moderator would be needed for this function, to prevent misuse. This could be a driver, or the main coach (described above).

A forum section for the drivers of a company and/or country where they could discuss work topics and post information about such issues was planned but never realized in V1 or V2 of DriveMate. This is a function which is not necessary for the coaching, but an add-on which was intended to increase the drivers' interaction with the app.

Also, a chat or instant messaging function could facilitate the contacts between the drivers as well as with the main coach.

App diagnostics

The privacy principles of DriveMate, as well as some resistance from the drivers concerning surveys, make it difficult to know how the users are using DriveMate. A diagnostic tool has been used for V2, but this does not deliver the kind of data needed for the present project. A future development which could enable other development would therefore be tailor-made diagnostic tools for DriveMate.

Self-evaluation function

One issue which was often reported during the testing of V1 was that no trip values were calculated. This often leads to a continuous problem, which could be solved by re-starting, but usually needed re-installation. Although V2 is more stable, and re-installation does not result in loss of data (which was the case in V1), it would be preferable to have some self-diagnostic function in DriveMate, which could react to such problems.

Auto-stop function

If drivers forget to end a trip when they should do so (i.e. when there is a logical difference between different parts, like belonging to different days), the app should end and record the trip after a certain amount of inactivity. This would create a problem concerning the self-reported traffic data, which are to be reported when the trip is ended, for which a solution is needed.

13.5.7 Evaluation of DriveMate V2

V2 of DriveMate is a more stable and useful version of the app as compared to V1, and it does have the basic features needed to implement and support coaching; recording of driving data, feedback on this, and delivery of coaching material according to a set schedule. This development can therefore be considered to be successful. The DriveMate app can be used by commercial company drivers as a support for their development as drivers, as planned.

However, the features of the app are still very rudimentary, and the full version could be expected to be a much more powerful tool for behaviour change.

13.6 Evaluation of O6/O7

For Objectives 6 and 7 - Safe speed/trajectory on inter-urban roads, the field trial took place on an exit lane in Eindhoven, Netherlands. Within the field trial of the Infrastructure Driver Nudge, we installed roadside markings in such a way that drivers who entered the exit lane at velocities above a predefined threshold could be exposed to various light patterns along the lane. Nine different light scenarios were tested, divided into four testing phases, including variations of light pattern, spacing between an activated set of two lights, brightness levels, as well as light movement speed.

According to the quantitative data, static light stimuli were most effective and showed the clearest results in our field trial. Lights moving towards the driver did however not always show a clear result. Lights moving towards the driver with a wider spacing were indeed effective for fast drivers but did not show a clear result for the fastest drivers, which should be elaborated further in follow-up studies. The overall traffic analysis indicates a positive impact of the nudging system on traffic safety. In particular, results show that mean speed can be reduced by 4.9 % and the ratio of speeding drivers can be decreased by 40 %. Nudged drivers decelerated earlier and drove slower in the curve, which leads to a lower radial acceleration and, thus, higher margin of safety. Please note that we could not control for potential learning effects resulting, for instance, from data of residents taking the exit frequently. The comparison of the initial baseline before activation of the system and an intermediate baseline after about two months of data collection showed differences for fast drivers but not for fastest drivers. This underlines potential sequence effects.

The online resident survey revealed a positive attitude of participants towards the nudging measure in general, even though it did not distinguish between individual scenarios such as static lights or lights moving towards the driver, but rather compared the activated nudging system in general to not system. The nudging measure was frequently reported to create awareness for the traffic situation and to improve the visibility of the curve. The additional on-site survey distinguished between selected scenarios but had limitations due to an inconsistent randomization. Nevertheless, the study revealed valuable qualitative insights into the attitude of drivers towards static lights and lights moving towards the driver. Both nudging scenarios were perceived positively, but especially the lights moving towards the driver were rated as appropriate to nudge drivers and received a higher acceptance rating. In both qualitative data collections, online resident survey and on-site survey with recruited drivers, participants rated the nudging system as most effective to reduce speed in comparison to the regular speed sign or speed cameras.

We executed the field trial for the infrastructure driver nudge at one location in Eindhoven, where habitual speeding could be a problem for traffic safety. However, results can be adapted to a variety of locations where speeding is problematic or where the road design requires attention of the driver. More precisely, it could be generalized to locations such as motorway exits or any other critical location, including straight road sections or tunnels, to slow down speeding drivers and to draw their attention to the road. Within the field trial, it was not possible to explicitly quantify driver's attention to the road. However, conclusions might be drawn from measured driving behaviour and the subjective attitude of drivers towards the system. With the Infrastructure Driver Nudge, we are targeting habitual speeding, which means that we are aiming to nudge drivers who are unaware of potential hazards towards safer behaviour, such as slowing down or focusing on the traffic situation. MeBeSafe aims not only to prevent accidents but also critical situations and almost-accidents. Although this benefit could only be indirectly measured in this field trial because of lower driving speed after nudging, it can also be inferred from the qualitative data that nudging measures have a beneficial impact. Particularly, the positive attitude of drivers towards the nudging measures indicates that the hidden benefit of the measure might be even bigger than the impact calculation relying on accident statistics. This relies on the assumption that whenever drivers feel safer and attribute safer driving behaviour to other traffic participants when encountering the nudging measure, safety margins increase.

Overall, the qualitative results of this field trial suggest that participants favoured the lights moving towards the driver over static lights and deemed them most appropriate to reduce speed. However, quantitative data showed ambivalent results for the lights moving towards the driver. Consistent findings could only be found for static light scenarios. These limitations make it difficult to identify the best light pattern based on traffic data. Nevertheless, the baseline was always the fastest scenario, indicating that the infrastructure nudging measure as a whole worked as intended to, i.e., it reduced speed. Hence, the nudging measure has an overall positive impact on traffic safety.

Future research should elaborate the findings of this field trial further and replicate them in order to support the current findings, including replication of the results at further locations. Implementation should focus on targeting relevant locations where habitual speeding could be an issue, in order to ensure correct functioning of the measure. Further, a large proportion of vehicles was nudged only in the middle of the exit ($x \approx 150$) although they were below the speed threshold at the beginning of the exit. For future applications of the nudging measure, the speed threshold should be determined based on average driver behaviour or an "optimal" speed profile. Traffic and weather conditions could also be considered to determine the speed threshold. Measures for PTW drivers should target them individually and ensure a sufficient database for a holistic analysis.

13.7 Evaluation of O8

One big advantage of the measure implemented, i.e. a visual nudge, is that acceptance is high among cyclists. Most cyclists are positive to the idea of lane markings to reduce speed and warn for dangerous intersections. This can be compared to commonly used solutions such as rumble strips, speed humps and chicanes, which all have very low acceptance and are perceived as unsafe by cyclists. Visual nudges show none of these negative impacts. Thus, even if the observed effect on speed may not be very high, the cost of implementation (both in acceptance and in monetary terms) is very low, which makes it a low risk investment.

Interestingly, the nudge had a larger impact on leisure cyclists than commuters (at least for the Swedish location), which can be interpreted as less experienced cyclists being easier to nudge. It follows that further studies of how to nudge commuting cyclists would be required if one wants to impact a location with a large proportion of commuting cyclists.

14 Costs of running the system

The costs of running the MeBeSafe countermeasures need to be deduced from the positive economic impact they will have in 2020, in order to present a balanced picture of their total economic impact. Hence, we need to add a countermeasure implementation cost estimate that is as precise as possible in 2020. This will provide the best support for future road safety investment decision making.

14.101 – Driver Alertness feedback

The in-vehicle nudging solution for increasing the likelihood that drivers will take a break when drowsiness goes beyond a certain threshold has two cost components. The first is implementing the display of the incentive in the vehicle, and the second is the cost of the incentives themselves.

The first cost is generally estimated to be low; vehicles with a drowsiness detection system already must have some means for displaying when drowsiness exceeds a certain level. Adding a description of getting a reward for stopping to the same HMI solution is a minor programming challenge that will have very limited impact on vehicle price.

The second cost is harder to estimate. For example, assuming that the rate of true positive drowsiness events is two per year and the reward is priced at 12 euro, the cost of running the system would be 2 euro per month per vehicle. As these numbers change linearly with the frequency of events and cost in of the reward, a precise prediction is not possible to make.

14.2 02 - Usage of safety ADAS to prevent close following

The in-vehicle nudging solution for increasing the usage of safety ADAS has two cost components. The first is providing a display for the nudging concept in the vehicle and the second is developing the programming of the concepts themselves.

The first is generally estimated to be low; fairly large digital displays are becoming commonplace in modern vehicles and securing part of this area for a nudging display is not so much a cost as a design decision. Naturally, the display needs to fulfil legal and other requirements for in-vehicle displays, but there is presumably no extra hardware cost for implementing this nudge.

The cost of developing concepts relevant to the nudging issue at hand are hard to estimate beforehand, since further field trials would be required to establish which concepts work best. However, if done at the scale and level of detail used in the MeBeSafe project, the cost is minor compared to all other costs that go into developing a modern vehicle.

14.3 O3 - In-vehicle nudging solution to direct driver attention to possible hazards

The in-vehicle nudging solution for directing driver attention has been presented as a system in 4 subsequent levels; from a straightforward system with basic nudging functionality to systems with increased nudging potential and implementation complexity. The implementation cost estimates for the different levels of system provided here, are based on the following assumptions:

- The costs are given per equipped vehicle.
- All indications are very rough estimates based on known sales prices for current state-of-the-art systems that make use of similar hardware components.
- No indication is provided for additional research and development activities.
- No costs are considered for systems that are already used in the vehicle for a different purpose; costs are not redistributed over all functions that make use of the existing available hardware.

14.3.1 GPS-staged HMI escalation

This basic nudging option, comparable to the solution used in the FOT makes use of:

- A Head-Up Display (HUD) is becoming standard equipment in premium cars. HUD are available from approximately 300 **€** (simple screen on top of the dashboard in basic vehicles) to 3000 **€** (as an implementation in the windscreen for premium vehicles).
- A navigation system (and consequently a navigation map and GPS localization) is becoming part of a vehicle's standard equipment package. In case a GPS navigation system needs to be purchased, this costs approximately 1000 **€** – 1500 **€**.

Which brings the total price to between 1300 € and 4500 €. There are no costs considered (0 €) in case a HUD and navigation system are already available in the vehicle.

14.3.2 HMI escalation using a static hazard model

The use of a static hazard model adds the need for an additional real-time static hazard estimation based on information already available in the solution from Section 14.3.1. In case this requires an additional ECU for making such hazard evaluations possible in real-time, the costs for an ECU are estimated at about 1500 **€, coming to a total cost of 2800 € - 6000 €.**

14.3.3 Integration with dynamic hazard model

The dynamic hazard model requires a detailed camera view over approximately 180 degrees at the front side of the car. Such view is needed to derive attributes of cyclists that support the prediction of their intended path for the upcoming seconds. Best quality is provided with a stereo view, so 2 forward-looking high-resolution cameras. Current AEB systems often make use of one or two forward looking cameras in combination with three forward looking radars. For cyclist prediction, the information from radars is currently only used for cyclist identification and providing reliable data on the current heading, speed and location of each cyclist in the direct vicinity of the vehicle. Radar is not used for determining the additional cyclist's attributes.

The dynamic hazard model makes full use of the system architecture provided by the static hazard model. Consequently, only little additional hardware is needed for the implementation of the dynamic hazard model compared to the system as described in Section 14.3.2. Possibly an additional camera for approximately 500 **€** is required. The dynamic hazard model is expected to run on the same ECU as the static model. The cost of the nudging solution therewith comes to a total of between 3300 **€** and 6500 **€**.

14.3.4 HMI inhibition using a driver direction of attention model

The highest level of adaptation to the driver comes with a detection system that in real-time determines the driver direction of attention. In addition to the system described in Section 14.3.3, to determine the driver direction of attention, a camera needs to be directed towards the driver, preferably from two different angles to cover the complete head and eye movement capabilities of the driver. Again, the system is expected to run on the same ECU as the static and dynamic hazard model. The extension of the equipment with 2 cameras directed towards the driver costs approximately 1000 **€ extra**. The most advanced in-vehicle nudging solution would then cost between 4300 **€** and 7500 **€**.

14.1 O4 - Behavioural change through online private driver coaching

The cost of implementing this feature in production vehicles can be broken down into two components; development of the app itself and the cost of acquiring access to a suitable natural speech interaction engine. The interactive quick guide used in the MeBeSafe pilots cost roughly 800 000 Euro to develop, and that was with a much wider feature set than required for MeBeSafe, so in the context of app development, this represents a minor to medium effort.

Gaining access to a state-of-the-art natural speech engine is a very different matter. These cannot really be purchased off the shelf and development is progressing rapidly, so it all depends on what collaborations are possible to establish and what the timeframe for deployment is. Giving a cost estimate is therefore not really possible.

14.2 O5: HGV driver behavioural coaching

In-Vehicle Monitoring Systems (IVMS) are often the standard within many logistics and transport companies. IVMS vary in terms of their complexity and costs. Among IVMS there are simple and advanced GPS, video and hazard warnings with telematics and emergency response systems. The DriveMate Application has the potential to replace current systems for the driver coaching aspect and deliver the same level of performance but at significantly lower cost. Also see D4.5 – Report on effective feedback.

Per company we expect that it would involve around €2,000 to €5,000 annually to run the DriveMate app. These costs include server capacity to collect and process the data, technical support and the costs of data connectivity (3G/4G network). However, as described above, there are several features that can improve the use and effectivity of the DriveMate app that have not yet been realised in this project. To add these features to the app would be an additional investment of about 200 – 300K€.

From a client perspective the DriveMate app will reduce IVMS costs and also improve road safety in a novel way and it allows increasing productivity and efficiency by reducing costs and making use of the latest technology. With the DriveMate app we can also nudge driving behaviour to reduce the fuel consumption through smoother driving (with less harsh braking and harsh acceleration), and potentially reduce maintenance costs.

14.3 O6 and O7 - Infrastructure Driver Nudge

In this estimate, the running cost of the Infrastructure Driver Nudge is split in cost for hardware, installation and software and apply to a location similar to the field test location described in this report. Cost for hardware and installation are initial cost to have the system on site (see Table 14-1). The needed software is calculated as a monthly fee for this example, targeting every vehicle passing the location. Estimated cost for software is € 6000/month for a 5-year contract. These cost are merely an indication based on a similar setup as the test location in Eindhoven.

Hardware		€ 85.000
• Lights	€ 40.000	
• Cameras	€ 15.000	
• Controllers, cabinets, misc.	€ 30.000	
Installation		€ 25.000
Total initial cost		€ 105.000

Table 14-1: Cost estimation for hardware of the Infrastructure Driver Nudge.

However, these costs are only an indication for a potential cost set-up. The infrastructure driver nudge could generally be used in any location where (especially habitual) speeding might be an issue.

14.4 O8 – Cyclist nudge

Implementation of the measure tested will cost about 300 € per location, based on estimations done by Gothenburg city. Cost will mostly be dependent on labour cost and local regulations for doing work in an active bike lane. The assumption is that the markings will last for at least 5 years. As previously discussed, as the nudge was noticed by many of the passing cyclists, there is a risk that the effect will wear off if it is implemented at too many locations. The recommendation is to put in this measure only in intersections that may be particularly dangerous. An estimation based on data from Gothenburg is that there might be about 20 such intersections in a mid-sized city. This would add up to about 2000 € per year to implement the measure. The Swedish road administration calculates the average cost for a bicycle accident to be SEK 34704 (EUR 3300) for the first 6 months, which means that less than one accident per year needs to be avoided due to the measure for the investment to be economically viable.

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