Improving clarity, cooperation and driver experience in lane change maneuvers

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Additional note

The research that has been conducted for this thesis is related to the dissertation that is currently being written by Adrian Haar.

Abstract

Many situations in traffic involve multiple road users and can only be solved by successful cooperation. However, 30% of cooperations in traffic fail, which indicates that there is potential for improvement (Benmimoun, Neunzig & Maag, 2004). In this study, lane change maneuvers were examined as a typical example of a situation that requires cooperation. Two ways of enhancing lane change maneuvers have been tested. Firstly, a contact-analogue head-up display has been used to support the regular turn signal. Secondly, the meaning of the regular turn signals has been revisited and a set of *enhanced semantics* that allows a distinction between *planning* and *starting a maneuver* has been proposed and assessed. This rephrasing of the meaning was based on evidence that suggested that regular turn signals might be unable to clearly and unambigiously communicate intentions between drivers in cooperative maneuvers (Haar, Kleen, Schmettow & Verwey, 2017). In order to evaluate the two approaches, a simulator study with 52 participants has been carried out to investigate the effect of using a contact-analogue HUD and the *enhanced semantics* on cooperation, clarity and the general perception of the situation. The participants were asked to drive on the left lane of a highway and encountered several situations in which another driver attempted to change to the participant's lane. On the one hand, objective measurements of cooperation have been obtained by counting the number of times that the participants allowed other drivers to change lanes. On the other hand, the participants were asked to fill in questionnaires to obtain subjective measurements of cooperative behavior, clarity and the way in which the driver experienced the situation. The results suggest that both approaches are beneficial for increasing the amount of cooperative behavior and in promoting the impression that other drivers are behaving cooperatively. Furthermore, the *enhanced semantics* improved the ability of participants to predict when exactly another driver initiated a lane change and what another driver was planning to do. Moreover, the lane change situations were rated as being a safer, more efficient and more comfortable experience when the HUD or the *enhanced semantics* were used.

Keywords: cooperation, head-up display, HUD, augmented reality, lane change, collaboration, turn signal

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There are traffic situations in which the cooperation between drivers could be enhanced. A common example is a situation in which a fast car is driving with 130km/h on the fast lane of a highway and approaches a much slower car that is driving 110km/h on an adjacent lane. The driver of the slower car sets the turn signal to communicate the intention to change to the faster lane. Most likely, this creates an uncomfortable feeling in the driver of the fast car and leaves him guessing whether he might have been overlooked. A quick decision has to be made between slowing down to let the other car in and speeding up to quickly escape the ambigious situation. The two drivers have to cooperate by adapting their behavior to each other in order to avoid a collision. Unfortunately, the driver's interpretation of the situation is the only thing upon which the decision can be based. Consequently, it is hard for the drivers to choose the correct behavior because it is unclear what the other driver's intentions are. This lack of certainty presents a dangerous source of misunderstandings, which in turn has the potential to cause accidents.

Sen, Smith and Najm (2003) found that about 9% of all accidents are related to lane chane situations. In general, false assumptions of others' actions have been identified as the cause of 4.5% of all car accidents (NHTSA, 2008). Therefore, false assumptions should be reduced by improving the communication between drivers. Historically, the turn signal is the main channel for communicating intentions for upcoming maneuvers. Alarmingly, a recent study by the Auto Club Europa (2008) with 394.000 drivers found that the turn signal is used incorrectly or too sparingly by many drivers. In line with this, doubts about its ability to communicate drivers' intentions unambigiously and clearly have been raised (Donges, as cited in Zimmermann, Bauer, Lütteken, Rothkirch & Bengler, 2014; Fekete, Vollrath, Huemer, Salchow, 2015; Haar, Kleen, Schmettow & Verwey, 2017). Since its introduction in 1939 there was not much of an evolution in the way turn signals work. Whereas existing turn signals could be modified or new technologies could be used to communicate drivers' intentions more clearly, this field has received only little attention in research. Therefore, this paper is an attempt to bridge this gap and to enhance the way in which drivers communicate their intentions in two ways: Firstly, *enhanced semantics* for the underlying meaning of turn signals will be proposed. Thus, the process of "setting a turn signal" will be split into: Planning a maneuver (step 1) and starting a maneuver (step 2). Secondly, Head-up displays will be used to visualize the intentions of other drivers. Eventually, if one or both of those approaches turn out to be useful, those findings might present a first step towards safer and more comfortable lane changes.

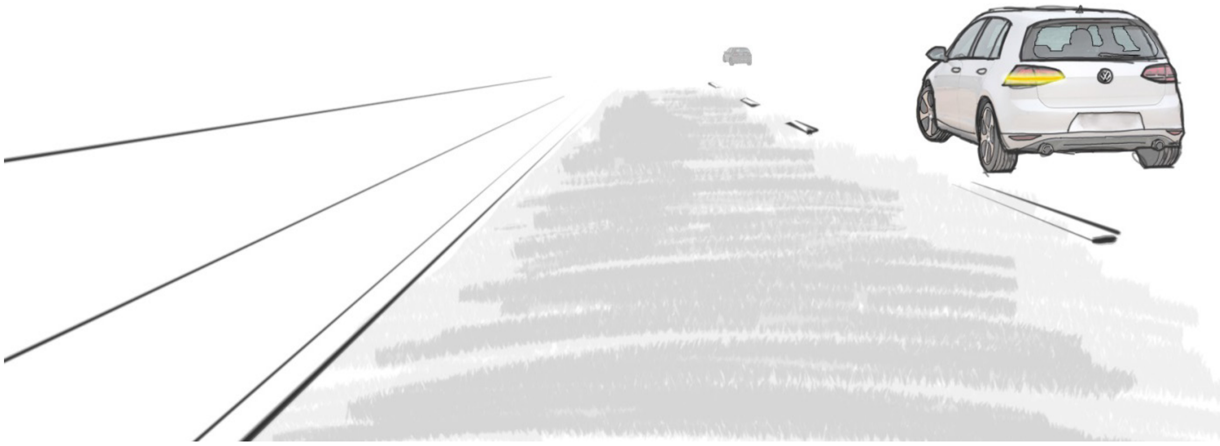


Figure 1. An example of an ambigious lane change situation. It is unclear whether the other driver will immediately change lanes or whether he merely wanted to communicate that he will change lanes behind the approaching car.

1.1 Cooperation among road users

Most traffic situations embrace multiple road users and often cooperation among them is required to solve a situation. Ellinghaus (1986) conducted a survey among 2000 motorists and identified lane changes as one of the most cooperative situations in traffic. In situations like these, drivers have to adapt their behavior to the behavior of another driver. For instance, the slower driver might use the turn signal to communicate the intention to change lanes. In response, the driver of the fast car might decide to slow down to create a gap for the slower car. Thus, by doing so, the driver of the fast car reacts to the behavior of the slower car's driver. Cooperation is also required in other situations, including intersections where all drivers have equal right of way and where hand gestures are the common way of arranging the order in which the drivers will enter the intersection (Björklund & Åberg, 2005).

Facilitating cooperative behavior in traffic is expected to have multiple positive effects. Benmimoun, Neunzig and Maag (2004) identified comfort and safety as core needs that are of immense importance to road users. Their study about cooperative behavior with more than 800 participants also revealed that 30% of all cooperations in traffic fail. This emphasizes that cooperation in traffic has huge potential for improvement that might be harnessed by the development of new advancd driver assistance systems. Improving cooperation between road users promises several advantages. Firstly, successful cooperation between drivers promises to increase safety by minimizing the number of accidents that occur due to misunderstandings. Secondly, it is likely that traffic is perceived as more comfortable when road users cooperate by e.g. opening a gap for a slower car or by changing to a slower lane when a faster car is approaching from behind. In line with this, Benmimoun et al. (2004) suggested that better cooperation would increase safety, comfort and efficiency of maneuvers and would thereby have an impact on the way that drivers perceive and experience the driving task. To refer to this more easily in the rest of the paper, the expression *driver experience* will be used as a more specific version of the well-known and more general expression of “user experience“. User experience itself is defined as “*a person's perceptions and responses that result from the use or anticipated use of a product, system or service”* (International Organization for Standardization, 2010). Analogously, the term *driver experience* refers to the driver's perception of safety, comfort and efficiency while driving or being seated in a car.

To get a better grasp of the processes that are involved in cooperative situations, several models of cooperative interactions have been proposed. Benminoun et al. (2004) suggested a model to describe the factors that play a role to determine whether or not a road user will cooperate. Their model suggests that the decision whether to engange in cooperation or not depends on the assessment of three factors in a given situation. Firstly, a driver assesses whether it would be safe to cooperate. Secondly, the costs of cooperating are assessed and thirdly, the other driver's need of help is estimated. Consequently, the model suggests that it is likely that drivers behave cooperatively if their safety won't be compromised, if the costs are not too high and if the other driver appears to really be in need of help.

Recently, Haar, Kleen, Albrecht, Schmettow and Verwey (2016) developed a new model of cooperation that extends Benminouns et al.'s (2004) model. The model describes the phases that drivers go through when encountering a situation that involves interactions and cooperation with others. It thereby suggests that cooperative situations involve reciprocal communication processes in which the involved drivers react to the other involved drivers' behavior. For instance, the driver of a slower car (partner car) might activate the turn signal to indicate the intention to change to the fast lane. In this situation, the driver on the fast lane (ego) has to perceive and interpret that behavior correctly and might eventually react by slowing down to create a gap. At this point, it is the turn of the driver of the slower partner car again. The perception and interpretation that the ego car slowed down to create a gap might eventually lead to the decision to begin the lane change maneuver. The model's focus on communication emphasizes the importance of clearly communicating intentions to facilitate successful cooperation among drivers. Therefore, it is expected that enhancing the way in which drivers communicate will make the execution of cooperative maneuvers easier.

The present study will focus on the part of the model that deals with the ego driver's perception of the partner's intention and the ego driver's decision about how to react to the partner's behavior. Furthermore, the ego driver's behavior ("execution") that results from this interaction will be examined. The respective parts of the model have been marked in Fig. 2. The exploration of the remaining parts of the model is potential material for future research.

With this in mind, this study will compare today's way of communicating during lane changes with two alternative approaches that promise to enhance communication and thereby benefit the cooperation among drivers. In the next sections a critical look at today's turn signals is taken and the two alternative approaches are introduced.

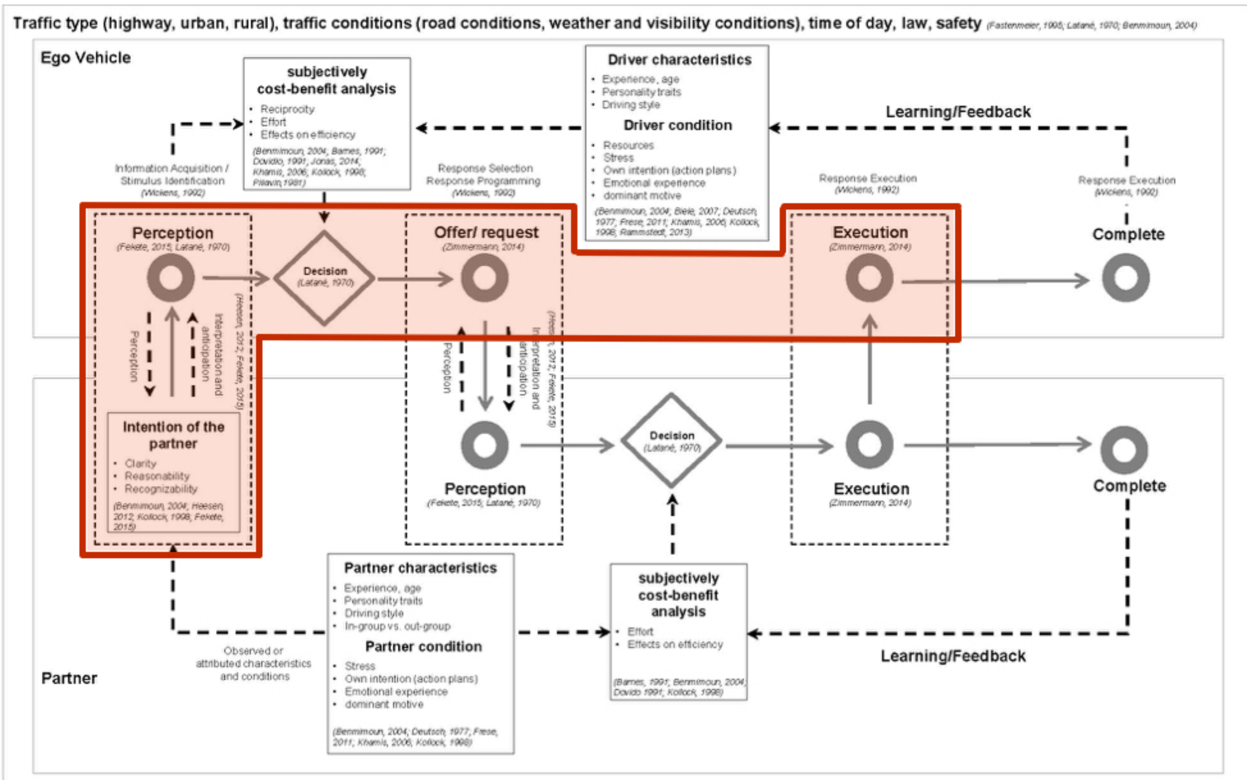


Figure 2. Haar et al.'s (2016) model of the processes that are involved in cooperative traffic situations. The marked area represents the parts of the model that the present study will examine

1.2 Enhanced semantics and a critical look at today's turn signals

According to the German road traffic regulations (StVO) §7 every lane change has to be signalized clearly and early enough by using the turn signal (Straßenverkehrsbehörde, 2013). The words clearly and early enough leave some room for interpretation about how exactly a turn signal should be used during lane changes. Salvucci and Liu (2002) mentioned that road users differ in the way in which they make use of the turn signal. They suggest that drivers can be divided into two groups: the first group uses the turn signal on highways to communicate that they are waiting for a gap; thus, that they are planning on changing a lane soon. The second group appears to use the turn signal to communicate the moment in which they are about to start a lane change. Even though the two styles of use differ a lot, both seem to satisfy the requirements of the German road traffic regulations. However, it seems that today's turn signal might be too limited to accommodate the style of both groups. In line with this, Haar et al. (2017) suggested that "the onedimensionality of regular turn signals might be too limited" to communicate the two different aspects of planning and starting a maneuver. Consequently, it seems that turn signals might be insufficient to unambigiously and clearly communicate intentions from one driver to another.

According to the basic semiotic framework that was first established by Morris in 1938, sign systems rely on syntax, semantics and pragmatics (Morris, 1972). Firstly, „syntax" refers to the way signs are interrelated in a system. Secondly, „semantics" refers to how signs (e.g. words and expressions) are associated with objects, actions and so forth. Thirdly, „pragmatics" include the context in which signs are used and thereby includes meaning that goes beyond the literal meaning of a phrase. This framework can be applied swiftly to the communication between road users. When drivers communicate with each other, they make use of turn signals to share information about their intentions with the world. The Cambridge Dictionary's definition of a turn signal reads *„one of the lights at the front and back of a road vehicle that flash to show which way the vehicle is turning"* („turn signal", n.d.). Thus, using a turn signal (the sign) is associated with a specific action and the *semantics* of using a turn signal are that a vehicle is turning into a given direction.

Given the findings of the study by Haar et al. (2017) that has been mentioned previously, one might argue that the semantics of nowaday's turn signals are too limited to accommodate the style of the two different groups of turn signal users. Consequently, a revision of the underlying semantics might be necessary and a set of *enhanced semantics* might be required. Nowaday's meaning of a turn signal could be described as "a driver informs another driver of an upcoming maneuver". However, this understanding does not allow to distinguish moments in which a driver is merely planning a maneuver from moments in which a driver is actually starting a maneuver. Consequently, the semantics of today's turn signals could be extended to make this distinction possible. Those *enhanced semantics* for turn signals would present a fundamental modification of the way in which turn signals are understood and should therefore be subject of thorough empirical testing.

In a first simulator study by Haar, Kleen, Schmettow and Verwey (in preparation) the the enhanced turn signal semantics were put to the test in a twofold approach. Firstly, regular turn signals were modified to comply with the *enhanced semantics*. Thus, the modified turn signals were able to switch between two signal patterns: On the one hand, they could display a dynamic signal pattern (also known as animated turn signal) and on the other hand, they could display a second signal pattern that looked like a typical turn signal pattern. The first pattern – the animated turn signal – meant that the driver was planning a maneuver. The second pattern was a regular flashing turn signal and indicated that the driver was starting a maneuver. See Figure 3 for a schematic representation of this concept. During the study, the participants were driving on the fast lane of a highway and throughout each trial, a number of slower cars on the adjacent lane tried to change to the participants' lane. When the participants were about 30m away from the slower car, the slower car's turn signal was activated and showed the first turn signal pattern (planning a maneuver). This was supposed to tell the driver that the other driver was merely looking for a gap and not about to change lanes yet. Once a gap had been opened and the slower driver was ready to start the lane change, the turn signal switched to the second pattern (starting a maneuver). This informed the participants that the other driver had decided to start the lane change and would pull over shortly. If the participant did not slow down to open up a gap, the turn signal of the slower car kept showing the first signal pattern (planning a maneuver) and the car did not change lanes.

Secondly, aside from modified turn signals, Haar et al. (in preparation) used head-up display (HUD) visualizations to put the *enhanced semantics* to the test. The same lane change situation has been simulated and – once again – the participants had to decide whether or not to let the other driver in. When the driver of the slower car was planning to change to the fast lane, the participants saw the first level of the HUD visualization (planning a maneuver) as depicted in Fig. 3. Once the participants slowed down, the other car started the lane change and the second HUD visualization (starting a maneuver) was displayed.

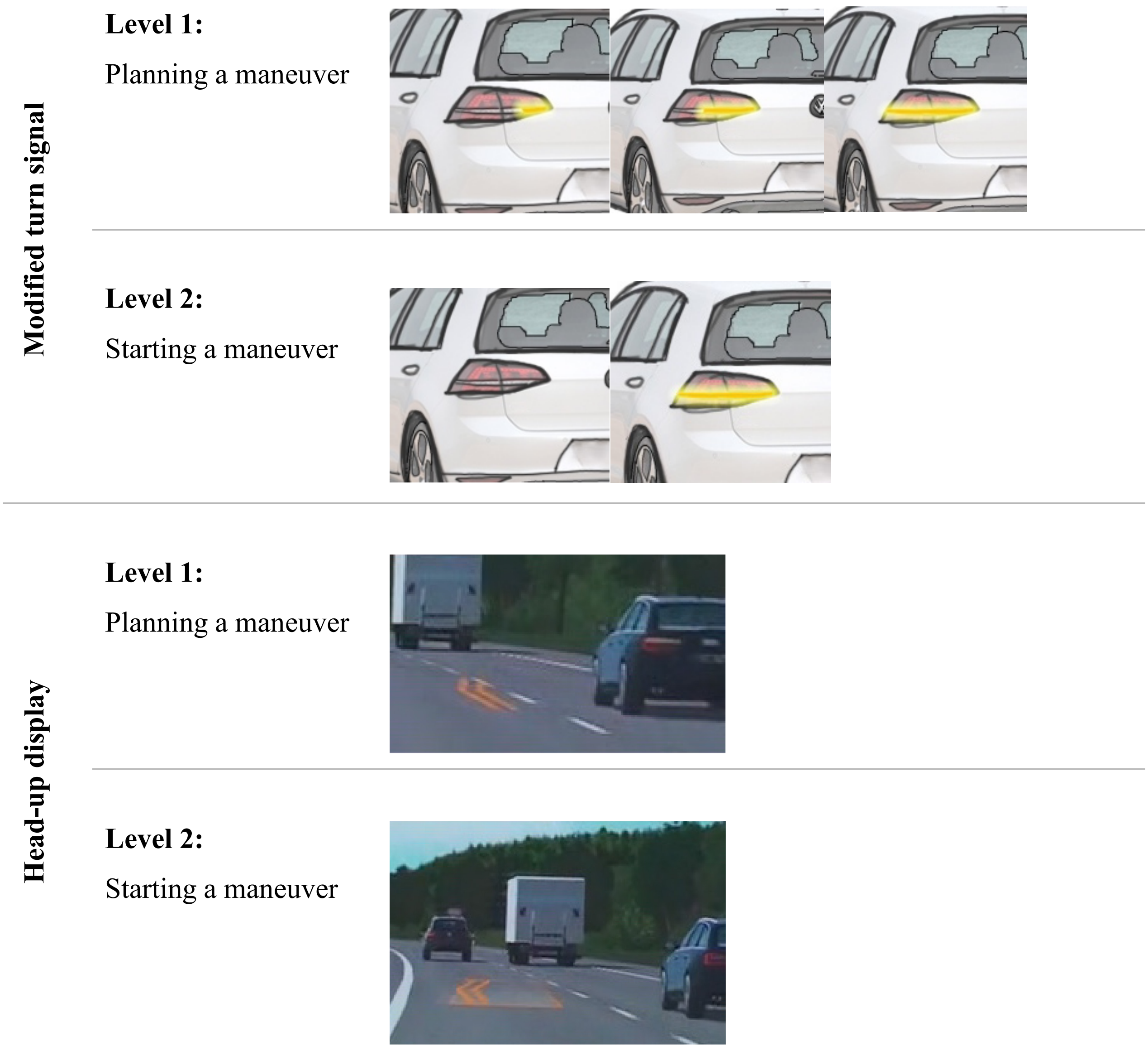


Figure 3. The concepts that have been tested in Haar et al.'s (in preparation) study. The turn signal with *enhanced semantics* is at the top and the HUD with *enhanced semantics* is at the bottom.

The underlying idea behind the experiment was to see whether the *enhanced semantics* can help the participants to understand the intentions of other drivers. In detail, the expectation was that the concepts that included the *enhanced semantics* would help the participants to tell whether another driver was merely looking for a gap or about to pull over on the participant's lane. Surprisingly, it could not be demonstrated that the *enhanced semantics* for turn signals increase clarity or the perceived amount of cooperation. Neither the modified indicator nor the HUD visualizations with the *enhanced semantics* could show any benefit of the *enhanced semantics*. However, there are three possible explanations for what might have held back the two concepts from unfolding their potential. Firstly, participants did not receive any instructions about the *enhanced semantics*. Hence, the participants might have failed to grasp the underlying idea behind the concept. Secondly, the participants might have overlooked that there were two different turn signal patterns and HUD visualizations. The two levels might have looked too similar to clearly distinguish them from each other. Thirdly, the participants had an average of 18.4 years of driving experience and could therefore be regarded as experienced drivers. Their extensive experience with regular turn signals might have made them blind for the distinction. Hence, they might have assumed that the enhanced turn signals and concepts would work in similar ways as the old ones. Consequently, even if the two signal patterns and the two HUD visualizations were visually distinct enough to tell them apart when looking at them separately and consciously, participants might have perceived them as one. Therefore, the participants might not have noticed or understood that the meaning of the turn signal had been modified; which is why they might have been unable to perceive that a line has been drawn between planning and starting a maneuver.

After all, those assumptions remain to be checked in a follow-up study that keeps those limitations in mind. If the *enhanced semantics* (the distinction between planning and starting a maneuver) prove to be effective, the increase in transparency could greatly benefit the way in which drivers communicate.

1.3 Head-up displays and Augmented Reality

An emerging technology that has gained more and more importance in the recent years are head-up displays. They allow the integration of digital information into the driver's field of view. The first version of a HUD was introduced by General Motors decades ago where they offered the presentation of basic information like the current speed on a fixed position in the windshield (Weihrauch, Meloeny & Goesch, 1989). However, technology has gone a far way since then and the possibilities that modern HUDs offer reach far beyond merely displaying speed information. One of the new features is the ability to *augment reality* by displaying information *contact-analogously*, thus at the location of the object to which it is related. For instance, when a warning is displayed, the object that caused the warning can be highlighted to direct the driver's attention accordingly (Haeuslschmid, Schnurr, Wagner & Butz, 2015). Volvo presented a similar concept in 2014 (see Fig. 4). However, for now those features have not found their way onto the market, yet. They are still participant of research and present a promising outlook to the possibilities that AR HUDs offer.

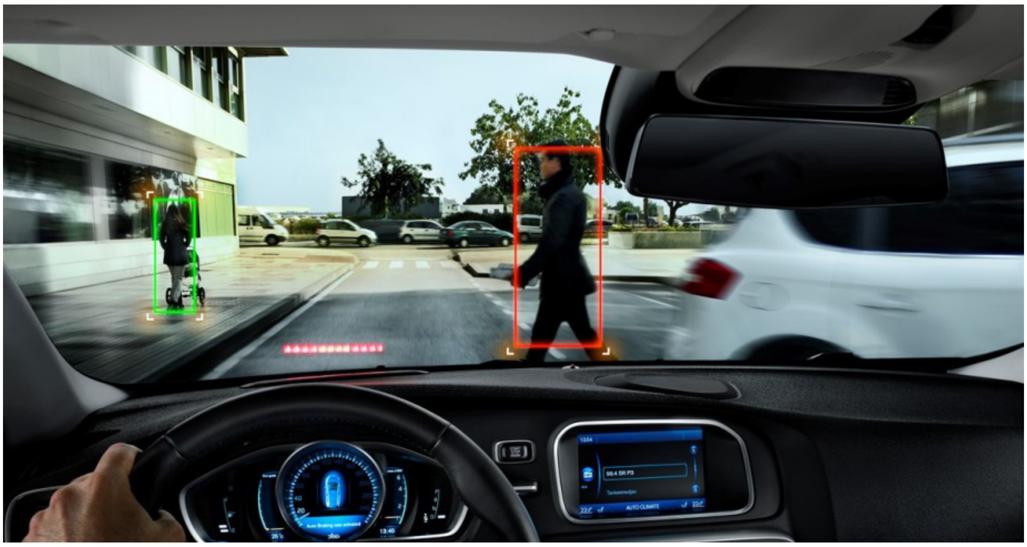


Figure 4. Volvo's concept of an augmented reality head-up display. A pedestrian is marked with a red outline to draw the driver's attention towards him (Volvo, 2014)

A lot of literature has been written about the advantages and disadvantages of using AR HUDs in an automotive context. For instance, drivers can be supplied with visual information without taking their eyes off the road and thereby lowers the probability for an accident (Cohen & Hirsig, 1990; Fadden, Ververs & Wickens, 1998). However, the information is displayed on top of the real world and can potentially cover objects or parts of the scenery which might make them practically invisible to the driver. Consequently, the driver might miss an important aspect of the situation, which might lead to accidents or stressful situations. Doyon-Poulin, Robert and Ouellette (2012) did research on the effects of occlusion in HUDs and came up with guidelines that can be used to minimize occlusion when designing visualizations for HUDs. A more extensive discussion of the pros and cons of using Augmented Reality Head-up displays can be found in Appendix A.

Zimmermann et al. (2014) tested a system that assisted drivers during lane changes with an AR HUD. The system established a connection between multiple cars and tried to find a suitable partner who could open a gap to make a lane change possible. Once a suitable partner had been found, the driver of that car saw a dialog that asked him if he agreed on the lane change. Furthermore, the car that requested the lane change was marked in the AR HUD. Once the partner agreed, the lane change was automatically executed. Another study simulated an AR HUD in a simulator study and specifically examined lane change situations in highway scenarios (Haar et. al, in preparation). They put further emphasis on the turn signal by supporting it with HUD visuals that were flashing synchronously and in the same orange color as the turn signal. They found that the use of a HUD increased the probability that a driver was willing to create a gap for a slower car. Hence, using a HUD stimulated cooperative behavior.

With those successful applications of head-up displays in mind, the question arises whether a more minimalistic design could prevent the negative effects of occlusion and still yield the same results. The following section presents the results of prestudies that have been conducted with the aim of finding a suitable design for a modified turn signal and a more minimalistic HUD visualization.

1.4 The prestudy: Finding good designs for the main study

In preparation for this study, a prestudy with 25 people has been carried out to develop a suitable design for the modified turn signal that includes the *enhanced semantics*. The prestudy had two main objectives: Firstly, finding a design in which the two levels of "planning a maneuver" and "starting a maneuver" are as intuitive as possible. Secondly, finding a design in which the two levels are visually distinct from each other and therefore easy to tell apart.

In the beginning of the prestudy, the participants were asked if they were familiar with the lane change situation and the discomfort that it might bring. All of the participants reported that they had experienced those situations and that they had experienced lane change situations that made them feel uncomfortable. Next, they were introduced to the idea of the *enhanced semantics* and the two level distinction that it brings as a potential solution to this problem and were presented with a number of different prototypes. There were two iterations of the prestudy. In the first iteration, four different designs were presented to ten participants. The participants' feedback and the results of the first iteration have been used as a starting point for the creation of four new turn signal designs that include the *enhanced semantics*. See Fig. 5 for an overview of the four new concepts of modified turn signals that have been compared in the prestudy. The second iteration was comprised of 15 participants and only the four new concepts were presented. In the end, one of the designs was chosen as being the most intuitive and the one in which the two levels were the easiest to tell apart. The final design of the modified turn signal that is based on the *enhanced semantics* can be seen in Fig. 6.

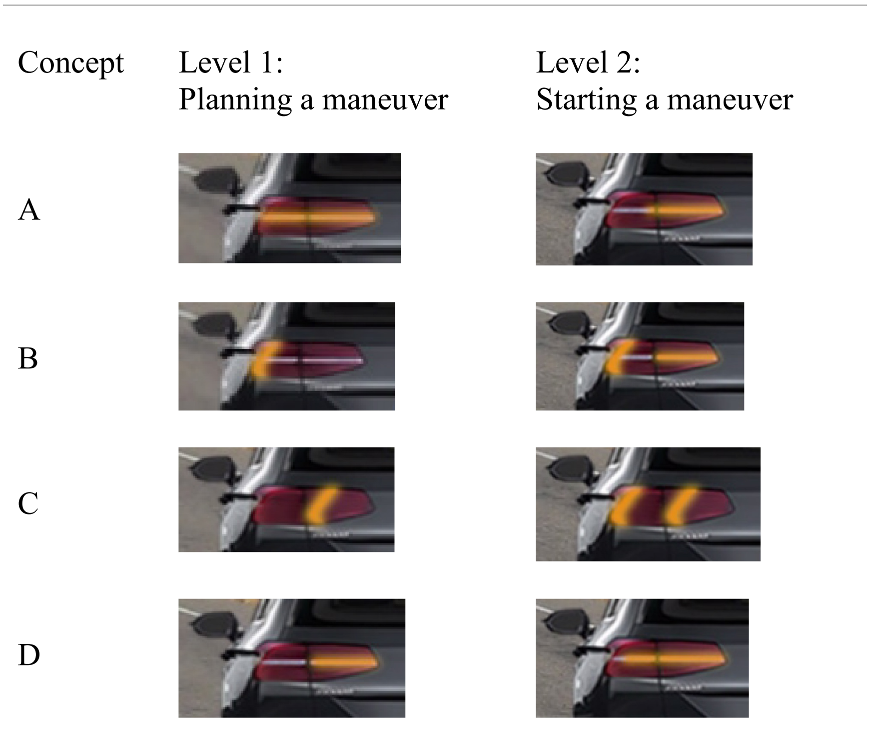


Figure 5. This is an overview of the designs that were compared in the prestudy. All of themare modified turn signals that have two patterns to visualize the *enhanced semantics*.

Upon completion of the experiment, the participants were asked about their opinion regarding the usefulness of the two levels that were introduced by the *enhanced semantics*. All of the participants reported that the distinction is an interesting idea and that they could imagine that it could make lane change situations clearer. As a bonus, the participants were presented with a concept for an Augmented Reality HUD visualization (see Fig. 7). This concept was based on the results of a prestudy that has been conducted in preparation for the study by Haar et al. (in preparation). It has been re-designed to minimize occlusion with objects of the real world and with Volkswagen's current design language in mind. The participants were told that this concept is an alternative approach to the ones presented and that it should not be compared directly to the other ones but seen as belonging to a separate category. The HUD concept received a lot of positive feedback and three participants expressed that it took them less effort to understand the meaning of the HUD visualization than it took to understand the modified turn signal.

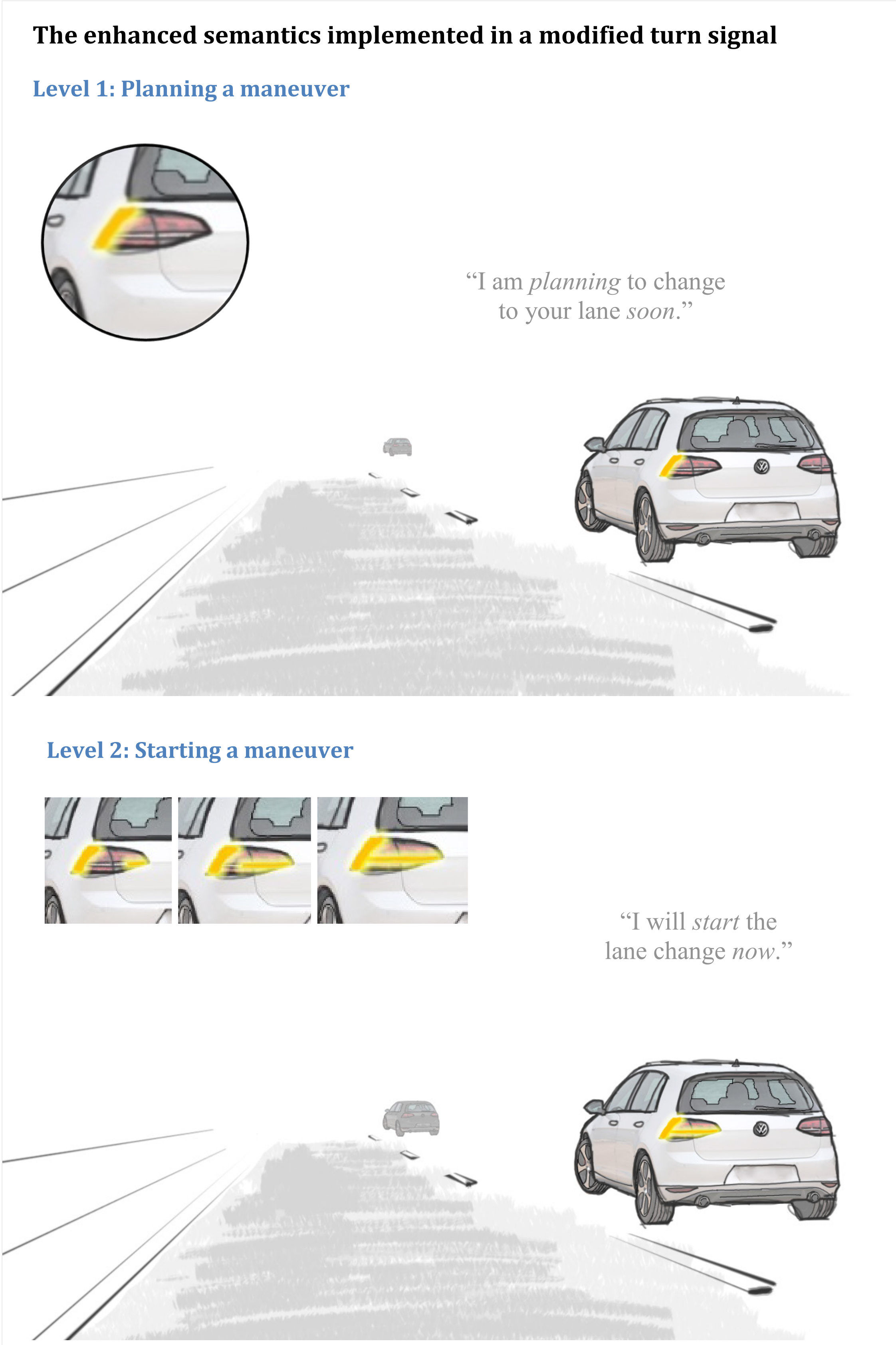


Figure 6. This figure shows the final version of the modified turn signal which resulted from the prestudy. It shows how the *enhanced semantics* are visualized in a modified turn signal.

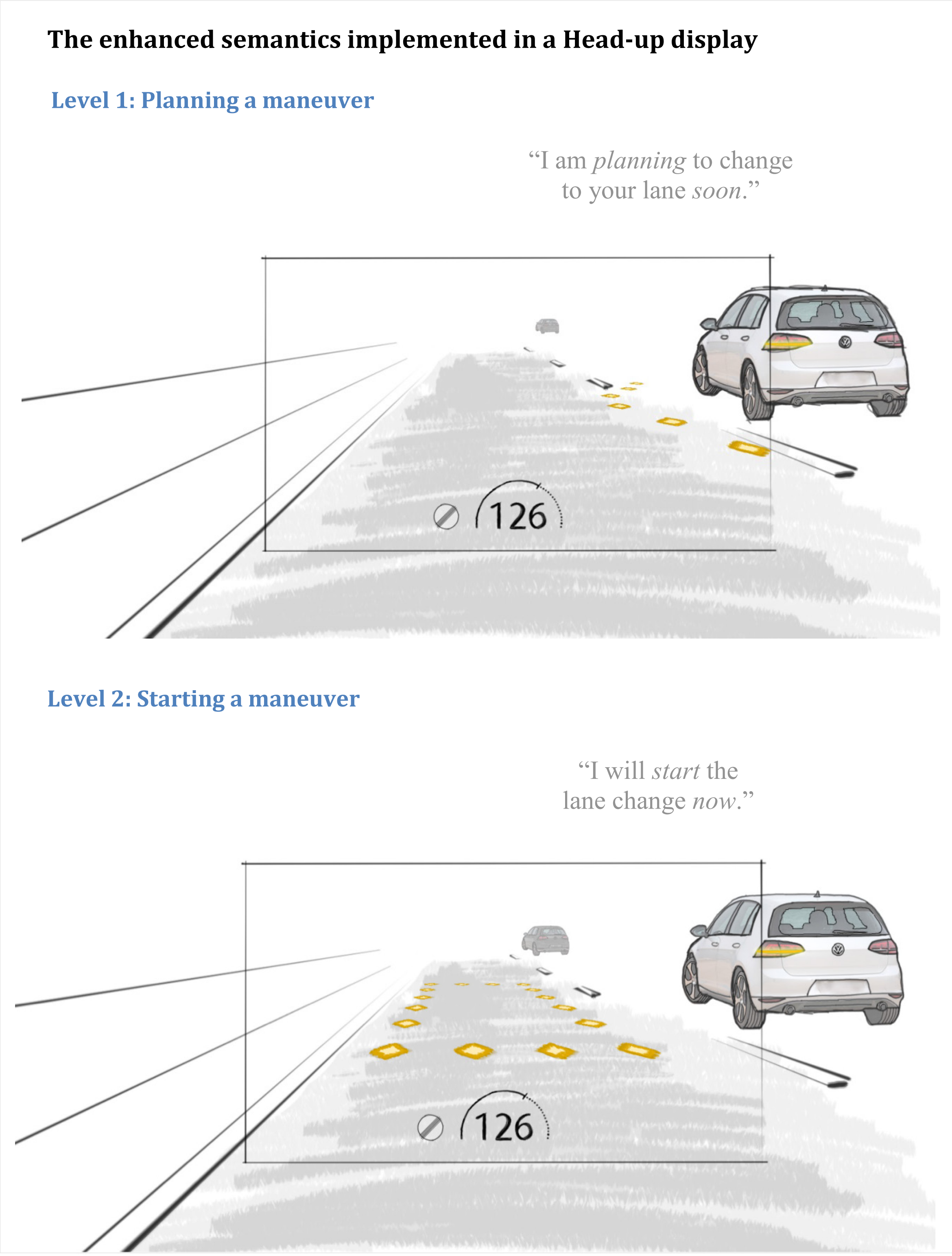


Figure 7. This figure shows the final HUD version that has been picked in the prestudy. It shows how the *enhanced semantics* are visualized by using a HUD.

1.5 The main study

The present study is an attempt to improve the interaction between drivers in cooperative lane changes in two ways: Firstly, by using HUDs and secondly, by dividing the intention communication process into two levels (planning and starting a maneuver). Whereas it could be shown that the use of a HUD stimulates cooperative behavior, it could not be shown that the *enhanced semantics* had an effect (Haar et al., in preparation). It has been proposed that the lack of providing instructions to the participants might have limited the study's potential to explore the effectiveness of the *enhanced semantics*. Main reason for this assumption was that participants might not have noticed or understood the distinction between planning and starting a maneuver. In addition, the two levels might have looked too similar and therefore participants might have failed to notice that the indicator was not a regular one. Therefore, the main goal of this paper is to re-investigate the ideas of Haar et al. (in preparation) and to assess their potential of making communication between drivers clearer and less ambigious. Firstly, Augmented Reality (AR) Head-up display visualizations are investigated in an attempt to see whether their ability to increase clarity in lane change maneuvers can be reconfirmed. Secondly, the *enhanced semantics* will be tested by using a modified turn signal on the one hand and HUD visualizations on the other hand. In order to deal with the limitation of the first study, instructions on the meaning of the *enhanced semantics* with the two level distinction will be provided. In addition, the two levels will be made more visually distinct from each other to separate them more clearly from each other.

There are three expected outcomes with regard to the effects of using a HUD and the *enhanced semantics* on *cooperation, clarity* and the *driver experience*. It is assumed that the same pattern will be found for the three entities in question. The interaction plot in Figure 8 illustrates the expectations and indicates that only main effects and no interaction effects are expected. It shows that the *enhanced semantics* will presumably yield higher ratings than the *old semantics.* At the same time, it is likely that using a HUD will lead to higher ratings than using no HUD. It is expected that there are no interaction effects, because there is no reason to assume that the *enhanced semantics* would work better in a HUD than in a modified turn signal. It is rather assumed that the effect of the *enhanced semantics* will not be affected by the medium that is used to communicate them. Furthermore, no saturation effects are expected, because cooperative lane change maneuvers appear to offer much room for improvement. Therefore, it is likely that the baseline ratings will be situated somewhere in the middle of the rating scales.

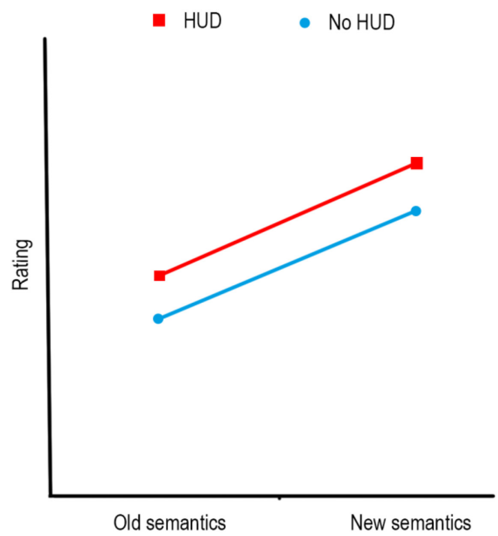


Figure 8. Interaction plot that shows the expected effects of the *enhanced semantics* and HUD usage on cooperation, clarity and driver experience

Firstly, it is expected that using a HUD to emphasize the meaning of a regular turn signal will have an effect on the amount of cooperative behavior. This expectation is based on the findings of the study by Haar et al. (in preparation). The HUD visualizations that were used in the original study have been re-designed with the aim to minimize occlusion with the real world. It will then be interesting to see whether those HUD visualizations will have a similar effect on the amount of cooperative behavior and the perception of cooperation during lane change situations as the original design. Aside from this, the effects of the enhanced turn signal semantics on cooperative behavior and the perception of cooperation will be examined.

Secondly, it is assumed that using a modified turn signal with *enhanced semantics* or HUD visualizations with *enhanced semantics* will allow the participants to get a better feeling for the exact moment in which another driver is starting a lane change maneuver. Thus, it will be investigated in how far the use of a HUD or the *enhanced semantics* has the potential to increase the clarity of the situation.

Thirdly, it is expected that the use of HUD visualizations and the *enhanced semantics* will lead to less stressful and more pleasant interactions during lane changes. As mentioned before, the degree to which a lane change is perceived as pleasant is refered to as *"driver experience"*.

Consequently, there are two main research questions that are subdivided into three parts. The first research question deals with the effect of using a HUD on clarity, cooperation and driver experience. The second research question is focused on the effects of applying the *enhanced semantics* and their effect on clarity, cooperation and driver experience.

Research question 1: *In how far does the use of a head-up display (HUD) affect clarity, cooperation and driver experience during lane changes?*

(a) *Cooperative behavior and the perception of cooperation*

(b) *Clarity about the exact moment in which another driver starts a lane change maneuver*

(c) *Driver experience (how comfortable and pleasant the lane changes feel)*

Research question 2: *What is the effect of using the "enhanced semantics" on clarity, cooperation and driver experience during lane changes?*

(a) *Cooperative behavior and the perception of cooperation*

(b) *Clarity about the exact moment in which another driver starts a lane change maneuver*

(c) *Driver experience (how comfortable and pleasant the lane changes feel)*

Method

2.1 Participants

A sample size of n = 48 or more participants was desired to make complete counterbalancing possible as it requires a multiple of 24 when four conditions are used. In order to deal with possible attrition, 55 participants have been invited. After all, n = 53 participants completed the study (46% female). One participant quit the study pre-maturely due to simulator sickness. Consequently, that participant has been removed from the sample and a total of n = 52 remains. Participant 24 accidentally quit the survey application which resulted in a failure to save the questionnaire data for one condition. Therefore, the questionnaire data for condition A has not been captured for participant 24. The remaining questionnaire scores of that participant score were included in the analysis. Furthermore, the logging of the driving data failed six times. All of the participants were employees of the Volkswagen AG. The recruitment was done via Volkswagen's Probandenpool (participant pool). Upon completion of the study, the participants received a small gift from the participant pool to compensate for the time that they spent to participate. All participants were German and all questionnaires and instructions were provided in German language. Good vision (with or without correction) and a driver's license were required for participation. On average, the participants drove 18068km (SD = 10910) per year. None of the participants stood in a relation to the experimenter that might have had an influence on the results.

2.2 Measures

Subjective as well as objective measurements were done to determine how the participants perceived the lane change situation and how much cooperative behavior the participant showed. The *subjective measurement* consisted of 18 questions that measured the quality of the lane changes in terms of comfort, efficiency, safety and the feelings that were evoked in the participant. Furthermore, the questionnaire included ratings of how clear the intentions and the timing of the other drivers were. Aside from this, the following entities were measured: the participant's feelings during the lane changes, the workload while driving and the degree to which the situation was assessed as being cooperative. See Appendix D for the full questionnaire and Appendix E for an investigation of the questionnaire's internal consistency and correlations. Three questions were based on Benmouni et al.'s (2004) findings that identified comfort, efficiency and safety as the core needs that people strive for while driving. The remaining questions were based on a questionnaire that has proven to measure what it purports to measure in a study by Zimmermann et al. (2014). The participants could give their ratings on a 7-point Likert-scale that ranged from *"I fully disagree"* to *"I fully agree"*. In addition, the participants were asked to rate the different concepts on the Van der Laan scale (Van der Laan, Heino & De Waard, 1997). The Van der Laan scale is used widely in usability testing and has been developed for the evaluation of HMI concepts. It consists of 9 items and measures the dimensions of *satisfying* and *usability*. The ratings are done on a 5-point Likert scale. Moreover, participants were invited to write down a more detailed description of how they perceived the lane change if they felt limited by the phrasing of the questions. Furthermore, the Driving Activity Load Index (DALI) was used to assess the workload of the participants during the driving task (Pauzié, 2008). Finally, the participants were asked to rank the four concepts to determine which concepts they liked the most.

The *objective measurement* of cooperative behavior consists of counting the number of lane changes in which the participant slows down to let the other car in. The more often a participant allowed a lane change, the more cooperative that behavior was regarded.

2.3 Apparatus and setting

Material. The traffic simulation software Virtual Test Drive (VTD) by Vires was used to create a scripted highway scenario. It included other road users that were controlled by the computer. When the participant approached those vehicles, a set of pre-defined actions has been executed. The scenario was based on the scenario that has been used in the study by Haar et al. (in preparation).

As outlined before, a modified turn signal concept that includes the *enhanced semantics* has been developed and evaluated in a prestudy with two iterations and a total of 25 participants. Similarly, the HUD concept that has been used was the result of a prestudy with two iterations that has been conducted prior to the study. A refinement of that concept has been done in preparation of this study (see 1.4, “Prestudy: Finding good designs for the main study”). The two concepts that resulted from those iterations can be seen in Fig. 6 and Fig. 7.

Experiment. When driving the scenario, the driver was driving on a highway with two lanes. The driver experienced a number of situations in which another car attempted to change to the driver’s lane. In those situations, the participant had to choose whether he let the other car in or not. Thus, he could accelerate or slow down (see Fig. 7). In total, there were five encounters in which the participant passed by a slower car. In three out of those five encounters, the car set the turn signal to change to the participant’s lane. In the other two situations the car did not attempt a lane change. An overview of the order in which those situations occurred can be seen in Figure 9. It took the drivers five to six minutes to complete the whole scenario.

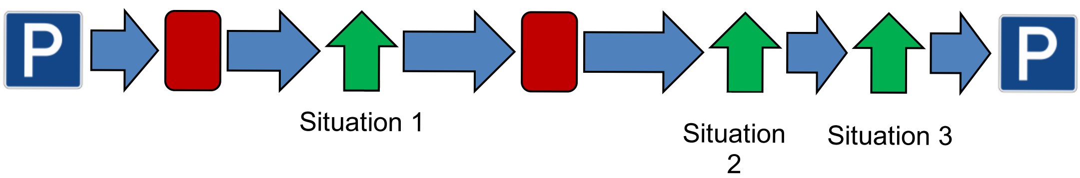


Figure 9. The order of the situations during the experiment. The red blocks represent encounters with other drivers who did not attempt a lane change. The green arrows represent encounters in which the other driver attempted a lane change.

Figure 10. The view on the driving simulator from within the lab demonstrator. This is the situation in which the driver had to decide whether to slow down or to let the other car in

Each participant took part in four conditions (with 5 situations each). The only thing that changed across those conditions was the kind of turn signal that has been used. Firstly, $condition_{Baseline}$ used a regular turn signal to allow a comparison with today's standard. Secondly, $condition_{ExtendedTurnSignal}$ used a modified turn signal with two phases (Fig. 6). Thirdly, $condition_{HUD}$ used a regular turn signal but it was supported by a HUD visualization during the planning phase (see Fig. 7). Thus, when the computer driver was planning to change lanes, a pulsating line was shown next to the other car. Fourthly, in $condition_{ExtendedHUD}$ the regular turn signal was accompanied by a HUD visualization that did not only emphasize the *planning phase* but also showed a visual for the *starting phase*. See table 1 for an overview of all four conditions.

Table 1

Overview of the four conditions that each driver had to complete

	Condition	Semantics	HUD
A	Baseline (regular turn signal)	Old semantics	Disabled
B	Turn signal with enhanced semantics	Enhanced semantics	Disabled
C	HUD	Old semantics	Enabled
D	HUD with enhanced semantics	Enhanced semantics	Enabled

Setting. The study took place in one of the fixed-base simulators in Volkswagen's Research and Development facility. A lab demonstrator with a real steering wheel, pedals and car seat and a display for the standard driving information has been used. The simulation was projected on three 4x4m canvases in their front and to their sides. To allow for a look in the rear mirror and the side mirrors, three flatscreens were placed behind the simulator to create an immersive experience (see Fig. 11). Prior to the conduction of the study, the University of Twente's ethics committee and Volkswagen's participant pool reviewed the procedures of the experiment.

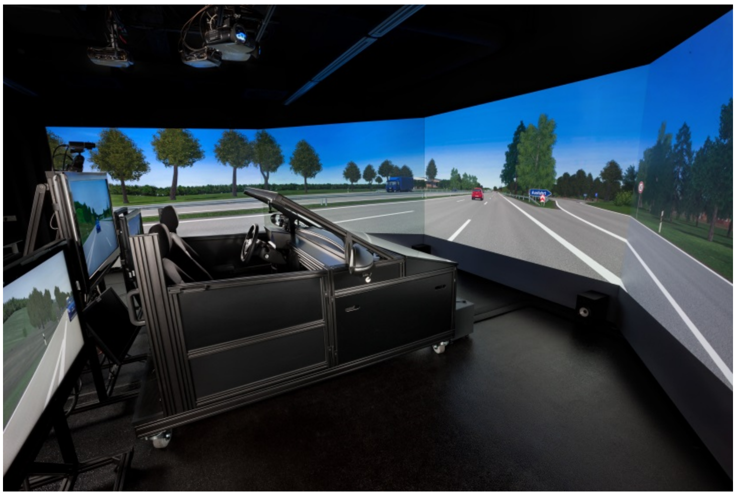


Figure 11. The fixed-base lab demonstrator in front of three 4x4m canvases. The two canvases at the very left and the very right have not been used in this study. Three additional mounted screens allowed the participant to take a look in the rear and side mirrors.

2.4 Design

This study was designed to allow for both, between-participant and within-participant observations. The independent variables were wether a HUD was used (*disabled* or *enabled*) and whether the *enhanced semantics* were applied (*old semantics* or *enhanced semantics*). The dependent variable was the amount of cooperative behaviour, which was measured by looking at whether the participants allowed the slower car to change lanes (objective) and by evaluating the participants' perception of the situation (subjective). Complete counterbalancing has been used to control for order and learning effects. Hence, the total number of participants had to be a multiple of 24 ('Finer points of design', 2001). Any participants that exceeded this number received their order of trials based on randomized counterbalancing. Thus, a total of 48 participants has been determined as the target sample size. In order to account for potential attrition, 55 participants were invited to take part in the study.

2.5 Procedure

At the start of the experiment, the researcher instructed the participants about the possible side effects that the use of a fixed-base simulator could have and informed them that they were free to cancel the experiment at any time without any further consequences. After doing so, the participants read a short introduction to the experiment and filled in a questionnaire on a tablet in which they had to answer basic questions about their personality and background. After doing so, the researcher guided the participants to the lab simulator, asked them to sit down in the driver's seat and to adjust the seat and mirrors to their preferences. The researcher then started a testdrive and sat down next to the participants in the passenger seat. He invited them to get used to the simulator by accelerating, braking, steering and changing lanes. This allowed them to get comfortable with the feeling of driving in a simulated environment and the simulator and its handling. Completing the testdrive took about four minutes. Subsequently, the researcher asked the participants how they felt and reminded them that they could stop the experiment at any time. Once the participants were all set, the researcher started the first condition. Upon completion of the first condition, the researcher asked the participants to fill in the first questionnaire on the tablet and told them that they could ask questions at any time. Then, the three other conditions were tested in the same manner (driving and then filling in a questionnaire about the drive). After the fourth questionnaire had been filled in, the participants were invited to ask open questions about the study and to leave remarks if desired. Lastly, to compensate for the time and the effort that the participants had invested, the researcher thanked them for their participation and rewarded them with a small gift.

2.6 Data analysis

This section will start with a conceptual description of the Linear Mixed Model (LMM) that explains the choice of the model's parameters. Next, the methods that have been used for the data analysis are introduced and an explanation for why the researchers refrained from using classical Null Hypothesis Significance Testing (NHST) is given.

2.6.1 Building the model

A LMM was built to predict the dependent variables, that is, the questionnaire ratings and the likelihood that the participants will let the other car in. For the estimation of *feeling of cooperation* and the *proportion of allowed lane changes*, logistic regression has been used, because those estimations were binomial (yes or no). For all other estimations, linear regression has been used. In order to get an estimate of the effect of using a Head-up-display, the model includes a group difference parameter for *HUD*. Similarly, a group difference parameter for *enhanced semantics* is included to get an estimation of their effect on the dependent variables. Furthermore, the combination of no HUD and old semantics serves as a baseline and is used as the model's intercept. Lastly, an interaction effect of HUD and *enhanced semantics* is included, to see how their effect changes when both manipulations are used concurrently. To sum up, the model has the following group level parameters: *Baseline (old semantics/no HUD)*, *HUD*, *enhanced semantics* and the *interaction of HUD and enhanced semantics*.

Table 2. *The regression model for predicting questionnaire ratings and cooperative behavior. The reference group for the interpretations is the group where no HUD and the old semantics were used.*

Parameter	*R model terms (stan_glmer)*	*Interpretation*
Fixed effects		
β_0	1	Reference rating when *no HUD* is used and when the *old semantics* are applied
$\beta_{\text{HUD}} x_{HUD}$	HUD	Difference between using a *HUD* and *not using a HUD* (when the *old semantics* are applied)
$\beta_{\text{Sem}} x_{Sem}$	EnhancedSemantics	Difference between *enhanced semantics* and *old semantics* (when *no HUD* is used)
$\beta_{\text{Sem\|HUD}} x_{Sem} x_{HUD}$	EnhancedSemantics:HUD	Interaction effect of using the *enhanced semantics* and a *HUD*
Participant-level random effects		
σ_P	Participant	Participant variation in reference rating when *no HUD* is used and when the *old semantics* are applied (β_0)
$\sigma_{HUD\|P}$	HUD:Participant	Participant variation in difference between using a *HUD* and *not using a HUD* (when the *old semantics* are applied) (β_{HUD})
$\sigma_{Sem\|P}$	EnhancedSemantics:Participant	Participant variation in difference between *enhanced semantics* and *old semantics* (when *no HUD* is used) (β_{Sem})

In addition, it is expected that the participants get different baseline scores when using no HUD and a regular turn signal with the old semantics. Therefore, the model has a varying intercept that is distributed normally around its mean. Using the model like this implies the assumption that using a HUD or the *enhanced semantics* has the same effect for each participant (the same slope). Yet, this is not very likely to be true. Rather, it is expected that the effect of HUD and the *enhanced semantics* vary for each participant. Some people might not like or understand the *enhanced semantics* or might simply have an aversion against HUDs, which would then affect the ratings. To deal with this variance, the model that has been chosen for the data analysis also includes varying slopes that are normally distributed around their mean. An overview of the model is given in Table 2. However, the model does not include a varying slope for the interaction effect of HUD and *enhanced semantics*. This is due to the fact that the model started to diverge during the sampling once it was included. This might be due to oversaturation of the model because there were was too little data for too many parameters.

A check of the model's fit has been carried out and none of the diagnostic values showed any indications that something might be wrong with the model. The sampling procedure will rely on Markov-Chain Monte Carlo sampling using the software STAN.

2.6.2 Credibility intervals and Bayesian estimations

The data analysis is not based on hypothesis testing or model comparisons but relies on quantitative interpretation of estimates. This is supposed to shift the focus away from the black-and-white of model comparisons to a more explorative approach that relies on point estimates of effect sizes and intervals around those point estimates (Schmidt, 1996). Doing so is regarded as "a more useful approach to interpreting study results" than the dichotomous NHST approach that roughly divides results into significant and non-significant results (Gardner & Altman, as cited in Kruschke, 2015). This is supported by a recent appeal of the American Statistical Association, in which serious doubts about the practice of NHST have been raised (Wasserstein & Lazar 2016). In detail, the statement brings forth the widespread misconceptions and misuses regarding NHST. This includes the problem of researchers selectively reporting *p*-values, omitting non-significant results or paying too little attention to a study's design or the quality of the measurements when making scientific inferences. However, this is not a new concern and has been raised year ago by authors like Lykken (1991) and Peng (2015) who gave a number of examples for studies that were impossible to replicate. Therefore, the authors of this paper will rely on the aforementioned point estimates and intervals around those point estimates and will provide the full data analysis protocol.

Furthermore, Bayesian estimation is chosen over frequentist methods. This decision is made for two reasons: Firstly, Bayesian credibility intervals have the advantage of being intuitively and easily interpretable by conveying the meaning that is often falsely attributed to *non-Bayesian* or *frequentist* confidence intervals: the probability that a certain value lies within the boundaries of an interval (Hoekstra, Morey, Rouder & Wagenmakers, 2014; McElreath, 2016). Secondly, Bayesian estimation engines allow the choice of a larger range of models. In other words, the Bayesian estimation engines allow the custom formulation of models that provides the best fit for given data. At the same time, Bayesian parameter estimation will still work where frequentist approaches will fail (e.g. non-linear multi level models).

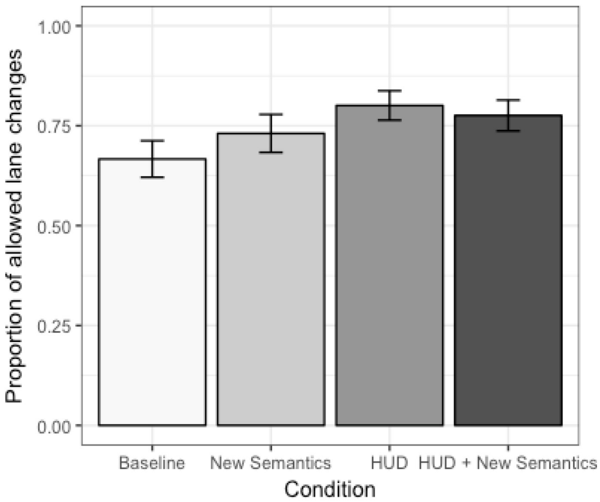
Each result will be reported in the same three-step fashion: Firstly, a point estimate of the effect size is given. Secondly, the credibility interval for that point estimate is provided to give an indication of how certain a given result is. Thirdly, the random effect variation is interpreted to examine in how far a given effect varies between participants.

Results

The results part will use the findings of the data analysis to answer the three research questions. In the process, subjective and objective measurements will be considered. Lastly, the ranking of the concepts will be presented.

Table 3. *Descriptive statistics of the questionnaires. N = 207, scale ranges from -3 to 3.*

	μ	σ
Cooperative behavior		
Perceived cooperativeness in own behavior	1.10	.97
Perceived cooperativeness in other's behavior	.20	1.40
Clarity		
Clarity of timing	.18	1.90
Clarity of intention	1.1	1.80
Driver experience		
Quality of the lane change maneuver	.90	1.40



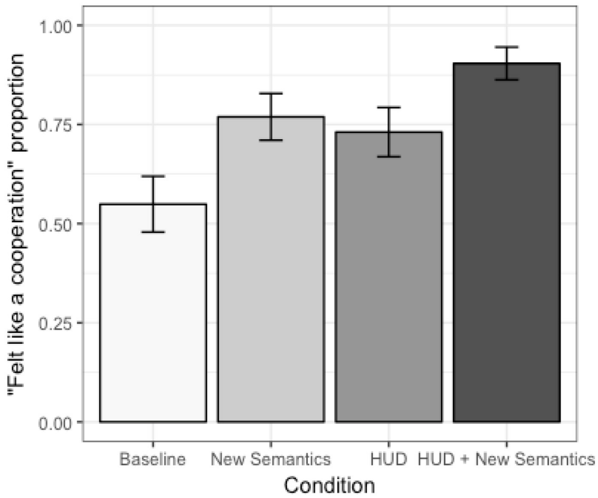


Figure 13. Left: The observed number of total lane changes of all participants with/without using a HUD or the *enhanced semantics*. Right: Bar chart depicting the number of times in which the participants reported that a lane change felt like a cooperation.

3.1 Cooperation

The first research question was related to finding out in how far cooperation and the perception of cooperation were affected by the use of a HUD or the *enhanced semantics*. To answer this question, the objective and subjective measurements are reviewed.

3.1.1 Observed cooperative behavior

A look at the left plot in Fig. 13 suggests that the participants allowed the other drivers to change lanes more often when the HUD, the *enhanced semantics* or a combination of both were used. This is underlined by the estimations of the LMM. When logistic regression is performed, the parameters are on a logit scale. They have to be transformed by exponentiating them in order to interpret them as odds. For better readability, Tables 4 and 5 include not only the log(odds) but also the transformed values (the odds) to make the results of the logistic regression more understandable.

According to Table 4, the odds that a participant allowed the other car to change lanes were *exp(.92)* = 2.51 to 1 when a regular turn signal and no HUD were used. With a certainty of 95% it can be assumed that this odd ratio lies between *exp(.39)* = 1.47 to 1 and *exp(1.49)* = 4.44 to 1. The variance of the intercept is 1.5 times bigger than its effect (*exp(1.33)* = 3.78). This indicates that whether or not someone was behaving cooperatively varied quite strongly between participants when only a regular turn signal was used.

Furthermore, using a HUD increased the likelihood that the partner car was allowed to change lanes by factor 2.56 = *exp(.94)*. On a 95% certainty level, it can be assumed that the value of this factor lies between *exp(.31)* = 1.36 and *exp(1.67)* = 5.31. Hence, it can be concluded with sufficient certainty that using a HUD increased cooperative behavior. The fact that the effect size is almost twice as large as its variation indicates that the positive effect of using a HUD differed only slightly from one participant to the next (*exp(.62)* = 1.86).

The left plot in Fig. 13 suggests that the *enhanced semantics* led to an increase in cooperative behavior by the participant. This is supported by the estimations of the model, which predict that using the *enhanced semantics* increased cooperative behavior by factor *exp(.45)* = 1.57. Yet, whereas the credibility interval includes mostly positive values, it also includes negative values and ranges from *exp(-.14)* = .87 to 1 to *exp(1.08)* = 2.94 to 1. Therefore, it can only be concluded that there is a trend that indicates that *enhanced semantics* have a positive effect on cooperativeness, but there is insufficient certainty to back this interpretation statistically on a 95% certainty level. The variation of the *enhanced semantics' effect* among participants is slightly larger than its effect (*exp(.64)* = 1.90). Hence, the effect of the *enhanced semantics* differs slightly from one participant to the next.

Table 4. *The coefficients table of Model 2 predicts how often the participant allowed a lane change on a logistic scale. The gray values in brackets are the odds (exp(log(odds))).*

	Fixed Effects			Random Effects
	log(odds)	*Lower 2.5%*	*Upper 2.5%*	*σ*
Intercept [No HUD / Old semantics]	.92 (2.51)	.39 (1.48)	1.49 (4.4)	1.33 (3.78)
HUD	.94 (2.56)	.31 (1.36)	1.67 (5.31)	.62 (1.86)
Enhanced semantics	.45 (1.57)	-.14 (.87)	1.08 (2.95)	.64 (1.9)
HUD:Enhanced semantics	-.61 (.54)	-1.48 (.23)	.19 (1.21)	-

Finally, using a HUD in combination with the *enhanced semantics* is estimated to have increased the odds for showing cooperative behavior by factor 2.18 = *exp(.94+.45-.61)*. However, the 95% credibility interval is extremely broad and ranges from .27 = *exp(.31-.14-1.48)* to 18.92 = *exp(1.67+1.08+.19)*. Therefore, there is a strong trend that indicates that using a combination of HUD and *enhanced semantics* does increase cooperative behavior. Yet, there is not sufficient certainty to draw this conclusion on a 95% level.

3.1.2 Perceived cooperative behavior

The bar chart in Figure 14 (on the right) delivers the impression that the number of times in which a lane change was perceived as a cooperation was much higher when a combination of HUD and the *enhanced semantics* was used than when only a regular turn signal and no HUD were presented. Similarly, it seems that using only the *enhanced semantics* or only a HUD led to an increased feeling of cooperation.

The model in Table 5 estimates that the odds ratio that a lane change was rated as being a cooperation was *exp(.21)* = 1.23 to 1 when the regular turn signal and no HUD were used. With a certainty of 95%, it can be assumed that this odds ratio lies between *exp(-.32)* = .73 to 1 and *exp(.75)* = 2.12 to 1. Hence, it can not be concluded with sufficient certainty that it was more likely that the lane changes were perceived as being a cooperation than being no cooperation.

Once a HUD was used, the proportion of lane changes that were described as cooperative increased by factor *exp(.80)* = 2.23. On a 95% certainty level, the value of this factor lies between *exp(0)* = 1 to 1 and *exp(1.62)* = 5.05 to 1. Consequently, there is sufficient certainty to conclude that using a HUD increased the perception of cooperation.

Moreover, using the *enhanced semantics* increased the proportion of times that a lane change was perceived as cooperation by factor *exp(1.01)* = 2.75. This value lies between *exp(.19)* = 1.21 to 1 and *exp(1.87)* = 6.49 to 1 with a certainty of 95%. Thus, this indicates that the *enhanced semantics* had a huge positive effect on the number of times that a lane changed was perceived as being a cooperation.

Lastly, the effect of using a HUD and the *enhanced semantics* together was very strong as it increased the odds for perceiving the situation as cooperation by factor 8.17 = *exp(.80+1.01+.29)*. However, the 95% credibility interval is very broad and runs from 0.45 = *exp(.19-.99)* to 172.39 = *exp(1.62+1.87+1.66)*. The interval includes mainly values that are greater than 1, which suggests that the combination of a HUD and the *enhanced semantics* had a positive effect on whether a lane change felt like a cooperation or not. However, there is not sufficient certainty to draw this conclusion on a 95% level of certainty.

Table 5. *The coefficients table of Model 1 that predicts the feeling of cooperation during lane changes on a logistic scale. The gray values in brackets are the odds (exp(log(odds))). The random effects of this model have been excluded, because they caused oversaturation of the model.*

	Fixed Effects			Random Effects
	log(odds)	*Lower 2.5%*	*Upper 2.5%*	*σ*
Intercept [No HUD / Old semantics]	.21 (1.23)	-.32 (.73)	.75 (2.12)	-
HUD	.80 (2.23)	0 (1)	1.62 (5.05)	-
Enhanced semantics	1.01 (2.75)	.19 (1.21)	1.87 (6.49)	-
HUD:Enhanced semantics	.29 (1.34)	-.99 (.37)	1.66 (5.26)	-

3.1.3 Degree to which the participants perceive their own behavior as cooperative

Looking at the boxplot in Figure 14 gives the impression that the participants always perceived their own behavior as cooperative with no regard to whether a HUD, the *enhanced semantics* or neither was used. Furthermore, it appears like there are no interaction effects. Therefore, the reporting of the results will focus on the main effects.

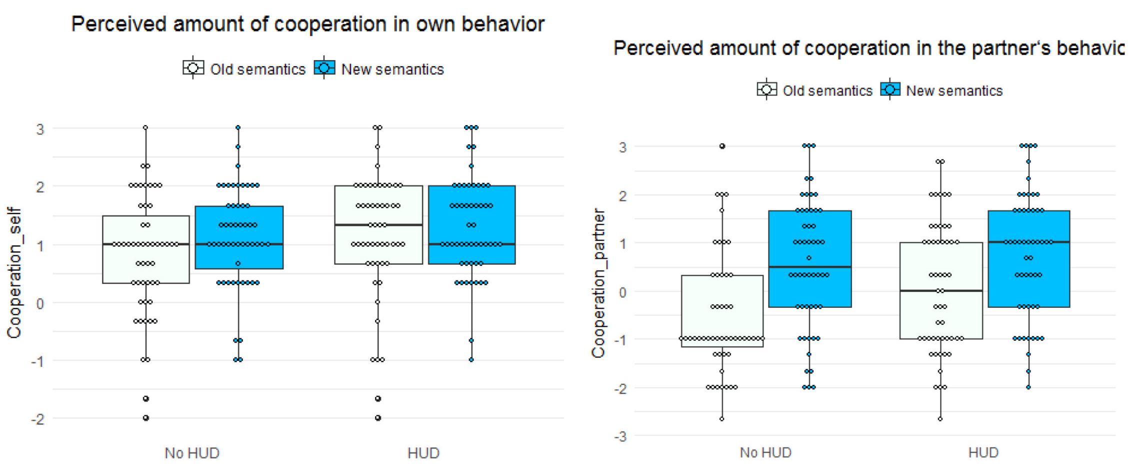


Figure 14. Boxplot of the amount of cooperation that the participants perceived in their own and the other driver’s behavior.

The model estimates that the baseline for the degree to which the participants perceived their own behavior as cooperative was .80, 95% CI [.54, 1.06] (see Table 6). However, the variation of the baseline scores is quite large (σ_0 = .53), which indicates that the degree to which the participants rate their own behavior as cooperative varies strongly from one participant to the next when the regular turn signal and no HUD is used.

Enabling the HUD visualizations or introducing the *enhanced semantics* had almost the same effect. Using only the HUD led to an increase of μ_1 = .34 and is expected to lie between .03 and .64 with a certainty of 95%. However, the HUD's effect varies strongly depending on the participant (σ_{HUD} = .26). Quite similar to the effect of the HUD, the *enhanced semantics* increased the ratings by μ_{Sem} = .32 (95% CI, [.01, .62]). The variation of the effect of the *enhanced semantics* is as large as its effect (σ_{Sem} = .32). Hence, the effect of the *enhanced semantics* on the self-cooperativeness ratings varies strongly depending on the participant.

Lastly, whereas using a combination of HUD and *enhanced semantics* appears to have a strong positive effect ($\mu_{Sem|HUD}$ = .49 = .34 + .32 - .17), the 95% credibility interval is very broad, ranging from -.53 (.03 + .01 - .57) to 1.5 (.64 + .62 + .24) and includes a high fraction of negative values, which prevents to draw any conclusions about the effectiveness of this combination with sufficient certainty.

Table 6. *The coefficients table of a model that predicts perceived amount of cooperation in own behavior.*

	Fixed Effects			Random Effects
	μ	*Lower 2.5%*	*Upper 2.5%*	*σ*
Intercept [No HUD / Old semantics]	.80	.54	1.06	.53
HUD	.34	.03	.64	.26
Enhanced semantics	.32	.01	.62	.32
HUD:Enhanced semantics	-.17	-.57	.24	-

3.1.4 Degree to which the other's behavior is perceived as cooperative

Figure 14 above indicates that the other driver's behavior is perceived as most cooperative when a HUD and the *enhanced semantics* are used in combination. At the same time, it seems like the *enhanced semantics* have a strong positive effect on how cooperative the other driver's behavior is perceived to be. Once again, there is no indication for a relevant interaction effect. Hence, the reporting of the results will focus on the main effects. When the regular turn signal is used (no HUD and the old semantics) the partner's behavior is perceived as being uncooperative (μ_0 = -.55, 95% CI [-.90, -.19]) (see Table 7). With a certainty of 95% this value lies between -.90 and -.19. The baseline rating varies by σ_0 = .51 from one participant to the next. This suggests that there is a lot of variance in the perceived amount of cooperation in the partner's behavior.

The difference to the baseline rating of perceived cooperativeness in the other driver is moderate μ_{HUD} = .59 when a HUD is used. The size of the HUD's effect lies between .10 and 1.05 on a 95% certainty level (μ_{HUD} = .59, 95% CI [.10, 1.05]). However, even though a HUD has a positive effect on the ratings, the resulting ratings are still situated around zero, which means that the partner's behavior is rated as being neither cooperative nor uncooperative. The effect of the HUD varies strongly by about σ_{HUD} = .46 between participants as the variation is almost as large as the estimated effect itself.

Once more, the effect of the *enhanced semantics* is more pronounced with an effect size of μ_{Sem} = 1.09, 95% CI [.64, 1.57]. This value lies between .64 and 1.57 with a certainty of 95%. Hence, using the *enhanced semantics* seems to have a dramatic impact on the perception that the other driver is in fact behaving cooperatively. The *enhanced semantics*' effect varies only slightly by σ_{Sem} = .40 depending on which participant is giving the rating.

Whereas the combination of HUD and semantics has a rather strong effect size of $\mu_{\text{Sem|HUD}}$ = 1.3 (.59 + 1.09 - .38), the uncertainty interval is very broad and thus prevents any conclusions from being drawn (95% CI [-.30, 2.88]). After all, using a HUD or the *enhanced semantics* has a positive impact on the ratings that measure perceived cooperativeness of the other driver, but in absolute numbers, the cooperativeness of the other partner is still being rated as being lower than the own cooperativeness.

An interesting observation is that the participants generally rate their own behavior as being much more cooperative than the others' behavior. Using the *enhanced semantics* or a combination of HUD and *enhanced semantics* brings the perceived cooperativeness of the other on par with the ratings for perceived self-cooperativeness.

Table 7. *The coefficients table of a model that predicts perceived amount of cooperation in the partner's behavior.*

	Fixed Effects			Random Effects
	μ	*Lower 2.5%*	*Upper 2.5%*	σ
Intercept [No HUD / Old semantics]	-.55	-.90	-.19	.51
HUD	.59	.10	1.05	.46
Enhanced semantics	1.09	.64	1.57	.40
HUD:Enhanced semantics	-.38	-1.04	.26	-

3.2 Clarity

The second research question dealt with the degree to which the HUD or the *enhanced semantics* helped the drivers to get a clearer picture of the situation. For doing so, two questionnaire scores will be examined: Firstly, how clear the other driver's intentions were and secondly, how clear the exact moment of the lane change was.

3.2.1 Clarity of the other driver's timing

The left boxplot in Figure 15 suggests that the other driver's timing is rather unclear when the regular turn signal and no HUD are used. It also leads to believe that a combination of HUD and the *enhanced semantics* leads to a very strong increase in clarity of timing. Similarly, enabling a HUD appears to lead to a strong increase in clarity of timing and using the *enhanced semantics* seems to trigger a slight increase. Moreover, there seem to be no interaction effects. Thus, only the main effects will be described.

All of the above is supported by the estimates that the model in Table 8 provides. The estimate for the clarity of timing ratings when a regular turn signal and no HUD are used is equal to μ_0 = -.91. With a certainty of 95% it can be assumed that this rating is in fact situated somewhere between -1.39 and -.43. This baseline rating varies moderately by about σ_0 = .45. The model estimates that the clarity of the other's timing is getting much clearer by about μ_{HUD} = .88 when a HUD is used, 95% CI [.19, 1.58]. This HUD's effect varied moderatley by about σ_{HUD} = .56.

An even stronger increase is observed when the *enhanced semantics* are introduced. Applying them leads to an increase of μ_{Sem} = 1.38 above the baseline rating (regular turn signal and no HUD). It can be assumed with 95% certainty that the effect size of using the *enhanced semantics* lies between .72 and 2.08 (μ_2 = 1.38, 95% CI [.72, 2.08]). Whereas the effect of the HUD varies moderately between participants, the effect of the *enhanced semantics* varies only slightly (σ_{Sem} = .50), when comparing it to its large effect size.

Lastly, using a HUD and the *enhanced semantics* together appears to have the strongest effect and leads to an increase of $\mu_{Sem|HUD}$ = 2.07 (.88 + 1.38 - .19). However, that combination has a very broad 95% credibility interval that runs from -.20 (.19 + .72 – 1.11) to 4.41 (1.58 + 2.08 + .75). The largest proportion of the interval's values is positive and therefore, there is a trend that indicates that using a HUD and the *enhanced semantics* together increases clarity about the other's timing. Still, the fact that the 95% CI also includes negative values implies that it can not be said with certainty that a combination of HUD and *enhanced semantics* increases the clarity of the other's timing.

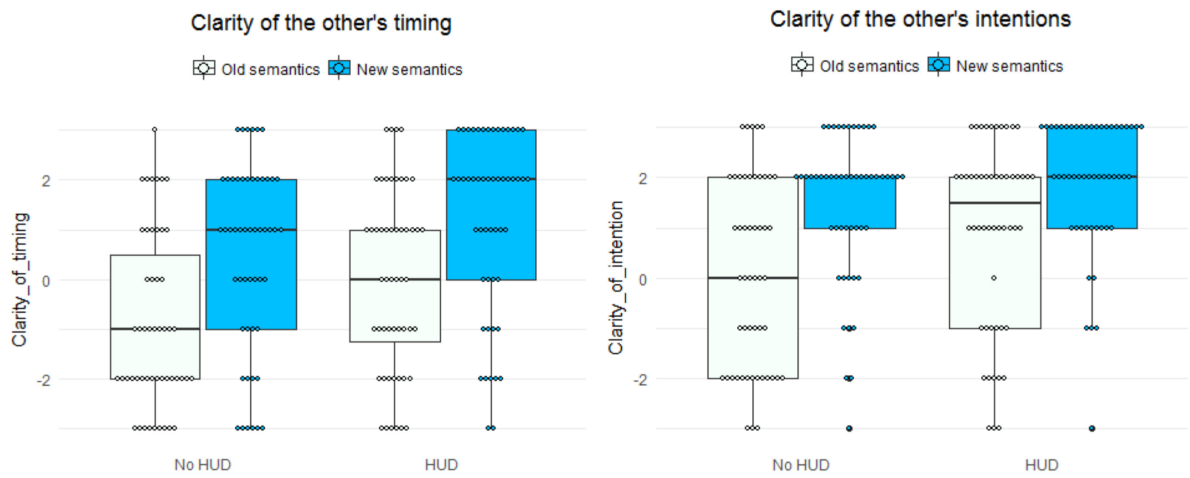


Figure 15. Left: Boxplot that depicts how clear it was when exactly the other driver started the lane change. Right: Boxplot that shows how clear the intentions of the other driver were to the participant.

Table 8. *The coefficients table of Model 1 that predicts the clarity of the other's timing.*

	Fixed Effects			Random Effects
	μ	*Lower 2.5%*	*Upper 2.5%*	σ
Intercept [No HUD / Old semantics]	-.91	-1.39	-.43	.45
HUD	.88	.19	1.58	.56
Enhanced semantics	1.38	.72	2.08	.50
HUD:Enhanced semantics	-.19	-1.11	.75	-

3.2.2 Clarity of the other driver's intentions

The right boxplot in Fig. 15 indicates that the intentions of the other driver are neither clear nor unclear when a regular turn signal and no HUD are used. The visualization also suggests that using a HUD, the *enhanced semantics* or a combination of both leads to a strong increase in clarity of the other driver's intentions. Once again, only the main effects are described, because the visuals do not suggest that there is a strong interaction effect.

In line with those observations, the estimations in Table 9 reveal that the clarity of the partner's intentions was rated as being neither very clear nor very unclear when a regular turn signal and no HUD was used (μ_0 = .05). With a certainty of 95% the baseline rating lies between -.40 and .50. Thus, it is is situated around zero with a very broad credibility interval. Comparing the estimation of the baseline rating with its variation (σ_0 = .45) reveals that the ratings vary strongly between the participants. The clarity of intention ratings increased strongly by $\mu_{\text{HUD}} = .88$ when a HUD was used. It can be expected that this value lies in the interval that runs from .26 to 1.49 with a 95% level certainty. The variation of this effect is rather small (σ_{HUD} = .39) when compared to the effect size. Hence, the positive effect of using a HUD on the clarity of the other driver's intentions seems to be quite strong for the whole sample of participants.

Once again, the *enhanced semantics* had an even stronger positive effect than the HUD and boosted the clarity of intention ratings by μ_{Sem} = 1.39. The 95% credibility interval reaches from .79 to 2. The effect size is four times as large as the variation (σ_{Sem} = .34), which indicates that the effect of the *enhanced semantics* varies only very slightly between the participants.

Using a combination of both, a HUD and the *enhanced semantics* yields a very strong effect size of $\mu_{Sem|HUD}$ = 1.83 (.88 + 1.39 - .44). However, the accompanying 95% credibility interval is very broad and ranges from -.25 (.26 + .79 – 1.3) to 3.93 (1.49 + 2 + .44). Thus, it can not be concluded on 95% certainty level that the effect of a combination of HUD and *enhanced semantics* will increase clarity of intention. Still, a large proportion of the interval is positive which indicates a trend towards a positive effect of using a combination of HUD and *enhanced semantics*.

Table 9. *The coefficients table of a model that predicts the clarity of the other's intentions.*

	Fixed Effects			Random Effects
	μ	*Lower 2.5%*	*Upper 2.5%*	*σ*
Intercept [No HUD / Old semantics]	.05	-.40	.50	.45
HUD	.88	.26	1.49	.39
Enhanced semantics	1.39	.79	2	.34
HUD:Enhanced semantics	-.44	-1.30	.44	-

3.3 Driver experience

The third research question focused on the impact of using a head-up display or the *enhanced semantics* on the driver experience during cooperative lane change situations. Thus, how pleasant and efficient the participants perceived driving experience to be.

3.3.1 Quality of the lane changes

The boxplot in Figure 16 indicates that a lane change is rated as having neither a high nor a low quality when a regular turn signal and no HUD are used. It also suggests that a combination of HUD and *enhanced semantics* leads to the highest quality of lane change ratings. Using a HUD in isolation seems to have a small positive effect and introducing the *enhanced semantics* appears to have a slightly stronger effect. The boxplot provides no indication of any relevant interaction effects. Hence, only the main effects will be described.

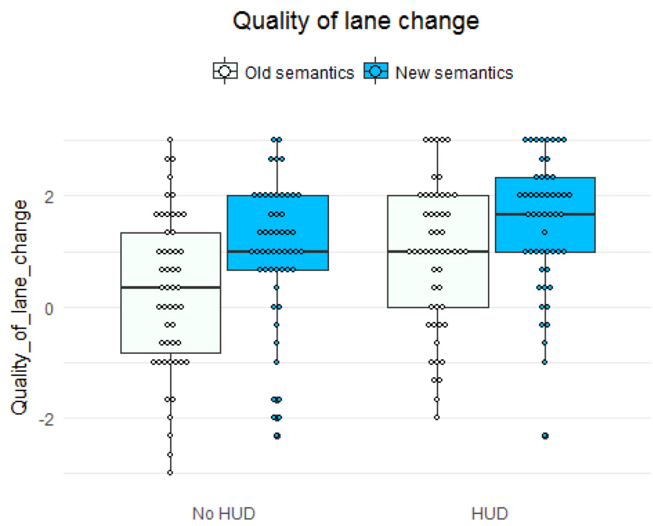


Figure 16. Boxplot that shows the degree to which the lane changes were perceived as being safe, efficient and comfortable.

Most of those first interpretations are supported by the model's estimates that are presented in Table 10. It predicts that the ratings for the quality of lane change are only slightly more positive than neutral, when a regular turn signal and no HUD are used. The effect size is equal to μ_0= .25 and the 95% credible interval spans from -.10 to .61. The large variation in the baseline ratings indicates that the ratings differ strongly from one participant to the next (σ_0 = .32).

Enabling a HUD increases the quality of lane change ratings by μ_{HUD}= .66. With a certainty of 95% this increase lies between .15 and 1.17. Hence, it can be claimed with certainty, that the use of a HUD has a positive effect on the perceived quality of the lane change. The HUD's effect varies slightly between participants (σ_{HUD} = .29).

The introduction of the *enhanced semantics* appears to have a similar effect on the increase of the quality of lane change ratings with an effect size of μ_{Sem}=.70 and a 95% credibility interval that runs from .22 to 1.19. Thus, another conclusion is that the *enhanced semantics* lead to strong increases in the quality of lane change ratings. This effect varies slightly between participants (σ_{Sem} = .27). To sum up, using either a HUD or the *enhanced semantics* both enhances driver experience.

The overall increase is highest when HUD and *enhanced semantics* are used together with an effect size of $\mu_{\mathrm{Sem|HUD}}$ = 1.24 (.66 + .70 - .12). The 95% credibility interval runs from -.44 (.15 + .70 - .12) to 2.91 (1.17 + 1.19 + .55). Apparently, the interval is very broad and includes negative values. Therefore, it can not be concluded on a 95% certainty level that a combination of HUD and *enhanced semantics* increases the perceived quality of lane change. However, the observation that the interval consists mostly of positive values, indicates a trend towards a positive effect of using HUD and *enhanced semantics* together.

Table 10. *The coefficients table of a model that estimates the quality of the lane change.*

	Fixed Effects			Random Effects
	μ	*Lower 2.5%*	*Upper 2.5%*	*σ*
Intercept [No HUD / Old semantics]	.25	-.10	.61	.32
HUD	.66	.15	1.17	.29
Enhanced semantics	.70	.22	1.19	.27
HUD:Enhanced semantics	-.12	-.81	.55	-

3.4 The ranking of the different concepts

The four concepts had to be ranked to identify which concepts have been liked the most. The combination of HUD and *enhanced semantics* was ranked as the best concept (see Fig. 17). With not much of a difference, the modified turn signal that included the *enhanced semantics* was ranked as the second best concept. The HUD with the *old semantics* followed up closely and was ranked third. Finally, the regular turn signal was ranked as the worst of all concepts and received only half as many votes as the concept that combined HUD and the *enhanced semantics*.

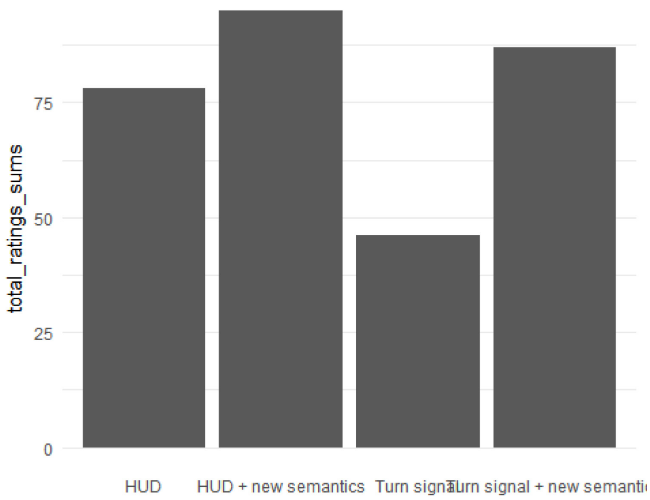


Figure 17. Bar charts that shows the ranking of the four concepts (the higher, the better).

More information on the driving behavior of each participant can be found in the complete data analysis protocol in Appendix G. More specifically, the braking and acceleration patterns are visualized.

Discussion

This section starts off by reviewing the main findings in a broader context and will then proceed by investigating the limitations that might have had an influence on the results. Next, a number of implications for future research will be examined. Finally, this section ends with a conclusion.

4.1 Findings

This study was conducted to learn more about the possibilities to improve lane change maneuvers that involve multiple road users. For doing so, two approaches have been examined. On the one hand, a HUD has been used as a support to a regular turn signal. On the other hand, nowaday's meaning of the turn signal has been revisited and *enhanced semantics* have been proposed and put to the test. Those enhanced semantics allow a distinction between the moment in which a driver is planning a maneuver and the moment in which the maneuver is started. In contrast, today's turn signals appear to be unable to make this distinction. Three research questions have been formulated to assess the impact of those approaches on *cooperation*, *clarity* and the *driver experience*.

4.1.1 Research question one: cooperation

The first research question examined the amount of observed *cooperative behavior* and the perceived degree of cooperation in two ways: Firstly, the number of times in which the participant allowed the other driver to change lanes was observed (objective measurement). Secondly, a questionnaire was filled in to get an estimation of the degree to which the participants regarded the situation as cooperative. Furthermore, the participants were asked to rate their own and the other's behavior in terms of cooperativeness (subjective measurement).

Cooperation. The *observed* numer of lane changes indicated that using a HUD could successfully stimulate cooperative behavior in the participants. In line with this, there were indications that using the *enhanced semantics* – or in other words, distinguishing between planning and starting of a maneuver – stimulated cooperative behavior as well.

When it comes to the *perception* of cooperation, similar observations could be made. Using the *enhanced semantics* drastically increased the impression that the lane change maneuvers were an act of cooperation between the two drivers. Analogously, using a HUD increased the degree to which the lane change maneuvers themselves were perceived as a cooperation between the participant and the other driver.

Cooperativeness. Aside from this, the participants also rated how cooperative their own and the other's behavior was. Interestingly, when the regular turn signal (old semantics) and no HUD were used, the participants rated their own behavior as cooperative and the other's behavior as uncooperative. In other words, the behavior of other drivers seemed to be perceived as being rather uncooperative than cooperative when only nowaday's regular turn signals are used. Hence, there appeared to be a general trend to interpret one's own behavior in lane change maneuvers as more cooperative than the other drivers'. Consequently, the perception of cooperative behavior appears to be distributed unevenly in those situations. This is in line with the well known cognitive bias of illusory superiority, where the own behavior and capabilities are regarded as being superior to others' (Hoorens, 1995).

When it comes to the perception of cooperativeness in their own behavior, using a HUD or introducing the *enhanced semantics*, both lead to a very slight increase. Subsequently, no matter whether or not a HUD or the *enhanced semantics* were used, the ratings for the perceived cooperativeness in the participant's own behavior remained about the same.

The ratings of perceived cooperativeness in the other's behavior were affected in a similar fashion by the concepts. However, the effects were far more pronounced. The participants received the other's behavior as drastically more cooperative when the *enhanced semantics* were used. It might be that the participants felt like the other drivers provided more information about their actions, when the *enhanced semantics* were used. Specifically, the other drivers communicated whether they were only planning to start a maneuver soon or whether they were about to start the maneuver by pulling over to the adjacent lane. Thus, using the *enhanced semantics* created the impression that the other driver acted cooperatively. In fact, the ratings climbed from "the behavior is rather uncooperative than cooperative" to about the same level of cooperativeness the participants had observed in their own behavior. Thus, the *enhanced semantics* facilitated a more balanced perception of cooperativeness between the involved drivers.

Enabling the HUD visualizations also led to higher levels of perceived cooperativeness in the other that were slightly lower than when the *enhanced semantics* were used. A possible explanation for this difference is that the other driver did not provide any extra information about his or her actions. The observed increase could then be explained by the notion that the HUD visualizations might have been interpreted as being produced by the other car or driver. This interpretation is based upon a number of comments in which the HUD visualizations have been described as something that originated in the other car: *"The other driver showed me that he wanted to change lanes by activating those HUD visualizations in my car"* or *"it seemed like the HUD visualizations belonged to the other car and that the other driver has triggered them"*. Thus, the HUD visualizations might have been perceived as something that the other driver intentionally activated, in order to support the participant's understanding of the situation. Interestingly, the regular turn signal shares the same characteristics as it is also controlled by the driver. However, it seems that the turn signal is no longer interpreted as being a cooperative act, which is something that might be explained by habituation and perceiving the action of setting a turn signal as something that is normal. To sum up all of the above, the first research question can be answered by saying that the HUD visualizations and the *enhanced semantics* had a positive effect on cooperative behavior and the perception of cooperation.

4.1.2 Research question two: clarity

The second research question dealt with the *clarity* of the other driver's actions. Thus, in how far the participants could easily tell what the other driver was about to do and when exactly the other driver wanted to initiate the lane change. Hence, the following two entities were measured: clarity of the other driver's timing and clarity of the other driver's intentions.

Clarity of the other driver's timing. The clarity of the other driver's timing was rated as being slightly unclear when a regular turn signal (old semantics) and no HUD were used. This undoubtedly supports the assumption that today's turn signals might be insufficient to clearly communicate the timing of another driver. This interpretation is based on the fact that the baseline ratings for clarity of timing are negative. It is also supported by the high variation in the ratings between the participants. This indicates that road users might have different interpretations of the meaning of a turn signal. In other words, when no HUD and a regular turn signal (old semantics) are used, it is unclear when another driver will execute a maneuver. This comes in support of the observations that have been made in a study by Haar et al. (2017). They suggested that regular turn signals might be interpreted in different ways and thereby insufficient for clearly communicating driver's intentions.

This is where the *enhanced semantics* appeared to provide benefits to the participants when compared to a regular turn signal. The participants reported that they were able to estimate the other driver's timing much better when the *enhanced semantics* were used. A simple explanation for this observation could be that the *enhanced semantics* allowed for more meaning in the communication of intentions. Hence, the information that can be transferred from one driver to the next is richer than the information that can be communicated by the means of regular turn signals.

Besides this, using a HUD also increased the clarity of the other's timing. However, the HUD visualizations did not increase clarity about the exact timing as much as the *enhanced semantics* did. Yet, this is a finding that one would expect, because the HUD visualizations alone did not provide any additional information about the exact timing. Therefore, the question arises why using a HUD received higher ratings for clarity of timing than the regular turn signal. One possible answer would be that the HUD visualizations were better able to capture the participants' attention than a regular turn signal. Hence, the increase in clarity of timing might be explained by a more salient visualization than the one that is provided by a regular turn signal. The ability of HUDs to direct the driver's attention has been described in a study by Liu (2003), where HUD visualizations have been used to help the driver to locate the source of an unforeseen event. Ultimately, both, using a HUD and introducing the *enhanced semantics* were very beneficial in estimating the other driver's timing.

Clarity of the other driver's intentions. The clarity of the other driver's intentions was rated as being neither high nor low when a regular turn signal (old semantics) and no HUD were used. Once the HUD visualizations were enabled, the clarity of the other driver's intentions during the lane change maneuver increased strongly. Thus, it was easier for the participants to understand the other driver's behavior. This might be explained by the findings of the aforementioned study by Liu (2003) which claim that using a HUD can benefit a driver's awareness of a situation and slightly reduce the required amount of attention that has to be paid. Similarly, Tönnis and Klinker (2006) found that the use of a contact-analogue HUD can help in directing a driver's intention. Thus, the improvement of clarity in the lane change situation might be explained by an improved awareness of the whole situation. Another explanation is that a HUD can put emphasis on a visual cue (e.g. a turn signal) that might be missed more easily (Damböck, Weißgerber, Kienle & Bengler, 2012). Hence, the

HUD might have aided in the perception of the other driver's intentions by visually emphasizing the turn signal's communication channel.

Whereas the effect of the HUD was already strong, applying the *enhanced semantics* provided the driver with even more clarity about the other driver's intentions. This might easily be explained with the same reasoning that also applied to the increase in clarity of timing. The *enhanced semantics* were designed to carry more meaning than the old semantics. More specifically, they were designed to distinguish between planning and starting a maneuver. Therefore, it does not come as a surprise that they are better able to communicate the other driver's plans and actions. Consequently, those high ratings for *clarity of the other driver's intentions* can be regarded as evidence for the notion that the *enhanced semantics* are indeed able to fulfill the desired effect. After all, the *enhanced semantics* and the HUD visualizations have both demonstrated the ability to increase clarity of the other driver's timing and clarity of the other driver's intentions.

4.1.3 Research question three: driver experience

The third research question considered the effects of HUD and the *enhanced semantics* on *driver experience*. In other words, the degree to which a lane change was perceived as being a pleasant experience that felt safe, comfortable and efficient.

When a regular turn signal and no HUD were used, the ratings for the perceived amount of safety, comfort and efficiency were slightly positive. Once the HUD visualizations were enabled, those ratings increased moderately, which indicates that the overall driver experience improved by HUD usage. This might be explained by the aforementioned positive effect of HUD usage on the clarity during a lane change. Aside from this, the findings suggested that using a HUD leads to the perception that the other driver is behaving more cooperatively. This in turn, is likely to produce more positive feelings than the perception that the other driver is behaving uncooperatively (as with the regular turn signal). The importance of a pleasant driving experience has been emphasized by the findings of Gkouskos, Normark and Lundgren (2014) who suggested that comfort and convenience are central user needs of road users.

Moreover, when the *enhanced semantics* were implemented, the lane changes became a more pleasant experience for the participants. The data suggests that the lane changes felt safer, more efficient and more comfortable when a distinction between planning and starting a maneuver has been made. This might be explained by the observation that using the *enhanced* *semantics* helps to get a better idea of the other driver's timing and intentions. Furthermore, the findings suggested that the *enhanced semantics* have the ability to facilitate the impression that the other driver is indeed behaving cooperatively. Therefore, it is not surprising that the *enhanced semantics* had a positive influence on driver experience. To sum up, HUD usage and the revisited semantics were able to increase the degree to which the lane changes were perceived as comfortable, safe and efficient. Those findings support Benmimoun et al.'s (2004) supposition that driver assistance systems have great potential for the improvement of collaborative maneuvers in traffic.

4.1.4 Other findings

In general, the majority of participants was very positive about the ideas underlying those concepts *("When I am on a familytrip, I am often driving large distances for longer time periods. In those situations I would really like to have a driver assistance system like this" or "I have often encountered those ambivalent situations and I am happy that there is research being done to eventually make them better"*).

Besides those findings that have been reported, similar positive effects of using a HUD or applying the *enhanced semantics* were found for all other measurements that have been carried out. For instance, using a HUD and introducing the *enhanced semantics* have been rated as being more useful and leading to more satisfaction than today's turn signals (see data analysis protocol in Appendix G).

4.2 Limitations

There are a couple of limitations with regard to the study's design that will be outlined below. Firstly, the participants have received an introduction into the meaning of the *enhanced semantics* prior to the first trial. Providing this introduction was required, because the results of the study by Haar et al. (in preparation) indicated that the participants might have failed to understand the meaning of the *enhanced semantics* when no explanation was provided. However, doing so might have had an influence on the results because the participants might have felt obligated to rate the presented concepts in a socially desirable way or their ratings might have been affected subconsciously to fit the participant's interpretation of what the experiment's purpose might be (Fisher & Katz, 2000; Orne, 2009). To minimize this effect, the introduction was phrased in an objective way in order to avoid any form of judgment in the choice of words and had the main goal of explaining the logic behind the *enhanced semantics* (see Appendix B: Introduction into the *enhanced semantics*). It is expected that objective measurements are more resistant against the influence of socially desirable behavior and demand characteristics than subjective measurements. Therefore, an influence of those biases would have led to deviations between the objective and the subjective measurements. However, the data showed that using the concepts did not only increase the subjective measurements but also the objective measurements. This suggests that the influence of providing the introduction in the beginning did not skew the results.

Secondly, a few participants commented that the trials became monotonous after a while. One might expect that this could have changed the participants' behavior within a trial in a way that they might have reacted differently to the first, second or third encounter within a trial. However, the figure in Appendix C (Order effect within the conditions) shows that there is no effect of the encounter. This indicates that the perceived repetitiveness did not allow the participants to predict and thereby adapt their behavior.

Thirdly, the sample consisted only of employees of the Volkswagen AG. One might argue that employees of the Volkswagen AG are open for innovations, which might in turn lead to more positive ratings. An internal comparison study has shown that the results of a study that was carried out with Volkswagen employees (internal participants) and external participants from the Spiegel institute indicated that there were no remarkable discrepancies between the ratings of the two groups. Furthermore, the participant pool performs a double pre-selection with a set of criteria and flexible assignment to groups when selecting participants for a sample (Sauro & Lewis, 2016). Therefore, the samples from the Volkswagen Participant Pool are considered to be representative.

Fourthly, the study was conducted in a simulator and not in a real car. This might have led to a less realistic experience than a study in a real car could provide. As Haar et al.' (2016) model describes collaborative maneuvers as complex situations that involve reciprocal processes and require multiple drivers to interact with each other. Therefore, the behavior of the computer-controlled driver has an impact on the way that the participant behaves. Subsequently, unrealistic behavior of the computer-controlled behavior might lead to behavior that is not representative of how the participant would usually react to a situation. For instance, it occurred that the computer-controlled drivers did not change lanes, when the gap that the participant opened was not big enough. Even though, this was something that some of the participants commented on after the experiment, some of them also reported that they had experienced similar behavior with real drivers.

Fifthly, the simulator did not have a real HUD installed. Instead, the HUD has been simulated by using a second beamer that projected the HUD visualizations ontop of the simulation (a projection ontop of a projection). Hence, the HUD visualizations were presented on the same distance layer and canvas as the simulation itself. Therefore, the HUD visualizations were displayed by using the same technology that was also used for showing the other cars' turn signals (projected onto the canvas). In a real car, the HUD would be more distinct from another car's turn signal, because it would be on a completely new layer; distance and technology-wise. Thus, it might be that the HUD visualizations would be more salient in a real car, because something *digital* would be projected onto the real world. In contrast, in the simulator, a digital HUD is projected onto a digital world. Therefore, the effects of using a HUD might be even more pronounced in a study with a real car.

Sixthly, the author of this paper put the focus on lane change maneuvers. Even though it is likely that the same effects would also apply to entering a highway, this remains to be checked. Thus, for now the findings are limited to collaborative lane changes.

Lastly, the analysis and results of the measurements that have not been presented in detail can be found in the data analysis protocol in Appendix G. This has been done to ensure that there was neither a selective reporting of desirable results, nor an omission of less desirable results. This holistic style of reporting each step and the full output of the analysis were provided in order to facilitate reproducible research and with the concerns of Gelman and Loken (2013) in mind.

4.3 Implications for future research

The findings of this study present a good starting point for further research. A number of interesting implications is outlined below.

It has been shown that the *enhanced semantics* and using a HUD can enhance lane change situations. Consequently, the question arises whether or not this also applies to other situations that require collaboration. Thus, one could investigate how the *enhanced semantics* or a HUD could be used in city situations or when entering a highway. Furthermore, it could then be examined if the logic of *planning* and *starting a maneuver* is also applicable in those situations or if a modification would be needed. This would help to understand whether the *enhanced semantics* present an opportunity to improve the communication between road users in a more general sense and not only in this specific maneuver.

Moreover, a real car study could be conducted to deal with the limitations of simulator studies have been investigated above. Furthermore, this would give an indication of whether or not the methodology of simulating a HUD yields similar results to the ones that are obtained when using a real HUD in a real car.

Aside from this, it would be interesting to get an idea of how long people would need to effectively relearn the semantics of a turn signal and would thereby give a better indication of how realistic an introduction of this change in semantics would be.

A couple of other questions are related to how all of this might look from the other driver's perspective. Would it be better if the driver of a car can manually trigger the planning/starting levels of the turn signal or should the sensors of a car detect the level that the driver is in? For instance, driver observation and machine learning could be used to interpret a driver's behavior in order to detect when a driver is about to start a maneuver. Alternatively, the vehicle's movement could be analyzed to predict when a driver is about to change lanes; to mention only a few possibilities. A similar implementation of a trajectory prediction technique has been presented by Google on the SXWS conference (SXWS, 2016).

The findings of this study confirm Haar et al.'s (2017) assumption that regular turn signals might have some room for improvement. Therefore, it would be of interest to put the turn signal's ability of communicating driver's intentions to the test. This could be done for a range of other scenarios in which the turn signal is used as communication channel (e.g. entering a highway or intersections with equal right of way).

Whereas this study showed that clarity, cooperation and driver experience could be improved by modifying turn signals or using a HUD, it would be interesting to see if cooperative maneuvers could be improved in even more ways. For instance, a closer look could be taken at the interaction between drivers too see how the communication between the drivers and the exectution of the maneuver could be enhanced (e.g. by using V2V communication). In many cases, it would be beneficial if information that is available in one car would be available in another car that is driving nearby. Think of a situation in which the sensors of a car detect the beginning of a traffic jam. The car could then send that information to cars that are following. This would allow them to brake early and might in turn save another driver from crashing into to the beginning of an unexpected traffic jam (Yang, Liu, Vaidya & Zhao, 2004). Furthermore, Van Arem, Van Driel & Visser (2006) demonstrated that V2V can have a positive effect on the traffic-flow by using cooperative adaptive cruise control. In the same fashion, V2V could be used for communicating drivers' intentions from one car to the next. There has been little research about two-way communication via V2V, but a paper by Ammoun, Nashashibi and Laurgeau (2007) proposed the development of a system that would allow cooperation between drivers during lane changes. However, the paper only explored the possibilities and identified the important factors during lane changes and the features that such a system should have. Their analysis is a glimpse at the possibilities that

V2V offers to enhance the communication between drivers. Still, most experimental studies on V2V lay their focus on the optimization of traffic-flow and the prevention of accidents. Thus, the research field of using V2V for communication and cooperation between drivers remains a field that is widely unexplored. Consequently, it would be interesting to see how the enhanced semantics could be used in conjunction with V2V communication to improve the cooperation between drivers.

The aforementioned model of Haar et al. (2016) explains the processes that are involved in cooperative maneuvers. In this study, the main focus was on the perception of cooperation, which is only one of the phases of a collaborative maneuver. In future research, the model could be used to systematically examine the other to investigate and possibly improve all aspects of cooperative maneuvers, such as the offering or request of a collaborative maneuver and its execution.

Not only in the present, but also in future contexts, it is important that the communication between drivers works efficiently. On the way to automated traffic, a transition phase of mixed traffic that consists of manually and autonomously driving cars will be inevitable. In that phase, it is of immense importance that other drivers know what autonomous cars are about to do. Eventually, this is exactly what the aim of this research project was: Finding a way to clearly communicate the upcoming maneuvers and movements of a car; no matter whether it is driving manually or autonomously. Still, further research could be conducted on the possible uses of the *enhanced semantics* in an environment with mixed or fully autonomous traffic. The application of those *enhanced semantics* would not be limited to manual driving but could also be used in autonomous driving. For instance, autonomous cars could use the *enhanced semantics* to allow other road users to better predict the upcoming maneuvers of an autonomously driving car (external communication).

In the same fashion, head-up display visualizations could be used for internal communication to increase the comfort and driver experience of passengers who are seated in an autonomous car of the future to create more transparency about the upcoming maneuvers of a car. For instance, the car could tell its passengers that it is planning to execute a maneuver and then also tell them when it is starting that maneuver that it had previously planned. This creates an interesting field of research and room for future investigations.

4.4 Conclusion

It has been shown that collaborative lane change maneuvers can be enhanced in two ways: by using a head-up display and by revisiting and rephrasing the meaning of regular turn signals. Both approaches have proven to be beneficial in increasing the amount of cooperative behavior and helped participants to tell when exactly another driver wanted to initiate a lane change and what another driver was planning to do. At the same time, the lane change situations were perceived as a safer, more efficient and a more comfortable experience. Moreover, a remarkable finding was that other road users were generally perceived as being uncooperative when a regular turn signal was used and that the use of the *enhanced semantics* created the impression that other road users were behaving cooperatively.

After all, those findings indicate that the regular turn signal as we know it today might be a relict of the past. Their capability of communicating intentions clearly and unambiguously should be questioned and supporting technologies and revised semantics should be investiaged. In the end, the findings of this study emphasize the importance of questioning well-established standards and demonstrate the ability of new technologies to enhance the way in which road users interact with each other.

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APPENDIX

APPENDIX A: *Augmented Reality Head-up Displays: Advantages and Disadvantages*

A lot of literature is written about the advantages and disadvantages of using HUDs in an automotive context. Firstly, when a HUD is used, the information is displayed at a distance and therefore the driver's eyes do not have to reaccommodate as often when switching between reading the displayed information and looking at the road (Ward & Parkes, 1994). Secondly, the use of HUDs reduces the amount of time that drivers spend taking their eyes off the road. Apparently, 90% of the driving task relies on visual information. Consequently, taking the eyes off the road dramatically affects the driver's performance and therefore increases the probability for an accident (Cohen & Hirsig, 1990; Fadden, Ververs & Wickens, 1998). Thirdly, the contact-analogue presentation of information can help in reducing divided attention. For instance, navigation information about the next turn could be positioned exactly at the beginning of the street in which the driver has to go. As a result, the driver can focus on the primary task of driving instead of searching for the information on a separate screen and then having to logically transfer and map that information into the real world (Gabbard, Fitch & Kim, 2014). In line with this, Kipper and Rampolla (2012) suggest that using AR can "enhance the user's perception of the surrounding environment" and thereby "assist in the decision-making process and actions".

Whereas the use of HUDs promises plenty of benefits, it also comes with a couple of drawbacks. Firstly, drivers might get distracted from the actual road situation by the information that is presented on the HUD and thereby miss information that is of importance for the driving task (Kipper & Rampolla, 2012). Secondly, there are still some challenges in tracking and recognizing objects in the real world. Thus, the computers that analyze the camera input might sometimes not be able to correctly distinguish objects from the background. This might lead to innacurate positioning of the augmented information; it is not known how much inaccuracy drivers can tolerate before the information becomes useless to the driver (Rabbi & Ullah, 2013). Thirdly, displaying additional graphics or information in the driver's field of view creates an additional source of distractions. This can affect the driver's safety as distractions of the driver in general are sought to be responsible for at least 8,3% of all road accidents (National Highway Traffic Safety Administration, 2014; Stutts, Reinfurt, Staplin & Rodgman, 2001; Young & Regan, 2007). Fourthly, due to the fact that the information is displayed on top of the real world, it can potentially cover objects or parts of the scenery which might make them practically invisible to the driver. This can happen if too much information is displayed at once or if the graphics take up too much screen estate. Consequently, the driver might miss an important aspect of the real world situation which might lead to accidents or stressful situations. Doyon-Poulin, Robert and Ouellette (2012) did research on the effects of occlusion in HUDs and came up with guidelines that can be used to minimize occlusion when designing visualizations for HUDs.

There is a large number of studies that have explored ways in which AR HUDs could be used in the automotive context. Firstly, HUDs have been used to increase visibility during poor visibility conditions. A study has been conducted in which a line was drawn above the street. Drivers could then simply follow that line to guide them to their destination even when they were not able to see the street due to fog or snow (Visual CableTM, 2009). In another study, the HUD highlighted the lane markings and outlines of other cars and successfully helped drivers to navigate through low visibility scenarios (Charissis & Papanastasiou, 2010). Secondly, AR HUDs have been used to facilitate the navigation task. One example is a study by Kim & Dey (2009) that demonstrated that elderly drivers make less navigation errors when supported by a HUD that displayed a transparent map on top of the real street. Thirdly, AR HUDs have been used in active safety systems. Kim, Wu, Gabbard & Polys (2013) conducted an experiment and found that an AR HUD crash warning system that superimposes information directly onto the street might promote safety and yield higher driver acceptance than crash warning systems that were displayed on regular displays. In another study, an AR HUD has been used to display a “braking bar” in front of the driver’s car and successfully helped the driver in estimating the time that it took to stop the car (Tönnis, Lange & Klinker, 2007).

APPENDIX B: Introduction into the enhanced semantics (German)

Beim Autofahren können Situationen auftreten, in welchen nicht ganz deutlich ist was die Absichten eines anderen Fahrers sind. Ein Beispiel dafür ist die Situation, die sie gleich in einem Video sehen werden. In dem Video fahren Sie auf der linken Spur einer Autobahn und sind mit einer hohen Geschwindigkeit unterwegs. Es erscheint ein langsameres Auto auf der rechten Spur und setzt den Blinker nach links. Sie müssen nun entscheiden wie Sie sich verhalten. Sie können weiter beschleunigen, um schnell an dem anderen Auto vorbeizufahren oder abbremsen, um das andere Auto vor Ihnen auf die Spur wechseln zu lassen. In dieser Situation kann es unter Umständen unklar sein was der andere Fahrer mit dem Setzen des Blinkers ausdrücken möchte. Es scheint als würden einige Fahrer den Blinker nutzen, um mitzuteilen, dass sie *planen* in Kürze einen Spurwechsel durchzuführen, während andere ihn scheinbar dafür nutzen, anderen Fahrern mitzuteilen, dass sie nun den *Spurwechsel beginnen*. In Folge dessen kann es unklar sein, auf welche Art und Weise der Fahrer in dieser Situation den Blinker benutzt. Hierdurch sind Ihnen die Intentionen des anderen Fahrers ggf. nicht komplett deutlich, aber dennoch müssen Sie eine Entscheidung treffen wie Sie sich verhalten.

Nun folgt ein kurzes Video, welches die beschriebene Situation näherbringen soll.

In dieser Studie werden verschiedene Technologien in der zuvor beschriebenen Situation angewandt. Dabei wird der Mehrwert neuer technologischer Systeme überprüft. Eines dieser Systeme schlägt vor den Blinkvorgang in zwei Stufen zu unterteilen. Dabei haben die zwei Stufen die folgende Bedeutung:

Stufe 1: Der Fahrer ***plant*** *die Spur zu wechseln*
Stufe 2: Der Fahrer ***beginnt*** *den Spurwechsel*

Das heißt, dass bei einem Blinkvorgang erst Stufe 1 (Planen) und dann Stufe 2 (Beginn des Spurwechsels) nach außen kommuniziert wird. Zusätzlich hierzu werden auch noch andere Konzepte vorgestellt. Bei dieser Studie geht es nicht um die technische Machbarkeit, sondern darum die Grundprinzipien hinter diesen Konzepten und die Visualisierungen zu überprüfen.

Wenn Sie irgendwelche Fragen haben sollten, wird Ihnen der Versuchsleiter diese sehr gerne beantworten.

APPENDIX C: Order effect within the conditions

If there was an order effect, then the number of lane changes might decrease or increase from the first to the last encounters with the partner car. The plot in Figure A.1 is meant to give a better idea of whether or not there is a learning effect that results from the repeated confrontation with the lane changes. There is no indication that the probability that a participant let another car in was affected by the moment in which the participant encountered the car (encounter 1, 2, or 3). The effect size is situated around zero μ_4= .01 and the 95% CI runs from -.03 to .05. The effect of Encounter varies by .06 between participants.

Consequently, it seems like the chance that a participant let the other car in was not affected by whether it was the first, second or third encounter within a trial.

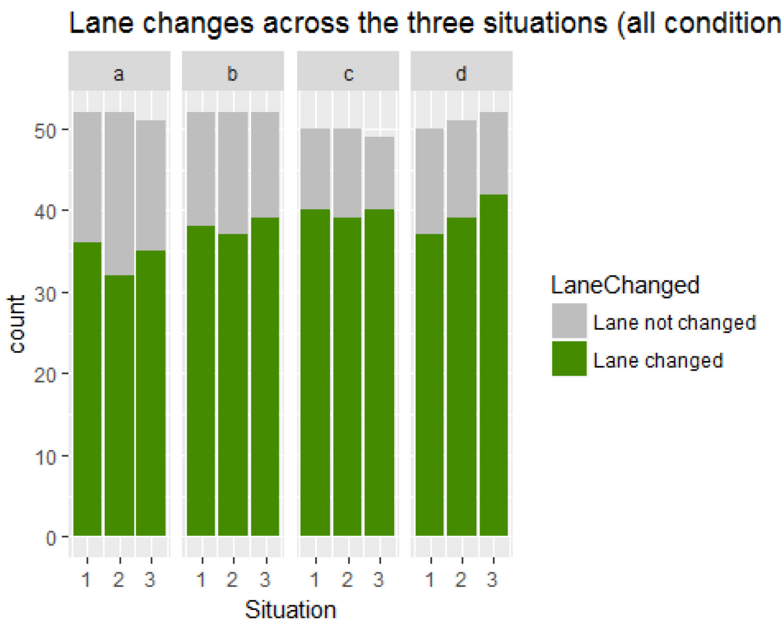


Figure A.1. The number of lane changes across the three situations.

Table A.1. *The coefficients table predicts how often the participants allowed a lane change. In addition to the other models, Encounter is added as a fixed effect and random slope.*

	Fixed Effects			Random Effects
	μ	*Lower 2.5%*	*Upper 2.5%*	*σ*
Intercept [No HUD / Old semantics]	.64	.54	.75	.16
HUD	.14	.04	.23	.08
Enhanced semantics	.07	-.02	.15	.06
HUD:Enhanced semantics	-.09	-.21	.03	-
Encounter	.01	-.03	.05	.06

APPENDIX D: Questionnaire that measures the perception of the lane change situation

Table D.1

The items that measure the perception of the lane change situation in its original German wording

Item
Wie komfortabel haben Sie die Spurwechselsituation wahrgenommen?
Wie sicher haben Sie sich während der Spurwechselsituation gefühlt?
Wie reibungslos haben sich die Spurwechselsituationen angefühlt?
Wie eindeutig war Ihnen die Spurwechsel Intention des anderen Fahrzeugs?
Wie eindeutig war der genaue Zeitpunkt des Spurwechsels?
Würden Sie die erlebten Spurwechsel-Situationen als Kooperation beschreiben?
Wie würden Sie die erlebten Spurwechsel Szenarien beschreiben? Frustrierend – zufriedenstellend Hektisch – entspannt Unkooperativ – kooperativ Unvertrauensvoll – vertrauensvoll
Wie würden Sie ihre eigene Rolle in den erlebten Situationen beschreiben? Störend – hilfsbereit Verzögernd – zeitsparend Hinderlich – unterstützend
Wie würden Sie den Partner, also das einfädelnde Fahrzeug, in den erlebten Situationen beschreiben? Störend – hilfsbereit Verzögernd – zeitsparend Hinderlich – unterstützend
Wie … war die Situation für Sie?

Hinderlich – förderlich

Unangenehm – angenehm

APPENDIX E: Internal Consistency and Correlations between the Questionnaires

The items that belong to the three questionnaires “quality of lane change”, “feeling during lane change” and “feeling during whole situation” appear to measure similar constructs. The degree of correlation between the three questionnaires is visualized in Fig. 10. In fact, the three questionnaires show strong correlations and therefore it is very likely that they have measured the same construct. This is not surprising as “feeling during lane change” and “feeling during whole situation” purport to measure almos the same thing.

Aside from the correlations, the internal consistency of the questionnaires is calculated to check whether the questionnaires are consistent in what they are measuring. Hence, Cronbachs alpha is calculated for each questionnaire to check for internal consistency. The questionnaires have the following values for cronbach's alpha: quality of lane change (α = .93), feeling during lane changes (α = .91), DALI (α = .93), the degree to which the participant rates his/her own behavior as cooperative (α = .66), the degree tho which the participant rates the partner's behavior as cooperative(α = .89), van der Laan - Usefulness (α = .78), van der Laan - Satisfaction (α = .86). Almost all of the questionnaires have good internal consistency. The only exception is the questionnaire that measures in how far the participant rates his/her own behavior as cooperative. According to (QUE) values for cronbachs alpha that lie around .65 are still acceptable, however higher values are preferred.

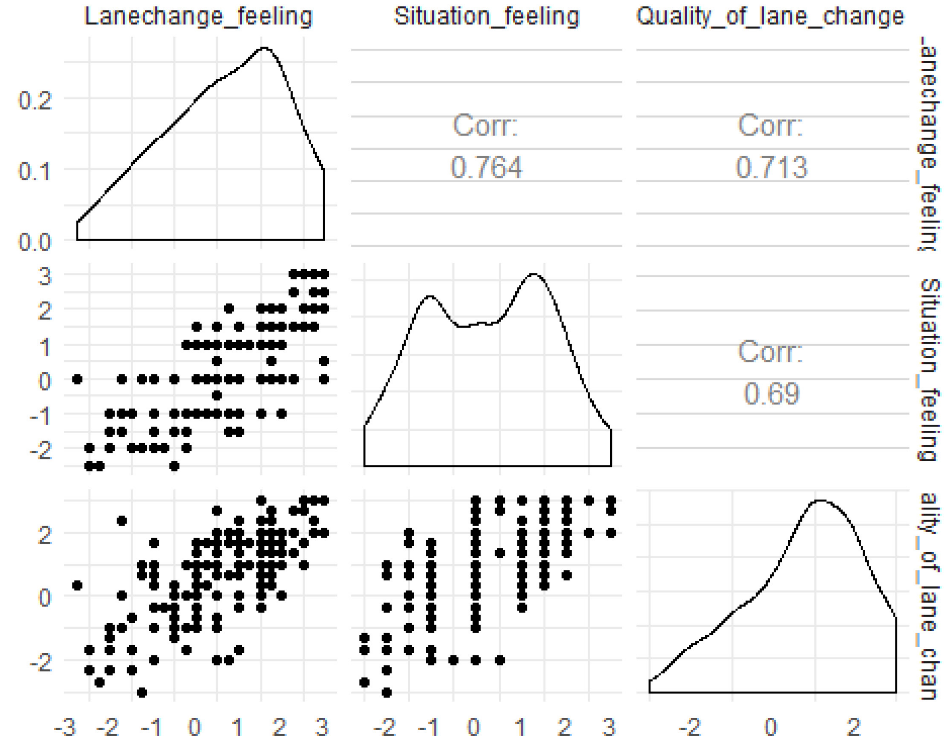


Figure E.1. The correlations between the three questionnaires that are suspected of measuring similar constructs.

APPENDIX F: ADDITIONAL ANALYSIS

F.1 Feelings during the Lane Changes

Figure F.1 reflects how the participants felt during the lane changes when the different concepts were used. Using a regular turn signal appears to lead to neutral feelings and a combination of HUD and *enhanced semantics* leads to the strongest increase in positive feelings during the lane changes. Apparently, using the *enhanced semantics* alone seems to increase positive feelings in a more pronounced way than using a HUD alone appears to do. The estimates of the model transport almost the same message. The participants rated the feeling during the lane changes as slightly more positive than neutral with an average of .23 when neither a HUD nor the *enhanced semantics* were used, 95% CI [-.11, .58] (see Table 10). Moreover, it suggests that the use of a HUD and the *enhanced semantics* drastically improve the way that participants feel during lane changes with effect sizes of ß = .58 and ß = .74, 95% CI [.13, 1.06] and 95% CI [.27, 1.21] respectively. A very high degree of uncertainty prevents the conclusion that a combination of HUD and *enhanced semantics* leads to even higher ratings (ß = 1.19 = .58+.74-.09, 95% CI [-.35, 2.82]). The high random intercept suggests that the ratings for the feeling during lane change vary strongly between participants (σ_b = .46).

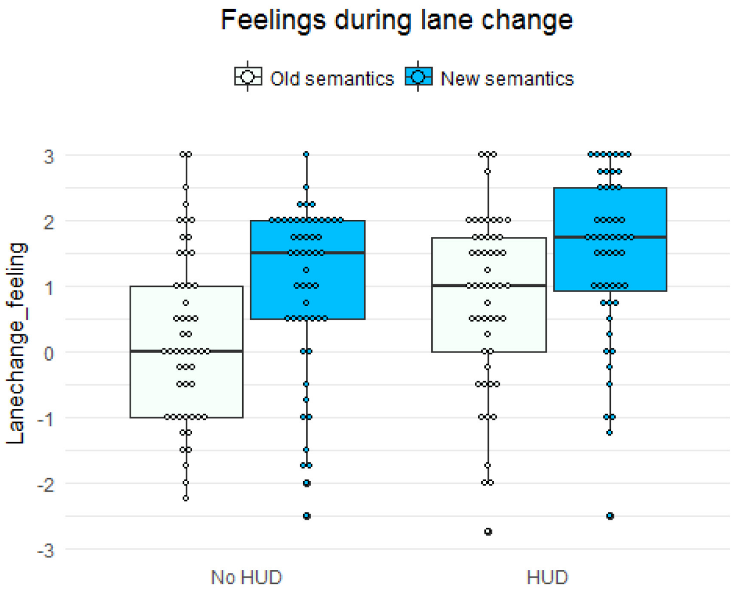


Figure F.1. Boxplot that shows how the participants felt during the lane change.

Table F.1. *The coefficients table of a model that predicts feeling during lane change.*

	Fixed Effects			Random Effects
	M	*Lower 2.5%*	*Upper 2.5%*	*SD*
Intercept [No HUD / Old semantics]	.23	-.11	.58	.46
HUD	.58	.13	1.06	.39
Enhanced semantics	.74	.27	1.21	.39
HUD:Enhanced semantics	-.09	-.75	.55	-

F.2 Workload

Figure 23 leaves not much room for interpretation and suggests that there is almost no difference in workload between the different concepts and the regular turn signal. Even though the differences are small, regular turn signals seem to come with the highest workload and the combination of HUD and *enhanced semantics* appears to yield the lowest workload ratings. Those interpretations can only slightly be supported by the model's estimates. Table 11 holds the estimates for workload during the driving activity. It suggests that the average rating was 37.1 when the regular turn signal was used, 95% CI [31.4, 43.5]. Using a HUD seems to lower the load on the participants during driving slighlty by -3 points on a scale of

100, 95% CI [-5.7, -.3]. In contrast, the *enhanced semantics* seem to have virtually no impact on the workload during driving with ß = -1.5, 95% CI [-4.3, 1.2]. The broad uncertainty interval that is situated around zero does not allow to draw any conclusions about an effect of using both, a HUD and the *enhanced semantics* (ß = -3.0 = -3-1.5+1.5, 95% CI [-12, 5.7]). Even though the standard deviation of the random slopes for HUD and *enhanced semantics* are large when compared to the mean of the fixed effects, the values are still so small that they can be neglected (σ_b = 4.2, σ_b = 4.2).

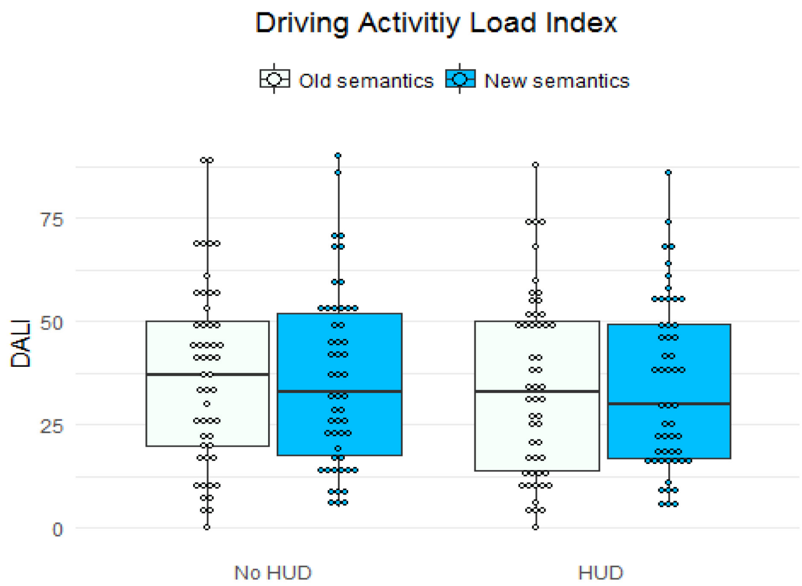


Figure F.2. Boxplot that gives an impression of the workload that the participants experienced.

Table F.2. *The coefficients table of a model that predicts Driving Activity Load Index.*

	Fixed Effects			Random Effects
	M	*Lower 2.5%*	*Upper 2.5%*	*SD*
Intercept [No HUD / Old semantics]	37.1	31.4	43.5	21.1
HUD	-3.0	-5.7	-.3	4.2
Enhanced semantics	-1.5	-4.3	1.2	4.2
HUD:Enhanced semantics	1.5	-2.0	4.8	-

F.3 Usefulness and Satisfaction

This section examines how useful and satisfying the participants rated the different concepts. Those ratings are based on the popular van der Laan scale (Van der Laan, Heino & De Waard, 1997)

F.3.1 Usefulness of using the HUD or the enhanced semantics

As illustrated by the boxplot in Figure 24, the regular turn signal receives the lowest usefulness ratings that appear to revolve somewhere around zero. In contrast, the other concepts seem to receive much higher ratings that seem to be quite similar. Those observations are reflected by the GLMM's output. The regular turn signal is rated as slightly useful with an effect size of ß = .21, 95% CI [.02, .39] (see Table 12). Introducing the *enhanced semantics* increases usefulness by .4, 95% CI [.14, .67]. At the same time, using a HUD increases the usefulness ratings by .25. With a certainty of 95% it can be said that this values lies between -.03 and .52. Hence, it is not absolutely certain that using a HUD really increases usefulness. This is underlined by the large standard deviation of the random slope of HUD (σ_b = .26). Using a HUD and the *enhanced semantics* at the same time seems to increase usefulness by ß = .54 = .25+.4-.11. However, the 95% credible interval is very broad and includes negative numbers. Therefore, it can not be said with certainty that using a HUD and the *enhanced semantics* together will increase usefulness, 95% CI [-.36, 1.46].

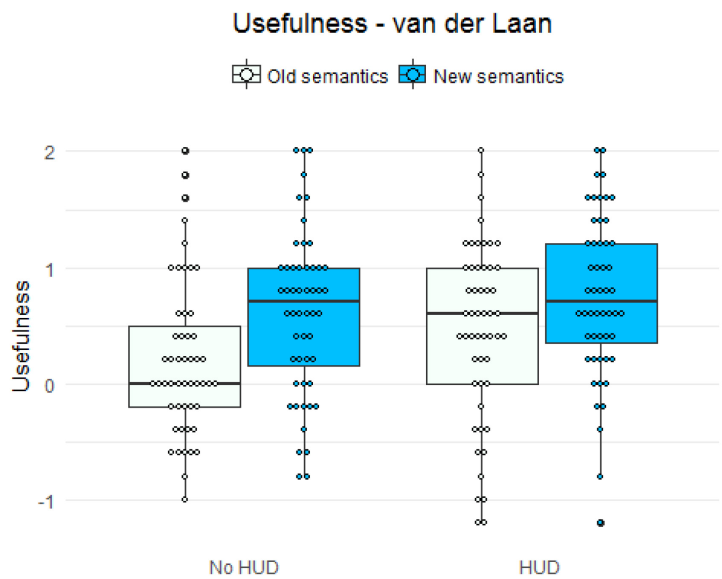


Figure F.3. Boxplot that depicts the usefulness ratings of the van der Laan scale that the concepts received.

Table F.3. *The coefficients table of a model that predicts the Usefulness dimension of the van der Laan scale.*

	Fixed Effects			Random Effects
	M	*Lower 2.5%*	*Upper 2.5%*	*SD*
Intercept [No HUD / Old semantics]	.21	.02	.39	.15
HUD	.25	-.03	.52	.26
Enhanced semantics	.40	.14	.67	.23
HUD:Enhanced semantics	-.11	-.47	.27	-

F.3.2 Satisfaction of using the HUD or the enhanced semantics

According to the boxplot in Figure 25, the regular turn signal is rated as being the least satisfactory to the participants. Using the *enhanced semantics* alone or a combination of the latter with a HUD, yields the highest satisfaction ratings. Those are closely followed by the ratings for using a HUD alone. Those assumptions are in line with the model's predictions that can be found in Table 13. Using the regular turn signal yields an average satisfaction score of ß = .19 with a 95% credible interval that runs from -.01 to .39 (see Table 13). Thus, using the regular turn signal appears to elicit neither feelings of satisfaction nor of dissatisfaction. On the one hand, the effect of using a HUD seems to revolve somewhere around zero with an effect size of ß = .14, 95% CI [-.14, .42]. Moreover, the standard deviation of the random effect of HUD is very high in comparison to the HUD's effect size (σ_b = .32 and ß = .14). On the other hand, using the *enhanced semantics* leads to an increase of ß = .40, 95% CI [.12, .67]. Consequently, it appears that using a HUD has no effect but applying the *enhanced semantics* will yield higher usefulness scores. Lastly, a broad 95% CI makes it impossible to make certain statements about the effects of using HUD and *enhanced semantics* in combination (ß = .51 = .14+.40-.05, 95% CI [-.45, 1.42]).

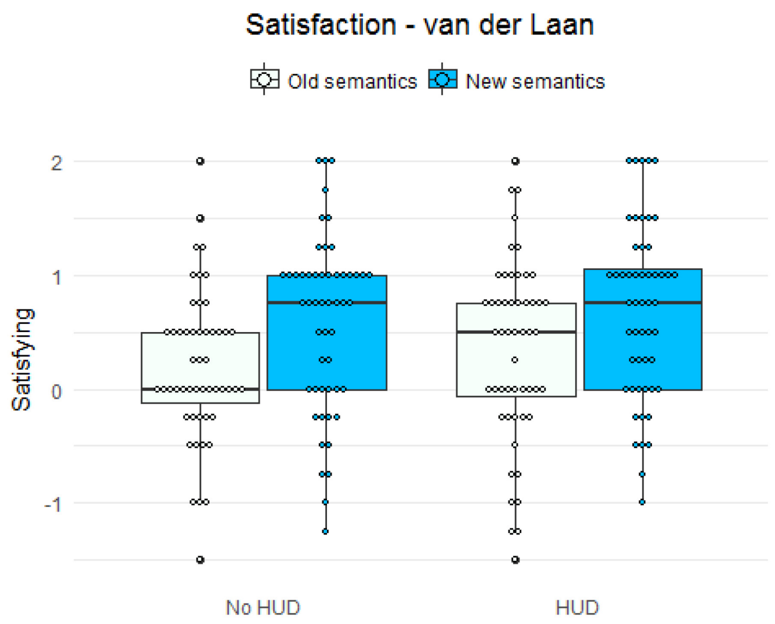


Figure F.4. Boxplot that depicts the satisfaction ratings of the van der Laan scale that the concepts received.

Table F.4. *The coefficients table of a model that predicts the Satisfaction dimension of the van der Laan scale*

	Fixed Effects			Random Effects
	M	*Lower 2.5%*	*Upper 2.5%*	*SD*
Intercept [No HUD / Old semantics]	.19	-.01	.39	.13
HUD	.14	-.14	.42	.32
Enhanced semantics	.40	.12	.67	.26
HUD:Enhanced semantics	-.05	-.43	.33	-

APPENDIX G: Data analysis protocol

Analysis of the subjective data

This document holds the data preparation and analysis of the questionnaire data (subjective).

Data preparation

Load the relevant libraries

```
.libPaths("C:/Users/VW8F1X8/R Space/Libraries")
library(rstanarm)

## Loading required package: Rcpp

## rstanarm (Version 2.15.3, packaged: 2017-04-29 06:18:44 UTC)

## - Do not expect the default priors to remain the same in future rstanar
m versions.

## Thus, R scripts should specify priors explicitly, even if they are just
 the defaults.

## - For execution on a local, multicore CPU with excess RAM we recommend
calling

## options(mc.cores = parallel::detectCores())

library(knitr)

library(tidyverse)

## Loading tidyverse: ggplot2
## Loading tidyverse: tibble
## Loading tidyverse: tidyr
## Loading tidyverse: readr
## Loading tidyverse: purrr
## Loading tidyverse: dplyr

## Conflicts with tidy packages -------------------------------------------
----

## filter(): dplyr, stats
## lag():    dplyr, stats

library(brms)

## Loading 'brms' package (version 1.9.0). Useful instructions
## can be found by typing help('brms'). A more detailed introduction
## to the package is available through vignette('brms_overview').
## Plotting theme set to bayesplot::theme_default().

##
## Attaching package: 'brms'

## The following objects are masked from 'package:rstanarm':
##
##     exponential, kfold, lasso, ngrps
```

```
library(bayr)

##
## Attaching package: 'bayr'

## The following objects are masked from 'package:brms':
##
##     fixef, ranef

## The following objects are masked from 'package:rstanarm':
##
##     fixef, ranef

## The following objects are masked from 'package:stats':
##
##     coef, predict

library(GGally)

##
## Attaching package: 'GGally'

## The following object is masked from 'package:dplyr':
##
##     nasa

#library(stargazer)
```

enable multi core usage

```
# options (mc.cores=parallel::detectCores ()) # Run on multiple cores
```

Import the raw questionnaire data

```
questionnaireData_raw <- as.data.frame(read_csv2("/Users/VW8F1X8/Desktop/S
tudie 3/Datenfreude/DATEN/Fragebogendaten/preparation/questionnaireData_pr
epared_v1.csv"))

## Using ',' as decimal and '.' as grouping mark. Use read_delim() for mor
e control.

## Parsed with column specification:
## cols(
##   .default = col_character(),
##   Subject = col_integer(),
##   `Im folgenden Abschnitt bewerten Sie bitte Ihre mentale Beanspruchung
 im zuvor erlebten Szenario auf den angegebenen Skalen.   Dazu ver<e4>nder
n Sie bitte den angezeigten Schieberegler auf das entsprechende Niveau von
 minimal 0 (gering) bis maximal 100 (hoch). [Wie hoch waren die Anforderun
gen an die globale Aufmerksamkeit?  Erkl<e4>rung: Insgesamt alle mentalen
(denken, entscheiden...), visuellen und auditiven Faktoren, die insgesamt
w<e4>hrend des Versuchs erforderlich sind, um die Gesamtleistung zu erziel
en]` = col_integer(),
##   `Im folgenden Abschnitt bewerten Sie bitte Ihre mentale Beanspruchung
 im zuvor erlebten Szenario auf den angegebenen Skalen.   Dazu ver<e4>nder
n Sie bitte den angezeigten Schieberegler auf das entsprechende Niveau von
 minimal 0 (gering) bis maximal 100 (hoch). [Wie hoch waren die visuellen
Anforderungen?  Erkl<e4>rung: Visuelle Faktoren, die w<e4>hrend des Versuc
```

```
hs erforderlich sind, um die Gesamtleistung zu erzielen (alles, was mit de
m Sehen zu tun hat)]` = col_integer(),
##   `Im folgenden Abschnitt bewerten Sie bitte Ihre mentale Beanspruchung
 im zuvor erlebten Szenario auf den angegebenen Skalen.   Dazu ver<e4>nder
n Sie bitte den angezeigten Schieberegler auf das entsprechende Niveau von
 minimal 0 (gering) bis maximal 100 (hoch). [Wie hoch waren die manuellen
Anforderungen?  Erkl<e4>rung: Manuelle Faktoren, die w<e4>hrend des Versuc
hs erforderlich sind, um die Gesamtleistung zu erzielen (alles, was mit de
r Handhabung zu tun hat)]` = col_integer(),
##   `Im folgenden Abschnitt bewerten Sie bitte Ihre mentale Beanspruchung
 im zuvor erlebten Szenario auf den angegebenen Skalen.   Dazu ver<e4>nder
n Sie bitte den angezeigten Schieberegler auf das entsprechende Niveau von
 minimal 0 (gering) bis maximal 100 (hoch). [Wie stark war das Stressnivea
u?  Erkl<e4>rung: Stress Niveau w<e4>hrend des Versuchsablaufs wie Irritat
ion, M<fc>digkeit, Unsicherheit, Entmutigung, etc.]` = col_integer(),
##   `Im folgenden Abschnitt bewerten Sie bitte Ihre mentale Beanspruchung
 im zuvor erlebten Szenario auf den angegebenen Skalen.   Dazu ver<e4>nder
n Sie bitte den angezeigten Schieberegler auf das entsprechende Niveau von
 minimal 0 (gering) bis maximal 100 (hoch). [Wie hoch war die zeitliche An
forderung?  Erkl<e4>rung: Gef<fc>hlte Belastung und spezifische Beeintr<e4
>chtigung durch die schnelle Abfolge der Aufgaben]` = col_integer()
## )

## See spec(...) for full column specifications.
```

Rename the variables / columns

```
colnames(questionnaireData_raw) <- c("Subject", "Condition", "Effort_of_at
tention", "Visual_demand", "Manual_demand", "Situational_stress", "Tempora
l_demand", "Feelings_of_comfort", "Feelings_of_safety", "Feelings_of_fluen
t_lane_change", "Clarity_of_intention", "Clarity_of_timing", "Feelings_of_
cooperation", "Situation_frustrating_satisfying", "Situation_hectic_relaxe
d", "Situation_uncooperative_cooperative", "Situation_unreliable_trustwort
hy", "OwnRole_disrupting_helpful", "OwnRole_delaying_timesaving", "OwnRole
_hindering_supportive", "Partner_disrupting_helpful", "Partner_delaying_ti
mesaving", "Partner_hindering_supportive", "Situation_hindering_beneficial
", "Situation_unpleasant_pleasant", "Concept_useful_useless", "Concept_ple
asant_unpleasant", "Concept_bad_good", "Concept_nice_annoying", "Concept_e
ffective_superfluous", "Concept_irritating_likeable", "Concept_assisting_w
orthless", "Concept_undesirable_desirable", "Concept_raisingAlertness_slee
pInducing", "Comments")
```

Fix the format of the data

```
library(car)

##
## Attaching package: 'car'

## The following object is masked from 'package:dplyr':
##
##     recode

## The following object is masked from 'package:purrr':
##
##     some
```

```
# we have to use lapply to recode the dataframe.
# see https://susanejohnston.wordpress.com/2012/07/18/find-and-replace-in-r-part-1-recode-in-the-library-car/

questionnaireData <- lapply(questionnaireData_raw, FUN = function(foo) recode(foo, "'- - -'='-3'; '- -'='-2'; '-'='-1'; 'o'='0'; '+'='1'; '+ +'='2'; '+ + +'='3'"))
questionnaireData <- data.frame(questionnaireData)

# "'---'='-3'; '--'='-2'; '-'='-1'; 'o'='0'; '+'='1'; '++'='2'; '+++'='3'"
```

Recode the variables
The following variables have to be recoded: "Concept_useful_useless"

"Concept_pleasant_unpleasant" "Concept_nice_annoying" "Concept_effective_superfluous"

"Concept_assisting_worthless" "Concept_raisingAlertness_sleepInducing"

```
questionnaireData$Concept_useful_useless <- as.numeric(lapply(questionnaireData$Concept_useful_useless, FUN = function(foo) recode(foo, "-2=2;-1=1;1=-1;2=-2")))

questionnaireData$Concept_pleasant_unpleasant <- as.numeric(lapply(questionnaireData$Concept_pleasant_unpleasant, FUN = function(foo) recode(foo, "-2=2;-1=1;1=-1;2=-2")))
questionnaireData$Concept_nice_annoying<- as.numeric(lapply(questionnaireData$Concept_nice_annoying, FUN = function(foo) recode(foo, "-2=2;-1=1;1=-1;2=-2")))
questionnaireData$Concept_effective_superfluous <- as.numeric(lapply(questionnaireData$Concept_effective_superfluous, FUN = function(foo) recode(foo, "-2=2;-1=1;1=-1;2=-2")))
questionnaireData$Concept_assisting_worthless <- as.numeric(lapply(questionnaireData$Concept_assisting_worthless, FUN = function(foo) recode(foo, "-2=2;-1=1;1=-1;2=-2")))
questionnaireData$Concept_raisingAlertness_sleepInducing <- as.numeric(lapply(questionnaireData$Concept_raisingAlertness_sleepInducing, FUN = function(foo) recode(foo, "-2=2;-1=1;1=-1;2=-2")))


rm(questionnaireData_raw) # clean the environment from the raw data
```

Calculate the subscales and add them as new variables to the dataframe

```
# van der Laan's usefulness subscale
questionnaireData$Usefulness <- (questionnaireData$Concept_useful_useless + questionnaireData$Concept_bad_good + questionnaireData$Concept_effective_superfluous + questionnaireData$Concept_assisting_worthless + questionnaireData$Concept_raisingAlertness_sleepInducing) / 5

# van der Laan's Satisfying subscale
questionnaireData$Satisfying <- (questionnaireData$Concept_pleasant_unpleasant + questionnaireData$Concept_nice_annoying + questionnaireData$Concept_irritating_likeable + questionnaireData$Concept_undesirable_desirable) / 4
```

```
# an overall rating of the perceived quality of the lane change
questionnaireData$Quality_of_lane_change <- (questionnaireData$Feelings_of_comfort + questionnaireData$Feelings_of_safety + questionnaireData$Feelings_of_fluent_lane_change) / 3

# how the subject felt about the lane change
questionnaireData$Lanechange_feeling <- (questionnaireData$Situation_frustrating_satisfying + questionnaireData$Situation_hectic_relaxed + questionnaireData$Situation_uncooperative_cooperative + questionnaireData$Situation_unreliable_trustworthy) / 4

# the following Situation_feeling will be exluded because this question was meant to measure how somebody felt about the situations. AHover, it was almost always the case that the people let the other ca rin and thereore, it will be sufficient to look at the ratings of the feeling during the lane changes.
# how the subject felt about the whole situation
questionnaireData$Situation_feeling <- (questionnaireData$Situation_unpleasant_pleasant + questionnaireData$Situation_hindering_beneficial) / 2

# is manual demand really part of the driving activity load index? I don't think so
questionnaireData$DALI <- (questionnaireData$Effort_of_attention + questionnaireData$Visual_demand + questionnaireData$Manual_demand + questionnaireData$Situational_stress + questionnaireData$Temporal_demand) / 5

# the degree to which the subject rates his/her own behavior as cooperative
questionnaireData$Cooperation_self <- (questionnaireData$OwnRole_disrupting_helpful + questionnaireData$OwnRole_delaying_timesaving + questionnaireData$OwnRole_hindering_supportive) / 3

# the degree to which the subject rates the partner's behavior as cooperative
questionnaireData$Cooperation_partner <- (questionnaireData$Partner_disrupting_helpful + questionnaireData$Partner_delaying_timesaving + questionnaireData$Partner_hindering_supportive) / 3
```

Add the new factors HUD and 2Levels

```
# make the value of HUD 1 if it is conditionC or D, else make it 0
# also make it a factor
questionnaireData$HUD <- factor(ifelse(questionnaireData$Condition == "c", "HUD", ifelse(questionnaireData$Condition == "d", "HUD", "No HUD")))

# make the value of TwoPhases 1 if it is conditionB or D, else make it 0
questionnaireData$Semantics <- factor(ifelse(questionnaireData$Condition == "b", "Enhanced semantics", ifelse(questionnaireData$Condition == "d", "Enhanced semantics", "Old semantics")))

# also relevel the factor HUD to make sure that "No HUD" is the reference value in intercepts
questionnaireData <- within(questionnaireData, HUD <- relevel(HUD, ref = "No HUD"))
questionnaireData <- within(questionnaireData, Semantics <- relevel(Semant
```

```
ics, ref = "Old semantics"))
questionnaireData <- within(questionnaireData, Feelings_of_cooperation <-
relevel(Feelings_of_cooperation, ref = "Ja"))
```

Prepare the theme (minimalist)

make it beautiful. Those theme settings handle the removal of many elements and adjusts the legend position.

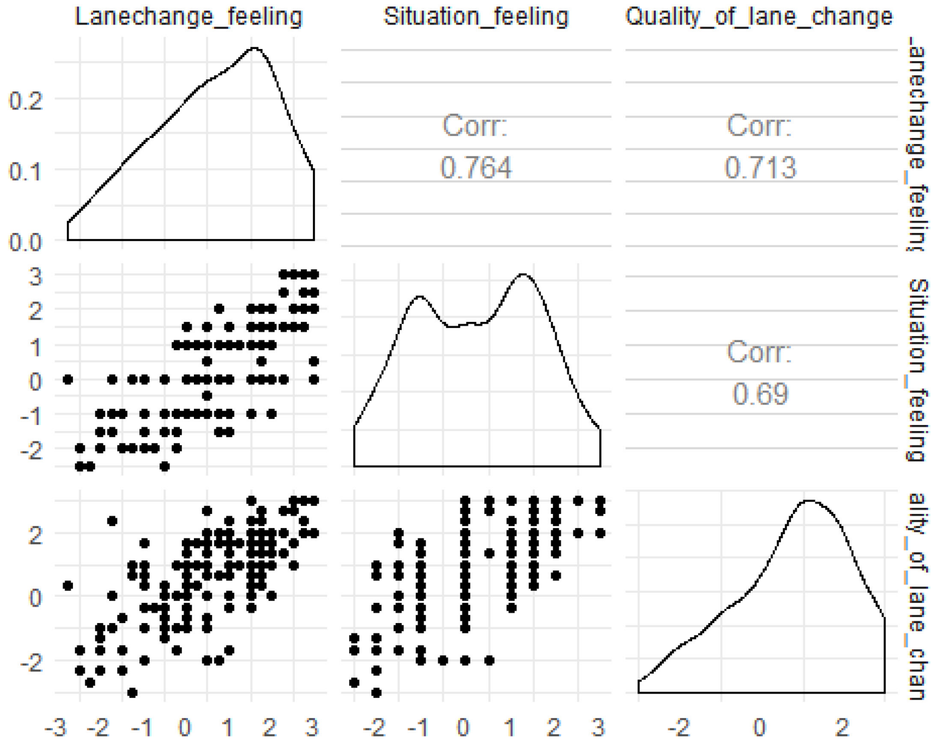
```
theme = theme_set(theme_minimal())
theme = theme_update(legend.position="top", legend.title=element_blank(),
axis.title.x=element_blank(), panel.grid.major.x=element_blank(), plot.tit
le = element_text(hjust = 0.5))

options(digits=2)
```

RESULTS

Before digging deeper into the ratings, the questionnaires are checked for internalconsistency.

Internal consistency and correlations between the questionnaires

```
questionnaireData %>%
  select(Lanechange_feeling, Situation_feeling, Quality_of_lane_change) %>
%
  distinct %>%
  ggpairs()

## Warning: Removed 1 rows containing non-finite values (stat_density).

## Warning in (function (data, mapping, alignPercent = 0.6, method =
## "pearson", : Removing 1 row that contained a missing value

## Warning in (function (data, mapping, alignPercent = 0.6, method =
## "pearson", : Removing 1 row that contained a missing value

## Warning: Removed 1 rows containing missing values (geom_point).

## Warning: Removed 1 rows containing non-finite values (stat_density).

## Warning in (function (data, mapping, alignPercent = 0.6, method =
## "pearson", : Removing 1 row that contained a missing value

## Warning: Removed 1 rows containing missing values (geom_point).

## Warning: Removed 1 rows containing missing values (geom_point).

## Warning: Removed 1 rows containing non-finite values (stat_density).
```




```
# calculate conrbachs alpha for each questionnaire.

# alpha: quality of lane change alpha
questionnaireData[,c("Feelings_of_comfort", "Feelings_of_safety", "Feeling
s_of_fluent_lane_change")] %>%
  psych::alpha()

##
## Reliability analysis
## Call: psych::alpha(x = .)
##
##   raw_alpha std.alpha G6(smc) average_r S/N    ase mean  sd
##       0.93      0.93     0.9      0.81  13 0.0085  0.9 1.4
##
##  lower alpha upper     95% confidence boundaries
## 0.91 0.93 0.95
##
##  Reliability if an item is dropped:
##                                raw_alpha std.alpha G6(smc) average_r  S
/N
## Feelings_of_comfort                 0.92      0.92    0.85      0.85 11
.2
## Feelings_of_safety                  0.89      0.89    0.80      0.80  8
.2
## Feelings_of_fluent_lane_change      0.88      0.88    0.79      0.79  7
.4
##                                alpha se
## Feelings_of_comfort               0.011
## Feelings_of_safety                0.015
## Feelings_of_fluent_lane_change    0.016
##
```

```
##  Item statistics
##                                  n raw.r std.r r.cor r.drop mean  sd
## Feelings_of_comfort            207  0.92  0.92  0.86   0.83 0.89 1.4
## Feelings_of_safety             207  0.94  0.94  0.90   0.86 0.99 1.4
## Feelings_of_fluent_lane_change 207  0.95  0.94  0.91   0.87 0.83 1.5
##
## Non missing response frequency for each item
##                                  -3   -2   -1    0    1    2    3 miss
## Feelings_of_comfort            0.01 0.05 0.12 0.14 0.30 0.26 0.11    0
## Feelings_of_safety             0.01 0.06 0.11 0.12 0.28 0.31 0.12    0
## Feelings_of_fluent_lane_change 0.02 0.06 0.13 0.14 0.27 0.27 0.12    0
```

```
# alpha: van der Laan's usefulness subscale alpha
questionnaireData[c("Concept_useful_useless","Concept_bad_good", "Concept_
effective_superfluous","Concept_assisting_worthless", "Concept_raisingAler
tness_sleepInducing")] %>%
  psych::alpha()
```

```
##
## Reliability analysis
## Call: psych::alpha(x = .)
##
##   raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd
##       0.78      0.78    0.78      0.42 3.6 0.023 0.51 0.73
##
##  lower alpha upper     95% confidence boundaries
## 0.73 0.78 0.83
##
##  Reliability if an item is dropped:
##                                       raw_alpha std.alpha G6(smc)
## Concept_useful_useless                     0.78      0.77    0.75
## Concept_bad_good                           0.68      0.68    0.67
## Concept_effective_superfluous              0.70      0.70    0.68
## Concept_assisting_worthless                0.70      0.70    0.68
## Concept_raisingAlertness_sleepInducing     0.81      0.82    0.80
##                                       average_r S/N alpha se
## Concept_useful_useless                     0.45 3.3    0.024
## Concept_bad_good                           0.35 2.1    0.035
## Concept_effective_superfluous              0.37 2.3    0.033
## Concept_assisting_worthless                0.37 2.4    0.032
## Concept_raisingAlertness_sleepInducing     0.54 4.6    0.022
##
##  Item statistics
##                                          n raw.r std.r r.cor r.drop mea
n
## Concept_useful_useless                 207  0.71  0.67  0.54   0.47 0.3
9
## Concept_bad_good                       207  0.84  0.84  0.81   0.73 0.5
5
## Concept_effective_superfluous          207  0.81  0.81  0.78   0.67 0.4
6
## Concept_assisting_worthless            207  0.80  0.80  0.77   0.66 0.5
3
## Concept_raisingAlertness_sleepInducing 207  0.47  0.53  0.32   0.29 0.5
```

```
9
##                                          sd
## Concept_useful_useless                 1.23
## Concept_bad_good                       0.94
## Concept_effective_superfluous          1.01
## Concept_assisting_worthless            1.00
## Concept_raisingAlertness_sleepInducing 0.78
##
## Non missing response frequency for each item
##                                          -2   -1    0    1    2 miss
## Concept_useful_useless                 0.05 0.26 0.18 0.28 0.23    0
## Concept_bad_good                       0.01 0.14 0.27 0.44 0.14    0
## Concept_effective_superfluous          0.03 0.15 0.26 0.43 0.13    0
## Concept_assisting_worthless            0.04 0.14 0.21 0.49 0.13    0
## Concept_raisingAlertness_sleepInducing 0.00 0.06 0.40 0.42 0.12    0
```

```
# alpha: van der Laan's Satisfying subscale
questionnaireData[c("Concept_pleasant_unpleasant","Concept_nice_annoying",
 "Concept_irritating_likeable","Concept_undesirable_desirable")] %>%
  psych::alpha()
```

```
##
## Reliability analysis
## Call: psych::alpha(x = .)
##
##   raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd
##       0.85      0.86    0.82       0.6   6 0.016 0.45 0.77
##
##  lower alpha upper     95% confidence boundaries
## 0.82 0.85 0.89
##
##  Reliability if an item is dropped:
##                               raw_alpha std.alpha G6(smc) average_r S/N
## Concept_pleasant_unpleasant        0.82      0.83    0.76      0.62 4.8
## Concept_nice_annoying              0.81      0.82    0.75      0.60 4.6
## Concept_irritating_likeable        0.81      0.81    0.74      0.58 4.2
## Concept_undesirable_desirable      0.81      0.82    0.76      0.60 4.6
##                               alpha se
## Concept_pleasant_unpleasant      0.021
## Concept_nice_annoying            0.022
## Concept_irritating_likeable      0.023
## Concept_undesirable_desirable    0.022
##
##  Item statistics
##                                 n raw.r std.r r.cor r.drop mean   sd
## Concept_pleasant_unpleasant   207  0.84  0.83  0.74   0.68 0.53 1.00
## Concept_nice_annoying         207  0.83  0.84  0.76   0.69 0.40 0.87
## Concept_irritating_likeable   207  0.84  0.85  0.79   0.73 0.39 0.79
## Concept_undesirable_desirable 207  0.85  0.84  0.75   0.70 0.49 1.00
##
## Non missing response frequency for each item
##                                 -2   -1    0    1    2 miss
## Concept_pleasant_unpleasant   0.01 0.17 0.24 0.42 0.16    0
## Concept_nice_annoying         0.01 0.13 0.42 0.34 0.10    0
```

```
## Concept_irritating_likeable   0.00 0.10 0.48 0.34 0.08    0
## Concept_undesirable_desirable 0.04 0.11 0.32 0.39 0.14    0

# alpha: how the subject felt about the lane change
questionnaireData[c("Situation_frustrating_satisfying","Situation_hectic_r
elaxed", "Situation_uncooperative_cooperative","Situation_unreliable_trust
worthy")] %>%
  psych::alpha()

##
## Reliability analysis
## Call: psych::alpha(x = .)
##
##   raw_alpha std.alpha G6(smc) average_r S/N  ase mean  sd
##       0.91      0.91    0.89      0.71 9.9 0.01 0.87 1.4
##
##  lower alpha upper     95% confidence boundaries
## 0.89 0.91 0.93
##
##  Reliability if an item is dropped:
##                                     raw_alpha std.alpha G6(smc) average
_r
## Situation_frustrating_satisfying         0.89      0.89    0.85      0.
72
## Situation_hectic_relaxed                 0.88      0.88    0.84      0.
72
## Situation_uncooperative_cooperative      0.88      0.88    0.84      0.
72
## Situation_unreliable_trustworthy         0.87      0.87    0.82      0.
69
##                                     S/N alpha se
## Situation_frustrating_satisfying    7.9    0.013
## Situation_hectic_relaxed            7.7    0.014
## Situation_uncooperative_cooperative 7.6    0.014
## Situation_unreliable_trustworthy    6.7    0.016
##
##  Item statistics
##                                       n raw.r std.r r.cor r.drop mean
sd
## Situation_frustrating_satisfying    207  0.87  0.88  0.81   0.77 0.92 1
.5
## Situation_hectic_relaxed            207  0.88  0.88  0.82   0.78 0.94 1
.5
## Situation_uncooperative_cooperative 207  0.89  0.88  0.83   0.79 0.86 1
.6
## Situation_unreliable_trustworthy    207  0.91  0.90  0.87   0.83 0.75 1
.6
##
## Non missing response frequency for each item
##                                       -3   -2   -1    1    2    3 miss
## Situation_frustrating_satisfying    0.01 0.07 0.18 0.31 0.32 0.11    0
## Situation_hectic_relaxed            0.01 0.05 0.20 0.31 0.32 0.11    0
## Situation_uncooperative_cooperative 0.02 0.08 0.18 0.26 0.35 0.10    0
## Situation_unreliable_trustworthy    0.02 0.08 0.21 0.30 0.29 0.10    0
```

```
# the following Situation_feeling will be exluded because this question wa
s meant to measure how somebody felt about the situations. AHover, it was
almost always the case that the people let the other ca rin and thereore,
it will be sufficient to look at the ratings of the feeling during the lan
e changes.
# alpha: how the subject felt about the whole situation
questionnaireData[c("Situation_unpleasant_pleasant","Situation_hindering_b
eneficial")] %>%
  psych::alpha()
```

```
## Warning in matrix(unlist(drop.item), ncol = 8, byrow = TRUE): Datenläng
e
## [12] ist kein Teiler oder Vielfaches der Anzahl der Spalten [8]

##
## Reliability analysis
## Call: psych::alpha(x = .)
##
##   raw_alpha std.alpha G6(smc) average_r S/N   ase mean  sd
##       0.87      0.87    0.77      0.77 6.8 0.018 0.49 1.4
##
##  lower alpha upper     95% confidence boundaries
## 0.84 0.87 0.91
##
##  Reliability if an item is dropped:
##                                raw_alpha std.alpha G6(smc) average_r  S
/N
## Situation_unpleasant_pleasant       0.77      0.77     0.6      0.77
NA
## Situation_hindering_beneficial      0.60      0.77      NA        NA 0.
77
##                                alpha se
## Situation_unpleasant_pleasant        NA
## Situation_hindering_beneficial    0.061
##
##  Item statistics
##                                  n raw.r std.r r.cor r.drop mean  sd
## Situation_unpleasant_pleasant  207  0.94  0.94  0.83   0.77 0.63 1.5
## Situation_hindering_beneficial 207  0.94  0.94  0.83   0.77 0.35 1.5
##
## Non missing response frequency for each item
##                                  -3   -2   -1    1    2    3 miss
## Situation_unpleasant_pleasant  0.01 0.08 0.26 0.31 0.27 0.07    0
## Situation_hindering_beneficial 0.00 0.09 0.32 0.34 0.20 0.04    0
```

```
# alpha: DALI
questionnaireData[c("Effort_of_attention","Visual_demand", "Manual_demand"
,"Situational_stress", "Temporal_demand")] %>%
  psych::alpha()
```

```
##
## Reliability analysis
## Call: psych::alpha(x = .)
##
##   raw_alpha std.alpha G6(smc) average_r S/N    ase mean sd
```

```
##       0.93      0.93    0.93      0.73  14 0.0076   35 21
##
##  lower alpha upper     95% confidence boundaries
## 0.92 0.93 0.95
##
##  Reliability if an item is dropped:
##                     raw_alpha std.alpha G6(smc) average_r S/N alpha se
## Effort_of_attention      0.91      0.91    0.89      0.73  11   0.0100
## Visual_demand            0.91      0.91    0.90      0.73  11   0.0099
## Manual_demand            0.91      0.91    0.90      0.72  10   0.0102
## Situational_stress       0.92      0.92    0.92      0.75  12   0.0088
## Temporal_demand          0.92      0.92    0.90      0.74  11   0.0092
##
##  Item statistics
##                       n raw.r std.r r.cor r.drop mean sd
## Effort_of_attention 207  0.90  0.89  0.87   0.83   45 25
## Visual_demand       207  0.90  0.89  0.87   0.83   46 27
## Manual_demand       207  0.90  0.91  0.88   0.85   31 23
## Situational_stress  207  0.86  0.86  0.81   0.78   29 23
## Temporal_demand     207  0.87  0.88  0.84   0.80   26 22
```

```
# alpha: the degree to which the subject rates his/her own behavior as coo
perative
questionnaireData[c("OwnRole_disrupting_helpful","OwnRole_delaying_timesav
ing", "OwnRole_hindering_supportive")] %>%
  psych::alpha()
```

```
##
## Reliability analysis
## Call: psych::alpha(x = .)
##
##   raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd
##       0.62      0.66    0.67       0.4   2 0.048  1.1 0.97
##
##  lower alpha upper     95% confidence boundaries
## 0.53 0.62 0.72
##
##  Reliability if an item is dropped:
##                              raw_alpha std.alpha G6(smc) average_r  S/N
## OwnRole_disrupting_helpful        0.41      0.42    0.27      0.27 0.73
## OwnRole_delaying_timesaving       0.85      0.85    0.75      0.75 5.86
## OwnRole_hindering_supportive      0.29      0.30    0.17      0.17 0.42
##                              alpha se
## OwnRole_disrupting_helpful      0.079
## OwnRole_delaying_timesaving     0.020
## OwnRole_hindering_supportive    0.095
##
##  Item statistics
##                                n raw.r std.r r.cor r.drop mean  sd
## OwnRole_disrupting_helpful   207  0.78  0.83  0.78   0.53 1.46 1.1
## OwnRole_delaying_timesaving  207  0.70  0.62  0.27   0.24 0.47 1.5
## OwnRole_hindering_supportive 207  0.83  0.87  0.84   0.61 1.34 1.2
##
## Non missing response frequency for each item
```

```
##                                 -3   -2   -1    1    2    3 miss
## OwnRole_disrupting_helpful   0.00 0.03 0.06 0.40 0.36 0.15    0
## OwnRole_delaying_timesaving  0.01 0.10 0.26 0.33 0.26 0.04    0
## OwnRole_hindering_supportive 0.00 0.02 0.12 0.35 0.41 0.11    0

# alpha: the degree to which the subject rates the partner's behavior as c
ooperative
questionnaireData[c("Partner_disrupting_helpful","Partner_delaying_timesav
ing", "Partner_hindering_supportive")] %>%
  psych::alpha()

##
## Reliability analysis
## Call: psych::alpha(x = .)
##
##   raw_alpha std.alpha G6(smc) average_r S/N   ase mean  sd
##       0.89      0.89    0.85      0.73 8.2 0.013  0.2 1.4
##
##  lower alpha upper     95% confidence boundaries
## 0.86 0.89 0.92
##
##  Reliability if an item is dropped:
##                              raw_alpha std.alpha G6(smc) average_r S/N
## Partner_disrupting_helpful        0.83      0.83    0.70      0.70 4.7
## Partner_delaying_timesaving       0.88      0.88    0.79      0.79 7.4
## Partner_hindering_supportive      0.83      0.83    0.71      0.71 4.8
##                              alpha se
## Partner_disrupting_helpful      0.024
## Partner_delaying_timesaving     0.016
## Partner_hindering_supportive    0.024
##
##  Item statistics
##                                n raw.r std.r r.cor r.drop mean  sd
## Partner_disrupting_helpful   207  0.92  0.92  0.86   0.81 0.23 1.5
## Partner_delaying_timesaving  207  0.89  0.89  0.78   0.74 0.11 1.6
## Partner_hindering_supportive 207  0.92  0.92  0.86   0.81 0.27 1.6
##
## Non missing response frequency for each item
##                                 -3   -2   -1    1    2    3 miss
## Partner_disrupting_helpful   0.01 0.11 0.34 0.31 0.18 0.05    0
## Partner_delaying_timesaving  0.01 0.13 0.38 0.26 0.15 0.07    0
## Partner_hindering_supportive 0.01 0.11 0.34 0.29 0.19 0.06    0

# check if the model already exists. If it does not, refit the model

if(file.exists("model_M_9_reduced.rda")) {
  load("model_M_9_reduced.rda") # load the model
} else {
  # the intercept, HUD and Semantics effect conditional on subjects
  # Thus, we look in how far the effect of HUD and Semantics differ condit
ional on subject
  # that means that this model does not only have a random intercept, but
also a random slope
  # therefore,
  M_9_reduced <- rstanarm::stan_glmer(Clarity_of_timing ~ HUD*Semantics +
```

```
(HUD + Semantics | Subject), data = questionnaireData, adapt_delta = 0.99)
 # fit the model
 save(M_9_reduced, file = "model_M_9_reduced.rda") # save the model to a f
ile
}

#BRMS model tryout
#M_9_brms <- brm(Clarity_of_timing ~ HUD*Semantics + (HUD*Semantics | Subj
ect), data = questionnaireData)
#system('g++ -v')
#system('where make')
# c++ compiler installation failure due to vw policy >> i'll simply procee
d with stan_glmer

# calculate the credible interval of the fixed effects
bayr::fixef(posterior(M_9_reduced)) %>% kable()
```

```
## Warning in sqrt(c(-1.29980915118854, -0.738843073916774,
## -1.07092018140616, : NaNs wurden erzeugt
```

model	type	nonlin	fixef	re_factor	re_entity	center	lower	upper
M_9_reduced	fixef	NA	Intercept	NA	NA	-0.91	-1.39	-0.43
M_9_reduced	fixef	NA	HUDHUD	NA	NA	0.88	0.19	1.58
M_9_reduced	fixef	NA	SemanticsEnhanced semantics	NA	NA	1.38	0.72	2.08
M_9_reduced	fixef	NA	HUDHUD:SemanticsEnhanced semantics	NA	NA	-0.19	-1.11	0.75

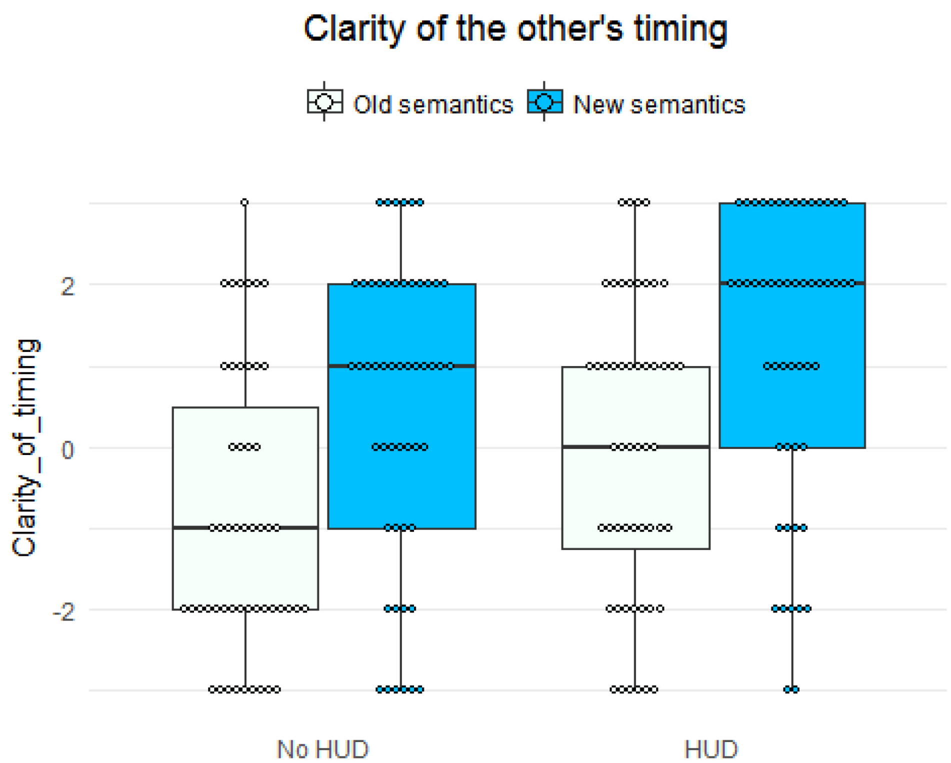
```
# extract the Random effect
print(M_9_reduced, digits = 2)
```

```
## stan_glmer
##  family:  gaussian [identity]
##  formula: Clarity_of_timing ~ HUD * Semantics + (HUD + Semantics | Subj
ect)
## ------
##
## Estimates:
##                                  Median MAD_SD
## (Intercept)                      -0.91   0.24
## HUDHUD                            0.88   0.35
## SemanticsEnhanced semantics            1.38   0.35
## HUDHUD:SemanticsEnhanced semantics -0.19   0.48
## sigma                             1.69   0.11
##
## Error terms:
##  Groups   Name                    Std.Dev. Corr
##  Subject  (Intercept)             0.446
```

```
##            HUDHUD                 0.565     0.03
##            SemanticsEnhanced semantics 0.499    -0.24  0.17
##  Residual                        1.695
## Num. levels: Subject 52
##
## Sample avg. posterior predictive
## distribution of y (X = xbar):
##          Median MAD_SD
## mean_PPD 0.18   0.17
##
## ------
## For info on the priors used see help('prior_summary.stanreg').
```

```
# plot the clarity of the other's timing
ggplot(questionnaireData, aes(x=HUD, y=Clarity_of_timing, fill=Semantics))
 +
  geom_boxplot(position = position_dodge(0.8)) +
  scale_fill_manual(values = c("mintcream", "deepskyblue1")) +
  geom_dotplot(binaxis = "y", stackdir = "center", dotsize = 0.5, position
 = position_dodge(0.8)) +
  ggtitle("Clarity of the other's timing")
```

```
## Warning: Removed 1 rows containing non-finite values (stat_boxplot).

## `stat_bindot()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 1 rows containing non-finite values (stat_bindot).
```



Influence of HUD and Semantics on the clarity of the partner's intentions

```
if(file.exists("model_M_10_reduced.rda")) {
  load("model_M_10_reduced.rda") # Load the model
} else {
```

```
  M_10_reduced <- rstanarm::stan_glmer(Clarity_of_intention ~ HUD*Semantic
s + (HUD + Semantics | Subject), data = questionnaireData, adapt_delta = 0
.99) # fit the model
  save(M_10_reduced, file = "model_M_10_reduced.rda") # save the model to
a file
}


# calculate the credible interval of the fixed effects
bayr::fixef(posterior(M_10_reduced)) %>% kable()

## Warning in sqrt(c(0.532561955678384, -0.120657960774557,
## -0.409870282935308, : NaNs wurden erzeugt
```

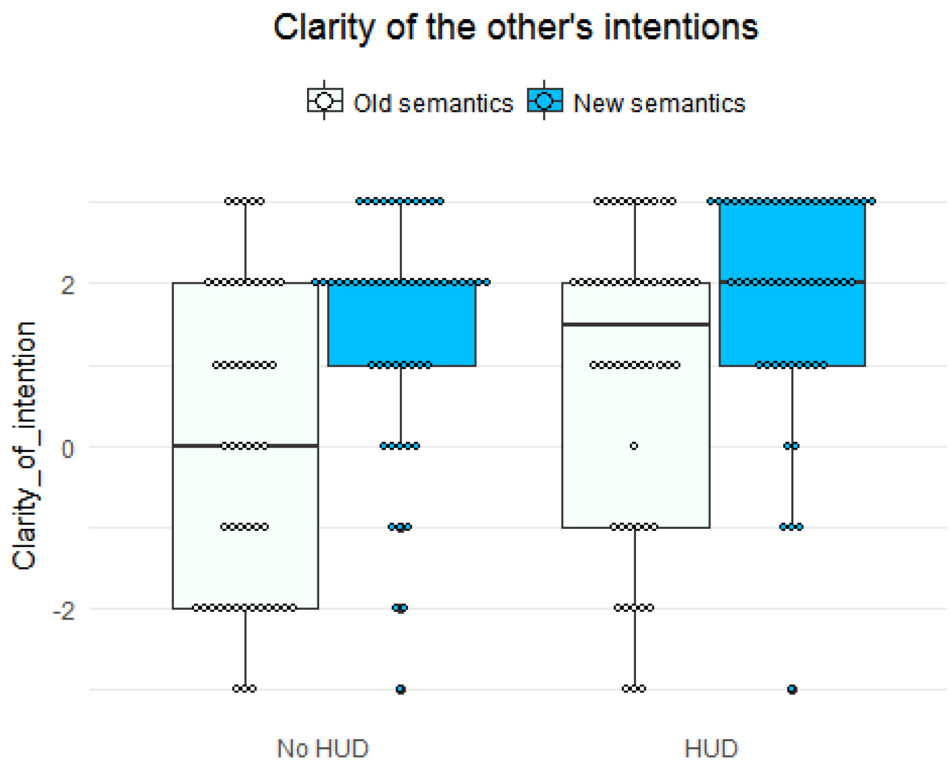
model	type	nonlin	fixef	re_factor	re_entity	center	lower	upper
M_10_reduced	fixef	NA	Intercept	NA	NA	0.05	-0.40	0.50
M_10_reduced	fixef	NA	HUDHUD	NA	NA	0.88	0.26	1.49
M_10_reduced	fixef	NA	SemanticsEnhanced semantics	NA	NA	1.39	0.79	2.00
M_10_reduced	fixef	NA	HUDHUD:SemanticsEnhanced semantics	NA	NA	-0.44	-1.30	0.44

```
# random effects
print(M_10_reduced, digits = 2)

## stan_glmer
##  family:  gaussian [identity]
##  formula: Clarity_of_intention ~ HUD * Semantics + (HUD + Semantics | S
ubject)
## ------
##
## Estimates:
##                                 Median MAD_SD
## (Intercept)                      0.05   0.23
## HUDHUD                           0.88   0.32
## SemanticsEnhanced semantics           1.39   0.31
## HUDHUD:SemanticsEnhanced semantics -0.44   0.45
## sigma                            1.58   0.10
##
## Error terms:
##  Groups   Name                        Std.Dev. Corr
##  Subject  (Intercept)                 0.451
##           HUDHUD                      0.395    -0.17
##           SemanticsEnhanced semantics 0.342    -0.35 -0.14
##  Residual                             1.582
## Num. levels: Subject 52
##
## Sample avg. posterior predictive
```

```
## distribution of y (X = xbar):
##          Median MAD_SD
## mean_PPD 1.07   0.15
##
## ------
## For info on the priors used see help('prior_summary.stanreg').
```

```
# plot the clarity of the other's intention
ggplot(questionnaireData, aes(x=HUD, y=Clarity_of_intention, fill=Semantic
s)) +
  geom_boxplot(position = position_dodge(0.8)) +
  scale_fill_manual(values = c("mintcream", "deepskyblue1")) +
  geom_dotplot(binaxis = "y", stackdir = "center", dotsize = 0.5, position
 = position_dodge(0.8)) +
  ggtitle("Clarity of the other's intentions")
```

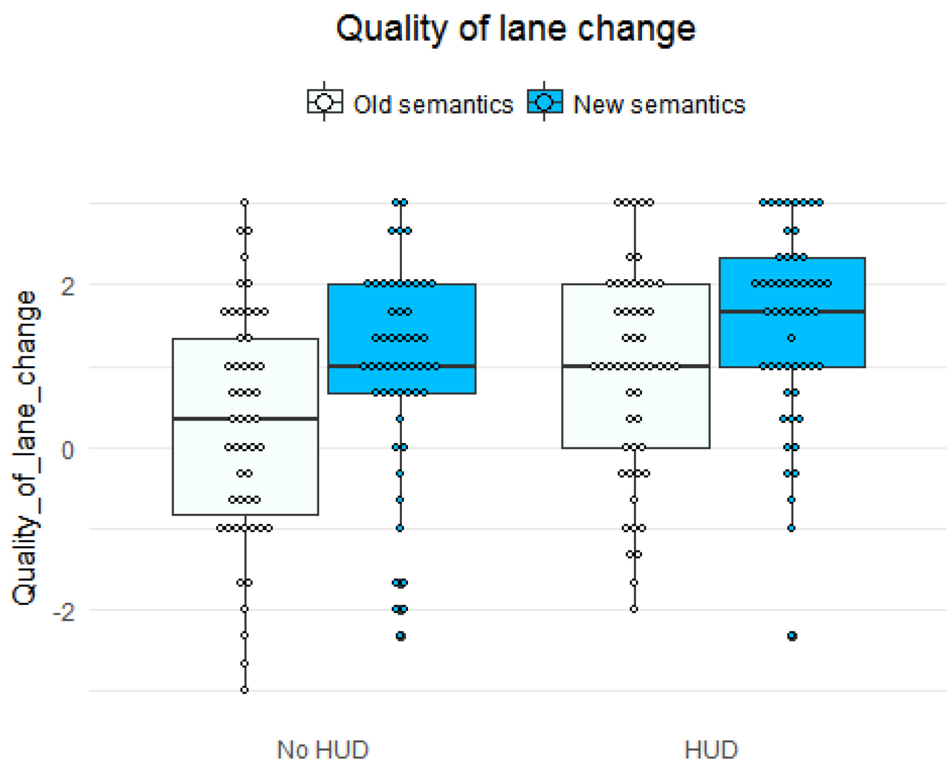
```
## Warning: Removed 1 rows containing non-finite values (stat_boxplot).

## `stat_bindot()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 1 rows containing non-finite values (stat_bindot).
```



Quality of the lane change

```
if(file.exists("model_M_3_reduced.rda")) {
  load("model_M_3_reduced.rda") # load the model
} else {
  M_3_reduced <- rstanarm::stan_glmer(Quality_of_lane_change ~ HUD*Semanti
cs + (HUD + Semantics | Subject), data = questionnaireData, adapt_delta =
0.99) # fit the model
  save(M_3_reduced, file = "model_M_3_reduced.rda") # save the model to a
file
}
```

```r
# quality of the lane change
ggplot(questionnaireData, aes(x=HUD, y=Quality_of_lane_change, fill=Semant
ics)) +
  geom_boxplot(position = position_dodge(0.8)) +
  scale_fill_manual(values = c("mintcream", "deepskyblue1")) +
  geom_dotplot(binaxis = "y", stackdir = "center", dotsize = 0.5, position
 = position_dodge(0.8)) +
  ggtitle("Quality of lane change")

## Warning: Removed 1 rows containing non-finite values (stat_boxplot).

## `stat_bindot()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 1 rows containing non-finite values (stat_bindot).
```




```r
# calculate the credible interval of the fixed effects
bayr::fixef(posterior(M_3_reduced)) %>% kable()

## Warning in sqrt(c(0.390291565591948, 0.33970268598937, 0.18004453621512
2, :
## NaNs wurden erzeugt
```

model	type	nonlin	fixef	re_factor	re_entity	center	lower	upper
M_3_reduced	fixef	NA	Intercept	NA	NA	0.25	-0.10	0.61
M_3_reduced	fixef	NA	HUDHUD	NA	NA	0.66	0.15	1.17

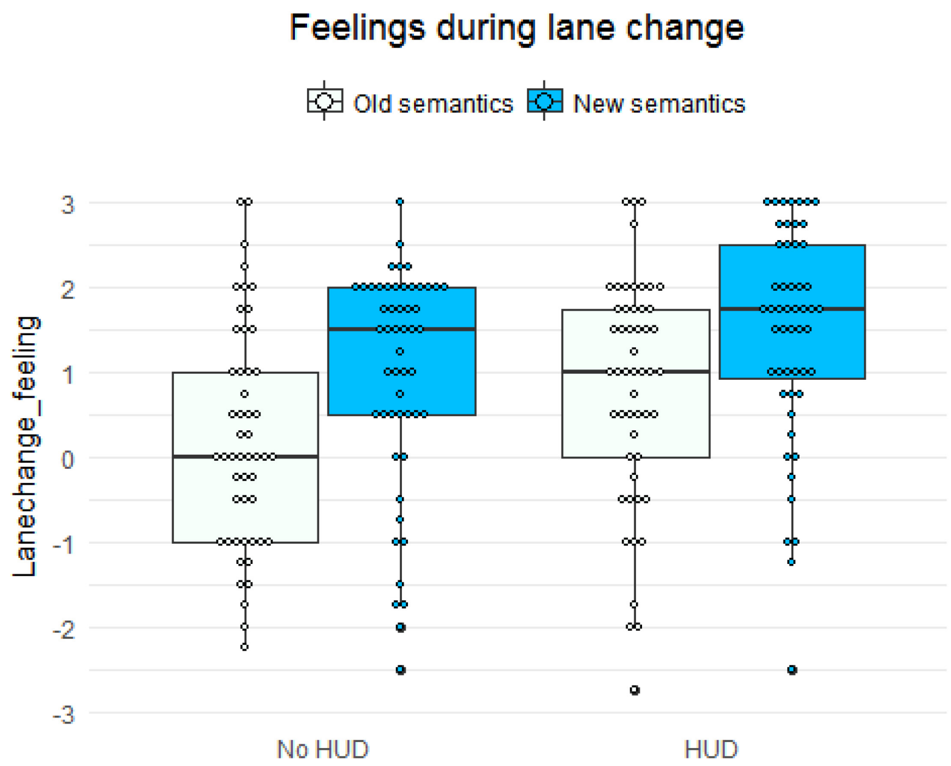
M_3_reduced	fixef	NA	SemanticsEnhanced semantics	NA	NA	0.70	0.22	1.19
M_3_reduced	fixef	NA	HUDHUD:SemanticsEnhanced semantics	NA	NA	-0.12	-0.81	0.55

```
# random effects
print(M_3_reduced, digits = 2)

## stan_glmer
##  family:  gaussian [identity]
##  formula: Quality_of_lane_change ~ HUD * Semantics + (HUD + Semantics |

##     Subject)
## ------
##
## Estimates:
##                                  Median MAD_SD
## (Intercept)                       0.25   0.18
## HUDHUD                            0.66   0.24
## SemanticsEnhanced semantics            0.70   0.24
## HUDHUD:SemanticsEnhanced semantics -0.12   0.33
## sigma                             1.25   0.08
##
## Error terms:
##  Groups   Name                        Std.Dev. Corr
##  Subject  (Intercept)                 0.325
##           HUDHUD                      0.290    -0.09
##           SemanticsEnhanced semantics 0.271    -0.37 -0.13
##  Residual                             1.251
## Num. levels: Subject 52
##
## Sample avg. posterior predictive
## distribution of y (X = xbar):
##          Median MAD_SD
## mean_PPD 0.91   0.12
##
## ------
## For info on the priors used see help('prior_summary.stanreg').
```

Feeling during lane change

```
if(file.exists("model_M_4_reduced.rda")) {
  load("model_M_4_reduced.rda") # Load the model
} else {
  M_4_reduced <- rstanarm::stan_glmer(Lanechange_feeling ~ HUD*Semantics +
 (HUD + Semantics | Subject), data = questionnaireData, adapt_delta = 0.99
) # fit the model
  save(M_4_reduced, file = "model_M_4_reduced.rda") # save the model to a
file
}

# feeling regarding the lane change
ggplot(questionnaireData, aes(x=HUD, y=Lanechange_feeling, fill=Semantics)
) +
```

```
   geom_boxplot(position = position_dodge(0.8)) +
  scale_fill_manual(values = c("mintcream", "deepskyblue1")) +
  geom_dotplot(binaxis = "y", stackdir = "center", dotsize = 0.5, position
 = position_dodge(0.8)) +
  ggtitle("Feelings during lane change")

## Warning: Removed 1 rows containing non-finite values (stat_boxplot).

## `stat_bindot()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 1 rows containing non-finite values (stat_bindot).
```




```
# calculate the credible interval of the fixed effects
bayr::fixef(posterior(M_4_reduced)) %>% kable()

## Warning in sqrt(c(0.394117828237422, -0.0475865414664676,
## 0.164445211537159, : NaNs wurden erzeugt
```

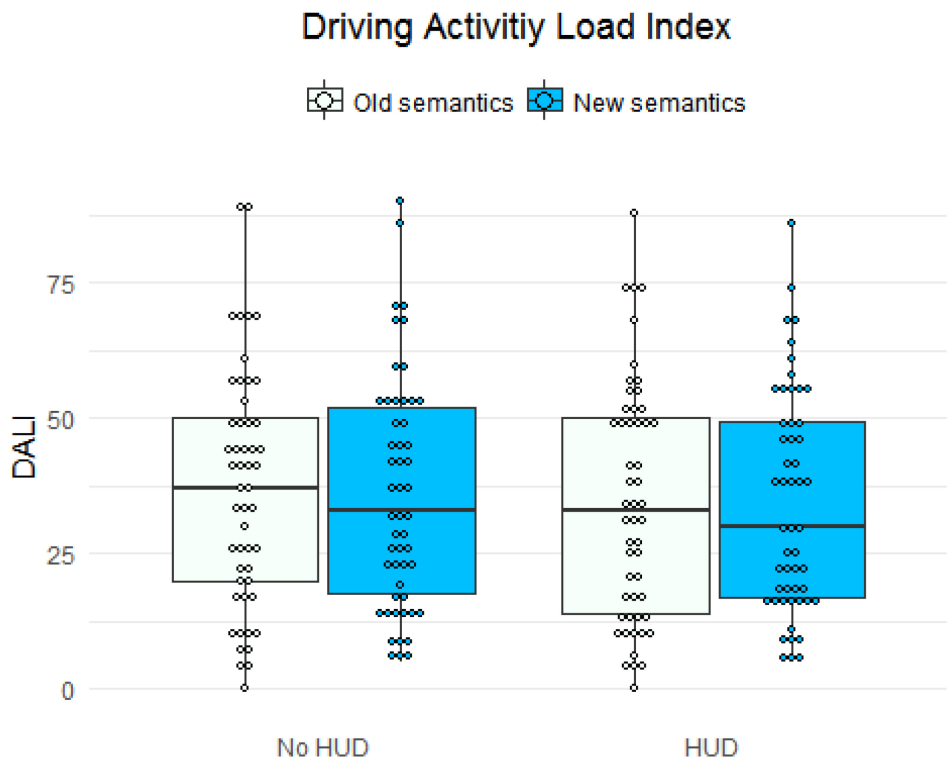
model	type	nonlin	fixef	re_factor	re_entity	center	lower	upper
M_4_reduced	fixef	NA	Intercept	NA	NA	0.23	-0.11	0.58
M_4_reduced	fixef	NA	HUDHUD	NA	NA	0.58	0.13	1.06
M_4_reduced	fixef	NA	SemanticsEnhanced semantics	NA	NA	0.74	0.27	1.21
M_4_reduced	fixef	NA	HUDHUD:SemanticsEnhanced semantics	NA	NA	-0.09	-0.75	0.55

```
# random effects
print(M_4_reduced, digits = 2)

## stan_glmer
##  family:  gaussian [identity]
##  formula: Lanechange_feeling ~ HUD * Semantics + (HUD + Semantics | Sub
ject)
## ------
##
## Estimates:
##                                    Median MAD_SD
## (Intercept)                         0.23   0.18
## HUDHUD                              0.58   0.24
## SemanticsEnhanced semantics         0.74   0.24
## HUDHUD:SemanticsEnhanced semantics -0.09   0.32
## sigma                               1.20   0.09
##
## Error terms:
##  Groups   Name                        Std.Dev. Corr
##  Subject  (Intercept)                 0.458
##           HUDHUD                      0.393    -0.04
##           SemanticsEnhanced semantics 0.386    -0.24 -0.20
##  Residual                             1.197
## Num. levels: Subject 52
##
## Sample avg. posterior predictive
## distribution of y (X = xbar):
##          Median MAD_SD
## mean_PPD 0.87   0.12
##
## ------
## For info on the priors used see help('prior_summary.stanreg').
```

Driving Load Activity Index

```
# check if the model already exists. If it does not, refit the model
if(file.exists("model_M_6_reduced.rda")) {
  load("model_M_6_reduced.rda") # Load the model
} else {
  M_6_reduced <- rstanarm::stan_glmer(DALI ~ HUD*Semantics + (HUD + Semant
ics | Subject), data = questionnaireData, adapt_delta = 0.99) # fit the mo
del
  save(M_6_reduced, file = "model_M_6_reduced.rda") # save the model to a
file
}

# DALI
ggplot(questionnaireData, aes(x=HUD, y=DALI, fill=Semantics)) +
  geom_boxplot(position = position_dodge(0.8)) +
  scale_fill_manual(values = c("mintcream", "deepskyblue1")) +
  geom_dotplot(binaxis = "y", stackdir = "center", dotsize = 0.5, position
 = position_dodge(0.8)) +
  ggtitle("Driving Activitiy Load Index")

## Warning: Removed 1 rows containing non-finite values (stat_boxplot).
```

```
## `stat_bindot()` using `bins = 30`. Pick better value with `binwidth`.
## Warning: Removed 1 rows containing non-finite values (stat_bindot).
```




```
# calculate the credible interval of the fixed effects
bayr::fixef(posterior(M_6_reduced)) %>% kable()

## Warning in sqrt(c(41.5054355707349, 38.9654092781574, 41.9998169040144,
  :
## NaNs wurden erzeugt
```

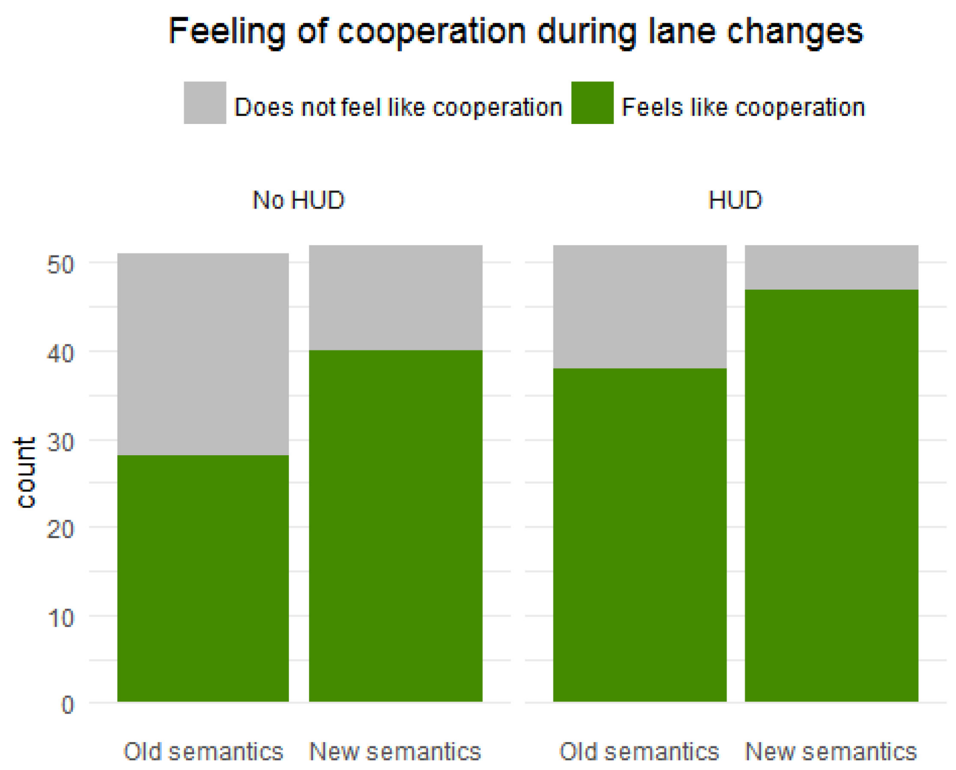
model	type	nonlin	fixef	re_factor	re_entity	center	lower	upper
M_6_reduced	fixef	NA	Intercept	NA	NA	37.1	31.4	43.5
M_6_reduced	fixef	NA	HUDHUD	NA	NA	-3.0	-5.7	-0.3
M_6_reduced	fixef	NA	SemanticsEnhanced semantics	NA	NA	-1.5	-4.3	1.2
M_6_reduced	fixef	NA	HUDHUD:SemanticsEnhanced semantics	NA	NA	1.5	-2.0	4.8

```
# random effects
print(M_6_reduced, digits = 2)

## stan_glmer
##  family:  gaussian [identity]
##  formula: DALI ~ HUD * Semantics + (HUD + Semantics | Subject)
## ------
##
## Estimates:
```

```
##                                Median MAD_SD
## (Intercept)                    37.15   2.97
## HUDHUD                         -3.04   1.33
## SemanticsEnhanced semantics         -1.53   1.37
## HUDHUD:SemanticsEnhanced semantics  1.47   1.65
## sigma                           6.05   0.53
##
## Error terms:
##  Groups   Name                     Std.Dev. Corr
##  Subject  (Intercept)              21.10
##           HUDHUD                    4.20    -0.17
##           SemanticsEnhanced semantics  4.20    -0.34  0.64
##  Residual                           6.07
## Num. levels: Subject 52
##
## Sample avg. posterior predictive
## distribution of y (X = xbar):
##          Median MAD_SD
## mean_PPD 35.29   0.60
##
## ------
## For info on the priors used see help('prior_summary.stanreg').
```

Perceived as cooperation or not?

```
# create a variable that holds the recodxed values of "ja" and "Nein"
questionnaireData$Feelings_of_cooperationNum <- ifelse(questionnaireData$F
eelings_of_cooperation == "Ja", 1, ifelse(questionnaireData$Feelings_of_co
operation == "n. a.", NA, 0))

# create a variable that holds the recodxed values of "ja" and "Nein"
questionnaireData$Feelings_of_cooperationLogical <- ifelse(questionnaireDa
ta$Feelings_of_cooperation == "Ja", TRUE, ifelse(questionnaireData$Feeling
s_of_cooperation == "n. a.", NA, FALSE))

# in general (all situations). plot is divided by condition
subset(questionnaireData, !is.na(Feelings_of_cooperationLogical)) %>%
    ggplot(aes(Semantics, fill=Feelings_of_cooperationLogical)) +
    geom_bar(na.rm = TRUE) +
    scale_fill_manual(labels = c("Does not feel like cooperation", "Feels
like cooperation"), values = c("gray", "chartreuse4")) +
    ggtitle("Feeling of cooperation during lane changes") +
  facet_grid(. ~ HUD)
```




```
if(file.exists("model_M_11_log.rda")) {
  load("model_M_11_log.rda") # load the model
} else {
  M_11_log <- rstanarm::stan_glmer(Feelings_of_cooperationNum ~ HUD*Semant
ics + (HUD + Semantics | Subject), data = questionnaireData, adapt_delta =
 0.999, family = binomial(link="logit")) # fit the model
  save(M_11_log, file = "model_M_11_log.rda") # save the model to a file

}
# calculate the credible interval of the fixed effects
bayr::fixef(posterior(M_11_log)) %>% kable()


## I think that this model is oversaturated. That's why there's another mo
del below that only includes fixed effects.
```

model	type	nonlin	fixef	re_factor	re_entity	center	lower	upper
M_11_log	fixef	NA	Intercept	NA	NA	0.39	-0.53	1.57
M_11_log	fixef	NA	HUDHUD	NA	NA	1.68	0.37	3.54
M_11_log	fixef	NA	SemanticsEnhanced semantics	NA	NA	2.18	0.76	4.3
M_11_log	fixef	NA	HUDHUD:SemanticsEnhanced	NA	NA	1.60	-0.59	4.34

semantics

```
# random effects
print(M_11_log, digits = 2)
```

```
stan_glmer
 family:  binomial [logit]
 formula: Feelings_of_cooperationNum ~ HUD * Semantics + (HUD + Semantics |
           Subject)
------

Estimates:
                              Median MAD_SD
(Intercept)                   0.39   0.48
HUDHUD                        1.68   0.77
SemanticsNew semantics       2.18   0.85
HUDHUD:SemanticsNew semantics 1.60   1.24

Error terms:
 Groups  Name                   Std.Dev. Corr
 Subject (Intercept)            2.30
         HUDHUD                 2.53     -0.01
         SemanticsNew semantics 2.24      0.16  0.38
Num. levels: Subject 52

Sample avg. posterior predictive
distribution of y (X = xbar):
         Median MAD_SD
mean_PPD 0.74   0.03

------
For info on the priors used see help('prior_summary.stanreg').
```

```
  M_11_log_no_sub <- rstanarm::stan_glm(Feelings_of_cooperationLogical ~
HUD*Semantics, data = questionnaireDataModified, adapt_delta = 0.999,  family =
binomial(link = "logit")) # fit the model

  bayr::fixef(bayr::posterior(M_11_log_no_sub)) %>% kable()
print(M_11_log_no_sub, digits = 2)
```

```
# this model includes only fixed effects and no random effects to prevent
oversaturation.

if(file.exists("model_M_11_log_no_sub.rda")) {
  load("model_M_11_log_no_sub.rda") # load the model
} else {
  M_11_log_no_sub <- rstanarm::stan_glm(Feelings_of_cooperationLogical ~ H
UD*Semantics, data = questionnaireData, adapt_delta = 0.999, family = bino
mial(link="logit")) # fit the model
  save(M_11_log_no_sub, file = "model_M_11_log_no_sub.rda") # save the mod
el to a file

}
# calculate the credible interval of the fixed effects
bayr::fixef(posterior(M_11_log_no_sub)) %>% kable()
```

model	type	nonlin	fixef	re_factor	re_entity	center	lower	upper
M_11_log_no_sub	fixef	NA	Intercept	NA	NA	0.2105683	-0.3202091	0.7543306
M_11_log_no_sub	fixef	NA	HUDHUD	NA	NA	0.8027760	0.0049578	1.6169735
M_11_log_no_sub	fixef	NA	SemanticsNew semantics	NA	NA	1.0109249	0.1888588	1.8681931
M_11_log_no_sub	fixef	NA	HUDHUD:SemanticsNew semantics	NA	NA	0.2927146	-0.9926977	1.6635161

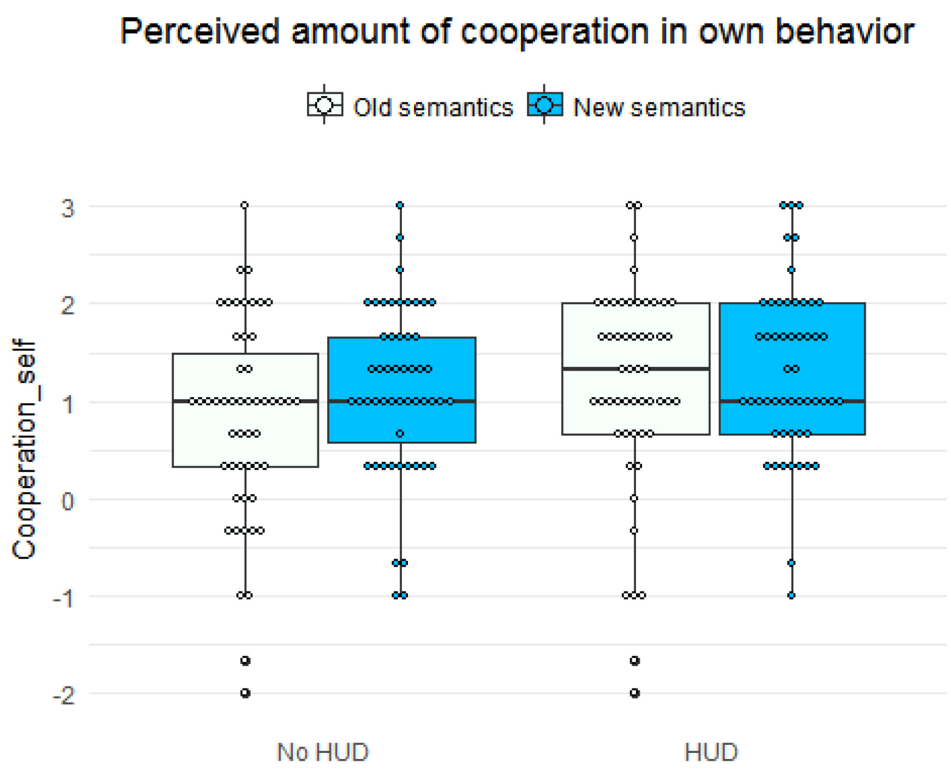
```r
# random effects
print(M_11_log_no_sub, digits = 2)
```

```
stan_glm
 family:  binomial [logit]
 formula: Feelings_of_cooperationLogical ~ HUD * Semantics
------

Estimates:
                              Median MAD_SD
(Intercept)                   0.21   0.28
HUDHUD                        0.80   0.40
SemanticsNew semantics        1.01   0.42
HUDHUD:SemanticsNew semantics 0.29   0.71

Sample avg. posterior predictive
distribution of y (X = xbar):
         Median MAD_SD
mean_PPD 0.74   0.04

------
For info on the priors used see help('prior_summary.stanreg').
```

How cooperative the subjects perceive their own behavior

```r
# check if the model already exists. If it does not, refit the model
if(file.exists("model_M_7_reduced.rda")) {
  load("model_M_7_reduced.rda") # load the model
} else {
  M_7_reduced <- rstanarm::stan_glmer(Cooperation_self ~ HUD*Semantics + (
HUD + Semantics | Subject), data = questionnaireData, adapt_delta = 0.99)
# fit the model
  save(M_7_reduced, file = "model_M_7_reduced.rda") # save the model to a
file
}

# Own cooperative behavior
ggplot(questionnaireData, aes(x=HUD, y=Cooperation_self, fill=Semantics))
+
  geom_boxplot(position = position_dodge(0.8)) +
  scale_fill_manual(values = c("mintcream", "deepskyblue1")) +
  geom_dotplot(binaxis = "y", stackdir = "center", dotsize = 0.5, position
```

```
 = position_dodge(0.8)) +
  ggtitle("Perceived amount of cooperation in own behavior")

## Warning: Removed 1 rows containing non-finite values (stat_boxplot).

## `stat_bindot()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 1 rows containing non-finite values (stat_bindot).
```




```
# calculate the credible interval of the fixed effects
bayr::fixef(posterior(M_7_reduced)) %>% kable()

## Warning in sqrt(c(0.84990409175607, 0.896879095142981, 0.80080083340314
5, :
## NaNs wurden erzeugt
```

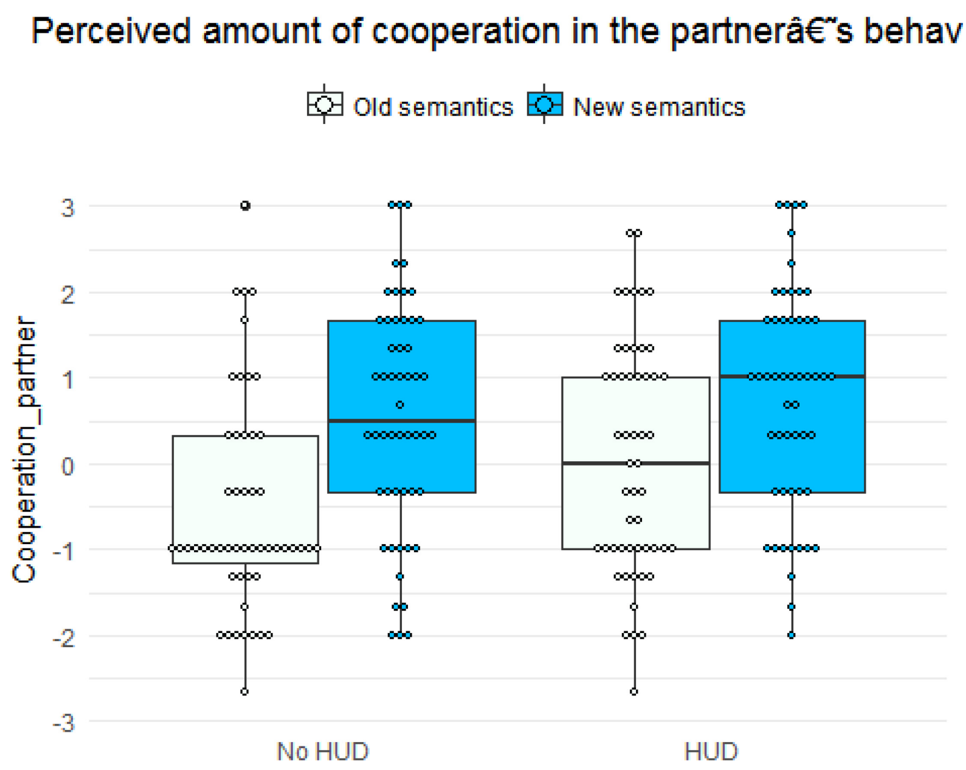
model	type	nonlin	fixef	re_factor	re_entity	center	lower	upper
M_7_reduced	fixef	NA	Intercept	NA	NA	0.80	0.54	1.06
M_7_reduced	fixef	NA	HUDHUD	NA	NA	0.34	0.03	0.64
M_7_reduced	fixef	NA	SemanticsEnhanced semantics	NA	NA	0.32	0.01	0.62
M_7_reduced	fixef	NA	HUDHUD:SemanticsEnhanced semantics	NA	NA	-0.17	-0.57	0.24

```
# random effects
print(M_7_reduced, digits = 2)
```

```
## stan_glmer
##  family:  gaussian [identity]
##  formula: Cooperation_self ~ HUD * Semantics + (HUD + Semantics | Subje
ct)
## ------
##
## Estimates:
##                                  Median MAD_SD
## (Intercept)                       0.80   0.13
## HUDHUD                            0.34   0.15
## SemanticsEnhanced semantics            0.32   0.16
## HUDHUD:SemanticsEnhanced semantics -0.17   0.21
## sigma                             0.77   0.05
##
## Error terms:
##  Groups   Name                     Std.Dev. Corr
##  Subject  (Intercept)              0.532
##           HUDHUD                   0.261     0.02
##           SemanticsEnhanced semantics 0.318    -0.13 -0.12
##  Residual                          0.771
## Num. levels: Subject 52
##
## Sample avg. posterior predictive
## distribution of y (X = xbar):
##          Median MAD_SD
## mean_PPD 1.09   0.08
##
## ------
## For info on the priors used see help('prior_summary.stanreg').
```

How cooperative the subjects perceive the partners' behavior

```
if(file.exists("model_M_8_reduced.rda")) {
  load("model_M_8_reduced.rda") # Load the model
} else {
  M_8_reduced <- rstanarm::stan_glmer(Cooperation_partner ~ HUD*Semantics
+ (HUD + Semantics | Subject), data = questionnaireData, adapt_delta = 0.9
9) # fit the model
  save(M_8_reduced, file = "model_M_8_reduced.rda") # save the model to a
file
}

# perceived cooperation of the partner
ggplot(questionnaireData, aes(x=HUD, y=Cooperation_partner, fill=Semantics
)) +
  geom_boxplot(position = position_dodge(0.8)) +
  scale_fill_manual(values = c("mintcream", "deepskyblue1")) +
  geom_dotplot(binaxis = "y", stackdir = "center", dotsize = 0.5, position
 = position_dodge(0.8)) +
  ggtitle("Perceived amount of cooperation in the partnerâ�˜s behavior")

## Warning: Removed 1 rows containing non-finite values (stat_boxplot).

## `stat_bindot()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 1 rows containing non-finite values (stat_bindot).
```




```
# calculate the credible interval of the fixed effects
bayr::fixef(posterior(M_8_reduced)) %>% kable()

## Warning in sqrt(c(-0.533858858428582, -0.717593343783349,
## -0.873573552923489, : NaNs wurden erzeugt
```

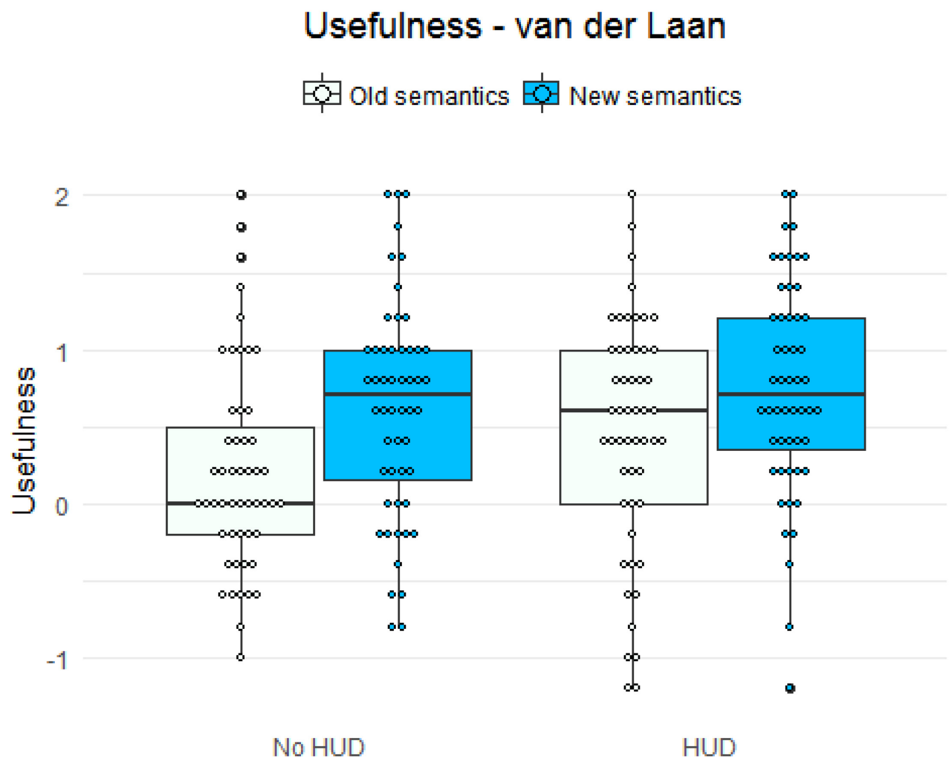
model	type	nonlin	fixef	re_factor	re_entity	center	lower	upper
M_8_reduced	fixef	NA	Intercept	NA	NA	-0.55	-0.90	-0.19
M_8_reduced	fixef	NA	HUDHUD	NA	NA	0.59	0.10	1.05
M_8_reduced	fixef	NA	SemanticsEnhanced semantics	NA	NA	1.09	0.64	1.57
M_8_reduced	fixef	NA	HUDHUD:SemanticsEnhanced semantics	NA	NA	-0.38	-1.04	0.26

```
# random effects
print(M_8_reduced, digits = 2)

## stan_glmer
##  family:  gaussian [identity]
##  formula: Cooperation_partner ~ HUD * Semantics + (HUD + Semantics | Su
bject)
## ------
##
## Estimates:
##                               Median MAD_SD
```

```
## (Intercept)                        -0.55   0.18
## HUDHUD                              0.59   0.23
## SemanticsEnhanced semantics          1.09   0.24
## HUDHUD:SemanticsEnhanced semantics -0.38   0.34
## sigma                               1.17   0.08
##
## Error terms:
##  Groups   Name                        Std.Dev. Corr
##  Subject  (Intercept)                 0.511
##           HUDHUD                      0.460     0.00
##           SemanticsEnhanced semantics 0.404    -0.12 -0.19
##  Residual                             1.168
## Num. levels: Subject 52
##
## Sample avg. posterior predictive
## distribution of y (X = xbar):
##          Median MAD_SD
## mean_PPD 0.20   0.11
##
## ------
## For info on the priors used see help('prior_summary.stanreg').
```

Usefulness of using the HUD or the enhanced semantics

```
# check if the model already exists. If it does not, refit the model
if(file.exists("model_M_1_reduced.rda")) {
  load("model_M_1_reduced.rda") # load the model
} else {
  M_1_reduced <- rstanarm::stan_glmer(Usefulness ~ HUD*Semantics + (HUD +
Semantics | Subject), data = questionnaireData, adapt_delta = 0.99) # fit
the model
  save(M_1_reduced, file = "model_M_1_reduced.rda") # save the model to a
file
}

# plot the Usefulness scale
ggplot(questionnaireData, aes(x=HUD, y=Usefulness, fill=Semantics)) +
  geom_boxplot(position = position_dodge(0.8)) +
  scale_fill_manual(values = c("mintcream", "deepskyblue1")) +
  geom_dotplot(binaxis = "y", stackdir = "center", dotsize = 0.5, position
 = position_dodge(0.8)) +
  ggtitle("Usefulness - van der Laan")

## Warning: Removed 1 rows containing non-finite values (stat_boxplot).

## `stat_bindot()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 1 rows containing non-finite values (stat_bindot).
```




```
# calculate the credible interval of the fixed effects
bayr::fixef(posterior(M_1_reduced)) %>% kable()

## Warning in sqrt(c(0.243968681409229, 0.195318273364611,
## 0.243023773324144, : NaNs wurden erzeugt
```

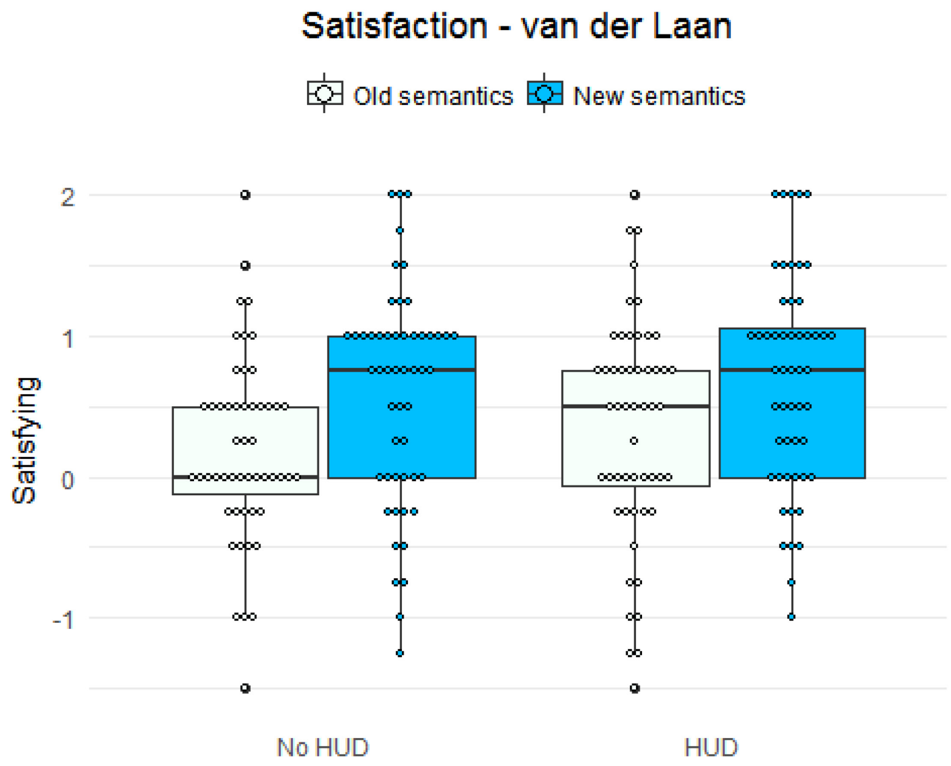
model	type	nonlin	fixef	re_factor	re_entity	center	lower	upper
M_1_reduced	fixef	NA	Intercept	NA	NA	0.21	0.02	0.39
M_1_reduced	fixef	NA	HUDHUD	NA	NA	0.25	-0.03	0.52
M_1_reduced	fixef	NA	SemanticsEnhanced semantics	NA	NA	0.40	0.14	0.67
M_1_reduced	fixef	NA	HUDHUD:SemanticsEnhanced semantics	NA	NA	-0.11	-0.47	0.27

```
# random effects
print(M_1_reduced, digits = 2)

## stan_glmer
##  family:  gaussian [identity]
##  formula: Usefulness ~ HUD * Semantics + (HUD + Semantics | Subject)
## ------
##
## Estimates:
##                                 Median MAD_SD
## (Intercept)                      0.21   0.09
```

```
## HUDHUD                         0.25   0.14
## SemanticsEnhanced semantics         0.40   0.14
## HUDHUD:SemanticsEnhanced semantics -0.11   0.19
## sigma                          0.65   0.04
##
## Error terms:
##  Groups   Name                        Std.Dev. Corr
##  Subject  (Intercept)                 0.150
##           HUDHUD                      0.261    -0.05
##           SemanticsEnhanced semantics 0.230    -0.17  0.35
##  Residual                             0.652
## Num. levels: Subject 52
##
## Sample avg. posterior predictive
## distribution of y (X = xbar):
##          Median MAD_SD
## mean_PPD 0.50   0.06
##
## ------
## For info on the priors used see help('prior_summary.stanreg').
```

Satisfaction of using a HUD or the enhanced semantics

```
# check if the model already exists. If it does not, refit the model
if(file.exists("model_M_2_reduced.rda")) {
  load("model_M_2_reduced.rda") # load the model
} else {
  M_2_reduced <- rstanarm::stan_glmer(Satisfying ~ HUD*Semantics + (HUD +
Semantics | Subject), data = questionnaireData, adapt_delta = 0.99) # fit
the model
  save(M_2_reduced, file = "model_M_2_reduced.rda") # save the model to a
file
}

# plot the Satisfying scale
ggplot(questionnaireData, aes(x=HUD, y=Satisfying, fill=Semantics)) +
  geom_boxplot(position = position_dodge(0.8)) +
  scale_fill_manual(values = c("mintcream", "deepskyblue1")) +
  geom_dotplot(binaxis = "y", stackdir = "center", dotsize = 0.5, position
 = position_dodge(0.8)) +
  ggtitle("Satisfaction - van der Laan")

## Warning: Removed 1 rows containing non-finite values (stat_boxplot).

## `stat_bindot()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 1 rows containing non-finite values (stat_bindot).
```




```
# calculate the credible interval of the fixed effects
bayr::fixef(posterior(M_2_reduced)) %>% kable()

## Warning in sqrt(c(0.396776375867817, 0.0893251313110427,
## 0.40110171877399, : NaNs wurden erzeugt
```

model	type	nonlin	fixef	re_factor	re_entity	center	lower	upper
M_2_reduced	fixef	NA	Intercept	NA	NA	0.19	-0.01	0.39
M_2_reduced	fixef	NA	HUDHUD	NA	NA	0.14	-0.14	0.42
M_2_reduced	fixef	NA	SemanticsEnhanced semantics	NA	NA	0.40	0.12	0.67
M_2_reduced	fixef	NA	HUDHUD:SemanticsEnhanced semantics	NA	NA	-0.05	-0.43	0.33

```
# random effects
print(M_2_reduced, digits = 2)

## stan_glmer
##  family:  gaussian [identity]
##  formula: Satisfying ~ HUD * Semantics + (HUD + Semantics | Subject)
## ------
##
## Estimates:
##                                Median MAD_SD
```

```
## (Intercept)                      0.19   0.10
## HUDHUD                           0.14   0.14
## SemanticsEnhanced semantics         0.40   0.14
## HUDHUD:SemanticsEnhanced semantics -0.05   0.19
## sigma                            0.69   0.05
##
## Error terms:
##  Groups   Name                        Std.Dev. Corr
##  Subject  (Intercept)                 0.131
##           HUDHUD                      0.321    -0.18
##           SemanticsEnhanced semantics 0.262    -0.36  0.02
##  Residual                             0.695
## Num. levels: Subject 52
##
## Sample avg. posterior predictive
## distribution of y (X = xbar):
##          Median MAD_SD
## mean_PPD 0.45   0.07
##
## ------
## For info on the priors used see help('prior_summary.stanreg').
```

Demographics

The demographic values and the additional questions are analyzed here.

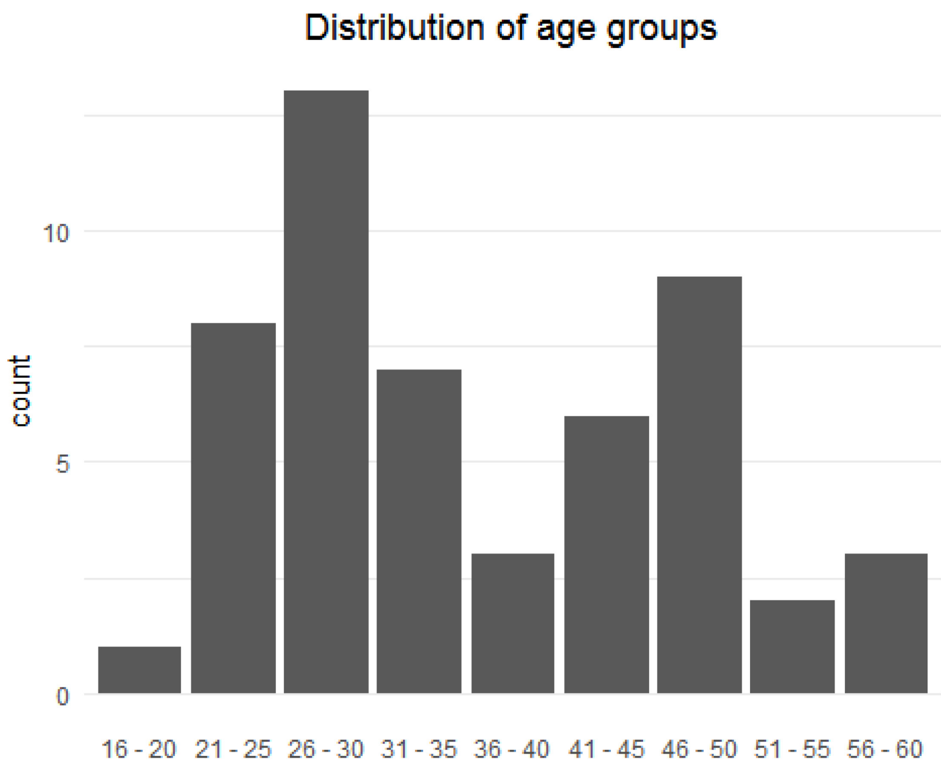
import the additional data

```
additional_qs_raw <- as.data.frame(read_csv2("/Users/VW8F1X8/Desktop/Studi
e 3/Datenfreude/DATEN/Fragebogendaten/preparation/demographic_variables.cs
v"))

## Using ',' as decimal and '.' as grouping mark. Use read_delim() for mor
e control.

## Warning: Missing column names filled in: 'X33' [33], 'X34' [34]

## Parsed with column specification:
## cols(
##   .default = col_character(),
##   `Bitte geben Sie zun<e4>chst Ihre Versuchspersonen Nummer an. Diese b
ekommen Sie von dem Versuchsleiter.` = col_integer(),
##   `[Wie viel km fahren Sie ungef<e4>hr im Jahr?]` = col_integer(),
##   `[Seit wie vielen Jahren sind Sie im Besitz eines F<fc>hrerscheins?]`
 = col_integer(),
##   `(Falls Sie die vorige Frage mit "Ja" beantwortet haben)  Wie h<e4>uf
ig haben Sie pro Monat dieses Gef<fc>hl?  <U+00A0>  <U+00A0>  <U+00A0>` =
col_integer()
## )

## See spec(...) for full column specifications.

colnames(additional_qs_raw) <- c("Subject", "Gender", "yearly_km", "years_
drivers_license", "experience_acc", "experience_tempomat", "experience_sid
e_assist", "experience_park_assist", "age", "helping_others_selfless", "he
lping_others_system_efficiency", "no_helping_others", "early_indication_ot
hers", "use_of_gestures", "letting_others_pass", "system_efficiency_selfle
```

```
ss", "selfish_driving", "braking_for_others_selfless", "easily_stressed",
"no_braking_for_others_selfish", "helping_others_giving_way", "personality
_reserved", "personality_optimistic", "personality_laziness", "personality
_relaxed", "personality_no_art", "personality_socializing", "personality_c
riticizing", "personality_tasks_thoroughly", "personality_nervous_insecure
", "personality_imagination", "X33", "X44", "Concept_raisingAlertness_slee
pInducing", "situationsInWhichTurnSignalWasInsufficient", "howManyTimesIns
ufficientAMonth", "WasTurnSignalInsufficientForLaneChange", "ranking_no1",
 "ranking_no2", "ranking_no3", "ranking_no4", "Comments" )

# additional_qs <-    lapply(additional_qs_raw, FUN = function(foo) recode
(foo, "'- - -'='-3'; '- -'='-2'; '-'='-1'; 'o'='0'; '+'='1'; '+ +'='2'; '+
 + +'='3'"))
# additional_qs <- data.frame(additional_qs)
```

Some frequencies of the demographics

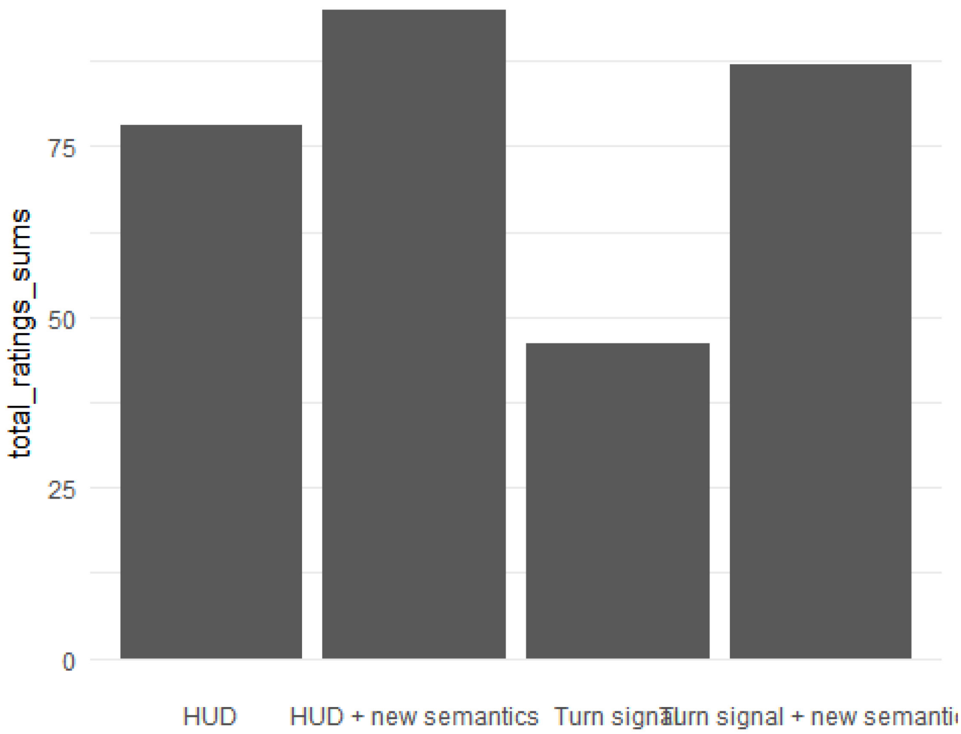
```
subset(additional_qs_raw, !is.na(age)) %>% # exclude NA values
  ggplot(aes(age)) +
  geom_bar(na.rm = TRUE) +
  scale_fill_manual(values = c("gray", "dodgerblue3")) +
  ggtitle("Distribution of age groups")
```



The ranking of the different concepts

```
##
##             Head Up Anzeige            Standard Blinker
##                          12                           5
## Zweistufige Head Up Anzeige        Zweistufiger Blinker
##                          20                          14
```

```
##
##             Head Up Anzeige            Standard Blinker
##                          13                           9
## Zweistufige Head Up Anzeige        Zweistufiger Blinker
##                          12                          17

##
##             Head Up Anzeige            Standard Blinker
##                          16                          13
## Zweistufige Head Up Anzeige        Zweistufiger Blinker
##                          11                          11

##
##             Head Up Anzeige            Standard Blinker
##                          10                          24
## Zweistufige Head Up Anzeige        Zweistufiger Blinker
##                           8                           9

## Don't know how to automatically pick scale for object of type data.fram
e. Defaulting to continuous.
```




```
# statistical analysis

sapply(additional_qs_raw$age, mean, na.rm=TRUE)

table(additional_qs_raw$age)

##
## 16 - 20 21 - 25 26 - 30 31 - 35 36 - 40 41 - 45 46 - 50 51 - 55 56 - 60

##       1       8      13       7       3       6       9       2       3
```

```
temp_age <- (18 + 23*8 +28*13 + 33*7 +38*3 +43*6+48*9+53*2 + 58*3)/52
temp_age

## [1] 36

median(additional_qs_raw$age)

## Warning in mean.default(sort(x, partial = half + 0L:1L)[half + 0L:1L]):
## argument is not numeric or logical: returning NA

## [1] NA

frequency(additional_qs_raw$age)

## [1] 1
```

General Linear Mixed Model

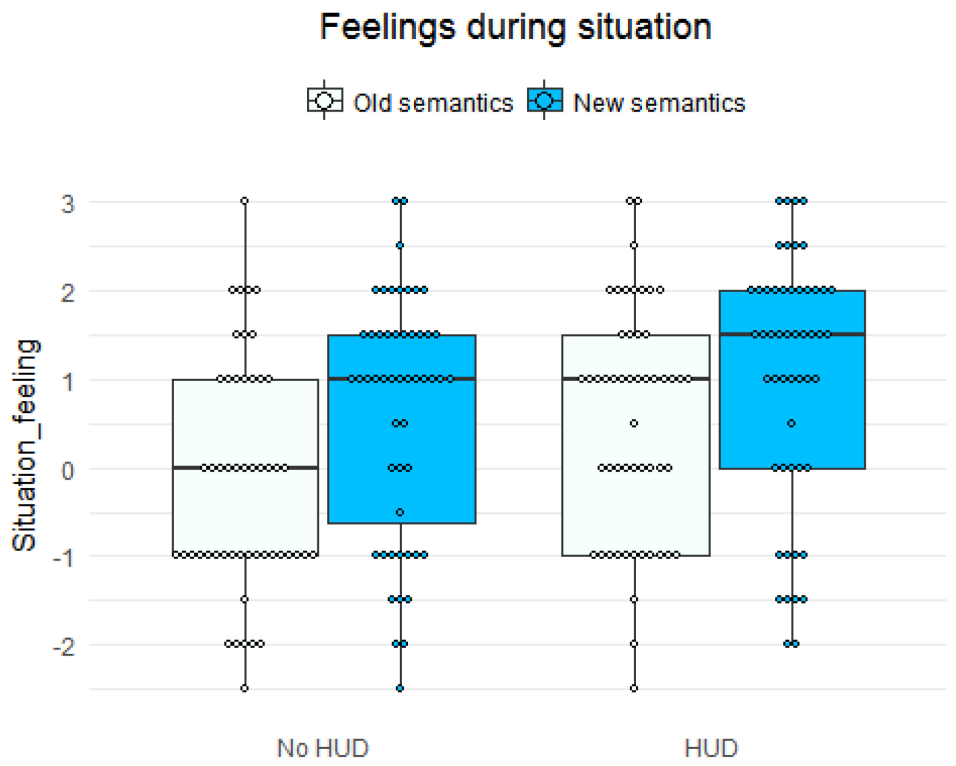
ALLOWS TO SEE WHETHER OR NOT THERE IS A LOT OF DIFFERENCE AMONG THE PARTICIPANTS. Because the normal STAN_GLM only reports the mean of the effects across the participants. So this way enables us to see what the values of the participants are. We can then take a look at the sigma (of the participants). A high sigma indicates that the effects differ a lot between the participants and thus that the HUD might work differently for all participants.

Plot the feeling regarding the whole situation

This is no longer used because it measures the same thing as lane change feeling does.

```
# check if the model already exists. If it does not, refit the model
if(file.exists("model_M_5.rda")) {
  load("model_M_5.rda") # load the model
} else {
  M_5 <- rstanarm::stan_glmer(Situation_feeling ~ HUD*Semantics + (HUD*Sem
antics | Subject), data = questionnaireData, adapt_delta = 0.9999999999999
) # fit the model
  save(M_5, file = "model_M_5.rda") # save the model to a file
}

if(file.exists("model_M_5_reduced.rda")) {
  load("model_M_5_reduced.rda") # load the model
} else {
  M_5_reduced <- rstanarm::stan_glmer(Situation_feeling ~ HUD*Semantics +
(HUD + Semantics | Subject), data = questionnaireData, adapt_delta = 0.99)
 # fit the model
  save(M_5_reduced, file = "model_M_5_reduced.rda") # save the model to a
file
}

# feeling regarding the whole situation
ggplot(questionnaireData, aes(x=HUD, y=Situation_feeling, fill=Semantics))
 +
  geom_boxplot(position = position_dodge(0.8)) +
  scale_fill_manual(values = c("mintcream", "deepskyblue1")) +
  geom_dotplot(binaxis = "y", stackdir = "center", dotsize = 0.5, position
```

```
 = position_dodge(0.8)) +
  ggtitle("Feelings during situation")

## Warning: Removed 1 rows containing non-finite values (stat_boxplot).

## `stat_bindot()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 1 rows containing non-finite values (stat_bindot).
```




```
# calculate the credible interval
bayr::fixef(M_5_reduced) %>% kable()

## Warning in sqrt(c(-0.340277258592002, -0.227633501094194,
## -0.267071098539806, : NaNs wurden erzeugt
```

model	type	nonlin	fixef	re_factor	re_entity	center	lower	upper
object	fixef	NA	Intercept	NA	NA	-0.19	-0.54	0.16
object	fixef	NA	HUDHUD	NA	NA	0.69	0.21	1.17
object	fixef	NA	SemanticsEnhanced semantics	NA	NA	0.82	0.35	1.29
object	fixef	NA	HUDHUD:SemanticsEnhanced semantics	NA	NA	-0.31	-0.97	0.34

Creating the special dynamite plot

Adrian Benjamin Haeske

2 10 2017

Load the libraries.

```
library(knitr)
library(rstanarm)

## Loading required package: Rcpp

## rstanarm (Version 2.15.3, packaged: 2017-04-29 06:18:44 UTC)

## - Do not expect the default priors to remain the same in future rstanar
m versions.

## Thus, R scripts should specify priors explicitly, even if they are just
 the defaults.

## - For execution on a local, multicore CPU with excess RAM we recommend
calling

## options(mc.cores = parallel::detectCores())

library(tidyverse)

## Loading tidyverse: ggplot2
## Loading tidyverse: tibble
## Loading tidyverse: tidyr
## Loading tidyverse: readr
## Loading tidyverse: purrr
## Loading tidyverse: dplyr

## Conflicts with tidy packages ------------------------------------------
----

## filter(): dplyr, stats
## lag():    dplyr, stats
```

remember that there are conditions where something is missing so, don't always divide by 3 for the average. instead, divide by the amount of numbers that were summed up.

1 c.3 3 a.3 3 d.1 3 d.2 4 c.1 4 c.2 4 d.1 15 c.3 27 c.1 27 c.2 27 c.3

I want to make a special plot. That plot shows the proportion of lane changes on the *y-axis*. It has the four different conditions on the *x-axis*. That is nothing new so far. However, for now I have simply displayed the count. And I have not calculated anything. Thus, I am now going to calculate the *proportion of lane changes for every individual participant*. (proportion of lane changes allowed in A, proportion of lane changes allowed in B, ...). This will allow me to display the sd of those proportions (e.g. in a dynamite plot).

Import the data that is related to the lane changes. (TRUE or FALSE for each conditon)

```
# check if the lanechangedtafile has already been read before and exists a
s rda file. If it does not, read it in!
if(file.exists("laneChangeData.rda")) {
  load("laneChangeData.rda") # load the model
} else {
  laneChangeData <- read_csv2("/Users/adrianhaeske/Desktop/DIE DATEN/Data/
Studie 3/Datenfreude/DATEN/laneChangeData.csv")
  save(laneChangeData, file = "laneChangeData.rda") # save the data to a f
ile
}

# convert from numerical to logical values
laneChangeData$LaneChanged <- as.logical(laneChangeData$LaneChanged)

# first I have to convert the False and True into Numericals in order to b
e able to plot them
laneChangeData$LaneChangedNumeric <- as.numeric(laneChangeData$LaneChanged
)
```

preparation Plot 1

```
tempLaneChangeData <- laneChangeData %>% # make a temp copy of the df
  na.omit()# remove all the NA values

LCPropListA <- list()
LCPropListB <- list()
LCPropListC <- list()
LCPropListD <- list()

for(vpNumber in 1:53) {
LCPropListA[vpNumber] <-
    tempLaneChangeData %>%
    filter(Condition=="a" & Subject == as.character(vpNumber)) %>% # selec
t only condition a and the current participant
    select(LaneChangedNumeric) %>% # select only the LaneChangedNumeric co
lumn
    colMeans() #calculate the mean of the column lanechangednumeric

LCPropListB[vpNumber] <-
    tempLaneChangeData %>%
    filter(Condition=="b" & Subject == as.character(vpNumber)) %>% # selec
t only condition a and the current participant
    select(LaneChangedNumeric) %>% # select only the LaneChangedNumeric co
lumn
    colMeans() #calculate the mean of the column lanechangednumeric

LCPropListC[vpNumber] <-
    tempLaneChangeData %>%
    filter(Condition=="c" & Subject == as.character(vpNumber)) %>% # selec
t only condition a and the current participant
    select(LaneChangedNumeric) %>% # select only the LaneChangedNumeric co
```

```
lumn
    colMeans() #calculate the mean of the column lanechangednumeric

LCPropListD[vpNumber] <-
    tempLaneChangeData %>%
    filter(Condition=="d" & Subject == as.character(vpNumber)) %>% # selec
t only condition a and the current participant
    select(LaneChangedNumeric) %>% # select only the LaneChangedNumeric co
lumn
    colMeans() #calculate the mean of the column lanechangednumeric
}

# combine the lists into a dataframe
LCPropDF <- do.call(rbind.data.frame, Map('c', LCPropListA, LCPropListB, L
CPropListC, LCPropListD))
colnames(LCPropDF) <- c("A","B", "C", "D") # rename the columns of this df

 LCPropListTotal <-c(LCPropListA, LCPropListB, LCPropListC, LCPropListD)
#LCPropListTotal <-append(LCPropListA, LCPropListB, LCPropListC, LCPropLis
tD)

 # LCPropListTotal is a list of 212. I want to turn it into num
LCNum <- as.numeric(unlist(LCPropListTotal))
```

Convert the data into the long format

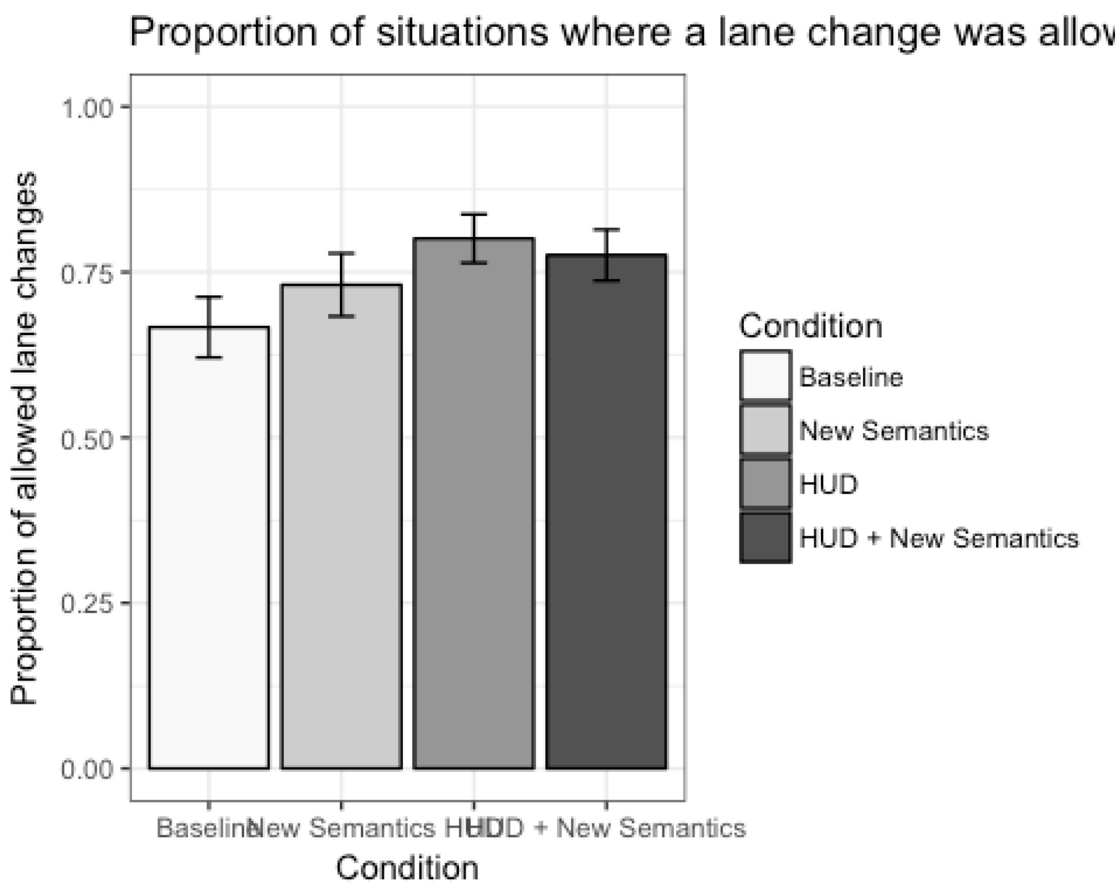
```
participantNumbers <- rep(1:53, times = 4) # create a column with the part
icipantnumbers (1,2,3,4,5,6,7,8,9,...)
# test <- test[-c(50, 103, 156, 209)] # remove the four entries with the v
pNumber == 50

conditions <- rep(c("A", "B", "C", "D"), times = c(53,53,53,53)) # create
a column with the conditions (A,A,A,A,A,A,A;A;A;A,A,A...)

# create a new df that will be filled in the long format
LaneChangePropabilitiesDF <- data_frame(participantNumbers, conditions, LC
Num)
colnames(LaneChangePropabilitiesDF) <- c("Participant", "Condition", "LCPr
oportion")

# turn conditions into a factor
LaneChangePropabilitiesDF$Condition <- as.factor(LaneChangePropabilitiesDF
$Condition)
```

Plot the data.. Plot number 1 http://www.cookbook-r.com/Graphs/Plotting_means_and_error_bars_%28ggplot2%29/

```
## Gives count, mean, standard deviation, standard error of the mean, and
confidence interval (default 95%).
##   data: a data frame.
##   measurevar: the name of a column that contains the variable to be sum
marizeed
##   groupvars: a vector containing names of columns that contain grouping
 variables
##   na.rm: a boolean that indicates whether to ignore NA's
```

```
##   conf.interval: the percent range of the confidence interval (default
is 95%)
summarySE <- function(data=NULL, measurevar, groupvars=NULL, na.rm=FALSE,
                      conf.interval=.95, .drop=TRUE) {
    library(plyr)

    # New version of length which can handle NA's: if na.rm==T, don't coun
t them
    length2 <- function (x, na.rm=FALSE) {
        if (na.rm) sum(!is.na(x))
        else       length(x)
    }

    # This does the summary. For each group's data frame, return a vector
with
    # N, mean, and sd
    datac <- ddply(data, groupvars, .drop=.drop,
      .fun = function(xx, col) {
        c(N    = length2(xx[[col]], na.rm=na.rm),
          mean = mean   (xx[[col]], na.rm=na.rm),
          sd   = sd     (xx[[col]], na.rm=na.rm)
        )
      },
      measurevar
    )

    # Rename the "mean" column
    datac <- rename(datac, c("mean" = measurevar))

    datac$se <- datac$sd / sqrt(datac$N)  # Calculate standard error of th
e mean

    # Confidence interval multiplier for standard error
    # Calculate t-statistic for confidence interval:
    # e.g., if conf.interval is .95, use .975 (above/below), and use df=N-
1
    ciMult <- qt(conf.interval/2 + .5, datac$N-1)
    datac$ci <- datac$se * ciMult

    return(datac)
}

#calculate se and stuff
summaryOfLC <- summarySE(na.omit(LaneChangePropabilitiesDF), measurevar =
"LCProportion", groupvars = "Condition")

## ------------------------------------------------------------------------
--

## You have loaded plyr after dplyr - this is likely to cause problems.
## If you need functions from both plyr and dplyr, please load plyr first,
 then dplyr:
## library(plyr); library(dplyr)
```

```
## ------------------------------------------------------------------------
--

##
## Attaching package: 'plyr'

## The following objects are masked from 'package:dplyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize

## The following object is masked from 'package:purrr':
##
##     compact

# change the names of the different levels of the condition factor
summaryOfLCTest <- summaryOfLC # backup copy of the summary dataframe
summaryOfLCTest$Condition <- factor(c("Baseline", "Enhanced semantics", "H
UD", "HUD + Enhanced semantics"), levels = c("Baseline", "Enhanced semanti
cs", "HUD", "HUD + Enhanced semantics")) # create an ordered factor

# plot the bars
# Error bars represent standard error of the mean
ggplot(summaryOfLCTest, aes(x=Condition, y=LCProportion, fill = Condition)
) +
    geom_bar(position=position_dodge(), stat="identity", colour = "black")
 +
    geom_errorbar(aes(ymin=LCProportion-se, ymax=LCProportion+se),
                  width=.2,                    # Width of the error bars
                  position=position_dodge(.9)) +
  coord_cartesian(ylim=c(0,1)) +
  theme_bw() +
  scale_fill_brewer(palette="Greys") +
  ggtitle("Proportion of situations where a lane change was allowed") +
  xlab("Condition") +
  ylab("Proportion of allowed lane changes")
```

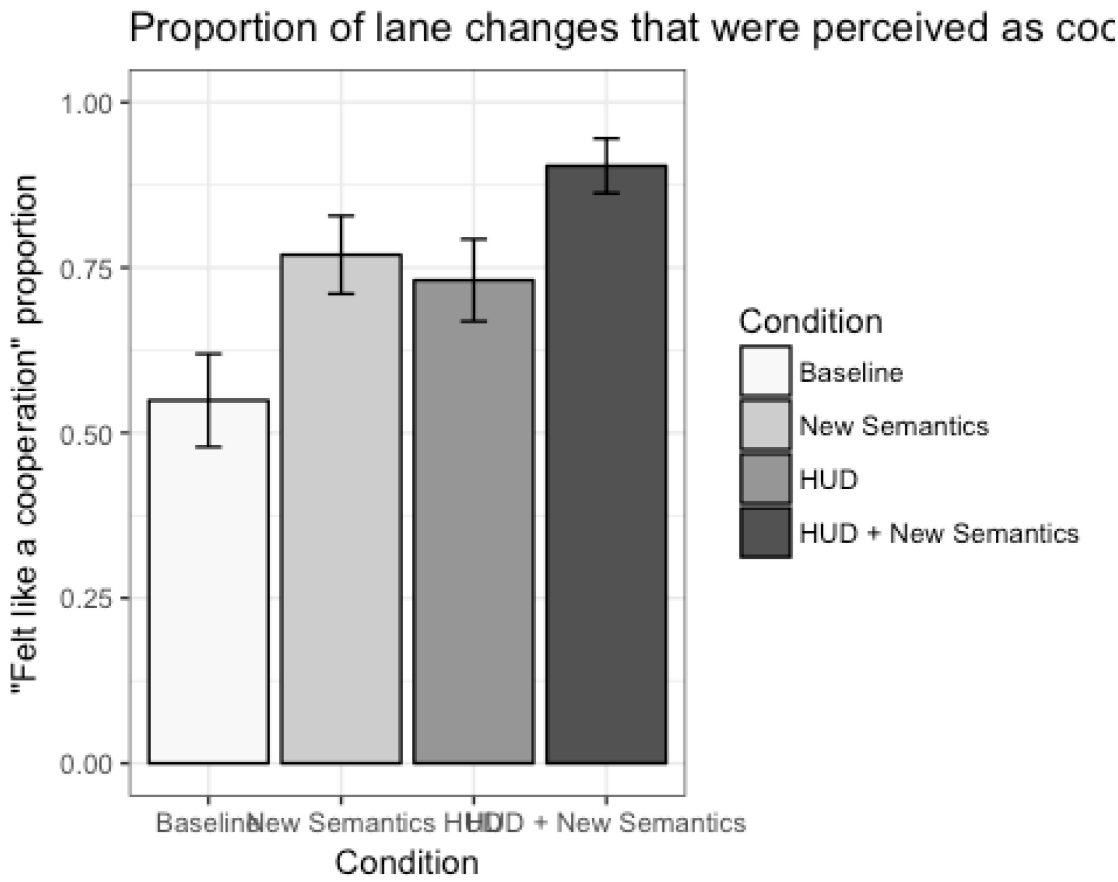


Plot number 2

preparation of the data for plot 2

```
# import the data
isCooperationDF <- read_csv2("isCooperationData.csv")

## Parsed with column specification:
## cols(
##   Participant = col_integer(),
##   Condition = col_character(),
##   isCooperation = col_character()
## )

# turn the isCooperation into a numeric
isCooperationDF$isCooperation <- as.numeric(isCooperationDF$isCooperation)

## Warning: NAs durch Umwandlung erzeugt

# calculate the se and means
cooperationSummary <- summarySE(na.omit(isCooperationDF), measurevar = "is
Cooperation", groupvars = "Condition")

# change the names of the different levels of the condition factor
cooperationSummary$Condition <- factor(c("Baseline", "Enhanced semantics",
 "HUD", "HUD + Enhanced semantics"), levels = c("Baseline", "Enhanced sema
ntics", "HUD", "HUD + Enhanced semantics")) # create an ordered factor

# plot the bars
# Error bars represent standard error of the mean
```

```
ggplot(cooperationSummary, aes(x=Condition, y=isCooperation, fill = Condit
ion)) +
    geom_bar(position=position_dodge(), stat="identity", colour = "black")
 +
    geom_errorbar(aes(ymin=isCooperation-se, ymax=isCooperation+se),
                  width=.2,                    # Width of the error bars
                  position=position_dodge(.9)) +
  coord_cartesian(ylim=c(0,1)) +
  theme_bw() +
  scale_fill_brewer(palette="Greys") +
  ggtitle("Proportion of lane changes that were perceived as cooperation")
 +
  xlab("Condition") +
  ylab('"Felt like a cooperation" proportion')
```



Analysis of the driving data

loading the libraries

Load the libraries.

```
# sicherstellen, dass er auch in meiner R Space Library schaut.
.libPaths("C:/Users/VW8F1X8/R Space/Libraries")
library(knitr)
library(rstanarm)

## Loading required package: Rcpp

## rstanarm (Version 2.15.3, packaged: 2017-04-29 06:18:44 UTC)

## - Do not expect the default priors to remain the same in future rstanar
m versions.

## Thus, R scripts should specify priors explicitly, even if they are just
 the defaults.

## - For execution on a local, multicore CPU with excess RAM we recommend
calling

## options(mc.cores = parallel::detectCores())

library(tidyverse)

## Loading tidyverse: ggplot2
## Loading tidyverse: tibble
## Loading tidyverse: tidyr
## Loading tidyverse: readr
## Loading tidyverse: purrr
## Loading tidyverse: dplyr

## Conflicts with tidy packages -------------------------------------------
----

## filter(): dplyr, stats
## lag():    dplyr, stats

library(bayr)

##
## Attaching package: 'bayr'

## The following objects are masked from 'package:rstanarm':
##
##     fixef, ranef

## The following objects are masked from 'package:stats':
##
##     coef, predict
```

This document holds the analysis of the driving data.

Importing the data

Import the filtered data.

```
# check if the datafile has already been read before and exists as rda fil
e. If it does not, read it in!
if(file.exists("filteredData.rda")) {
  load("filteredData.rda") # load the model
} else {
  filteredData <- read.csv("/Users/VW8F1X8/Desktop/Studie 3/Datenfreude/DA
TEN/filteredDataStudyThree.csv")
  save(filteredData, file = "filteredData.rda") # save the data to a file
}
```

Import the data that is related to the lane changes. (TRUE or FALSE for each conditon)

```
# check if the lanechangedtafile has already been read before and exists a
s rda file. If it does not, read it in!
if(file.exists("laneChangeData.rda")) {
  load("laneChangeData.rda") # load the model
} else {
  laneChangeData <- read_csv2("/Users/VW8F1X8/Desktop/Studie 3/Datenfreude
/DATEN/laneChangeData.csv")
  save(laneChangeData, file = "laneChangeData.rda") # save the data to a f
ile
}

# convert from numerical to logical values
laneChangeData$LaneChanged <- as.logical(laneChangeData$LaneChanged)
```

Add the new factors HUD and 2Levels

```
# make the value of HUD 1 if it is conditionC or D, else make it 0
# also make it a factor
laneChangeData$HUD <- factor(ifelse(laneChangeData$Condition == "c", "HUD"
, ifelse(laneChangeData$Condition == "d", "HUD", "No HUD")))

# make the value of TwoSemantics 1 if it is conditionB or D, else make it
0
laneChangeData$Semantics <- factor(ifelse(laneChangeData$Condition == "b",
 "Enhanced semantics", ifelse(laneChangeData$Condition == "d", "Enhanced s
emantics", "Old semantics")))

# also relevel the factor HUD to make sure that "No HUD" is the reference
value in intercepts
laneChangeData <- within(laneChangeData, HUD <- relevel(HUD, ref = "No HUD
"))
laneChangeData <- within(laneChangeData, Semantics <- relevel(Semantics, r
ef = "Old semantics"))
```

Visualizations

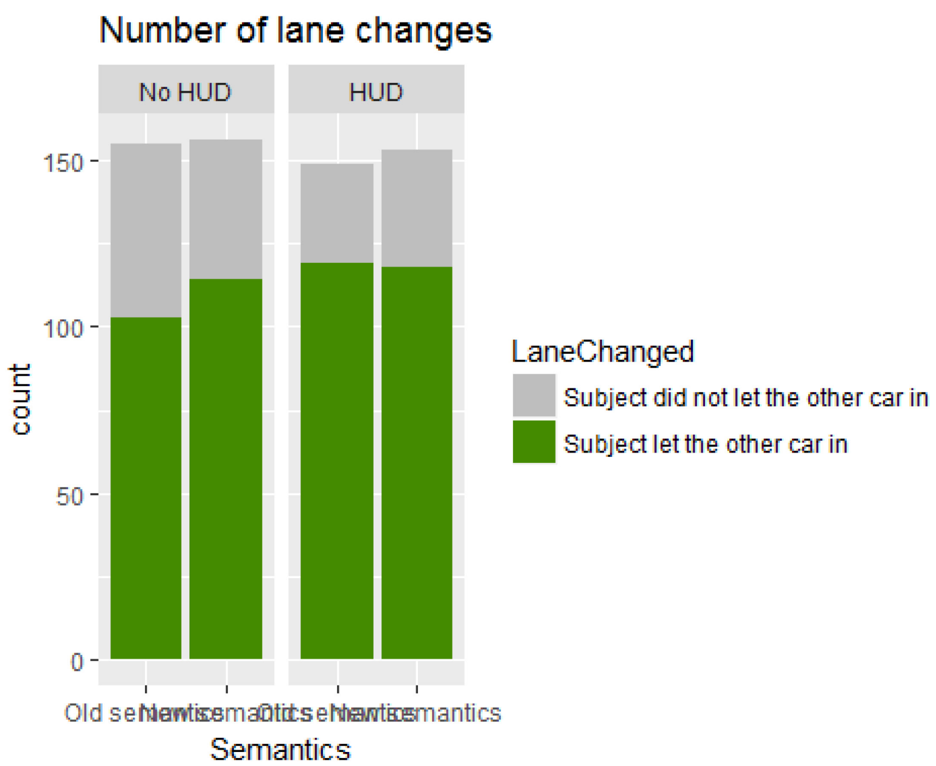
Cooperation (lane changes)

NUMBER OF TIMES IN WHICH THE CAR WAS LET IN

Here I will look for the moments in which the subject let the other car in. This will be regarded as the objective measurement of cooperative behavior.

Number of times that the subjects allowed the partner to perform a lane change

```
# first I have to convert the False and True into Numericals in order to b
e able to plot them
laneChangeData$LaneChangedNumeric <- as.numeric(laneChangeData$LaneChanged
)

# laneChangeData %>%
#   ggplot(aes(x=LaneChanged)) +
#   stat_count(fill="lightgreen") +
#   ggtitle("HUD")

# in general (all situations). plot is divided by condition
subset(laneChangeData, !is.na(LaneChanged)) %>%
    ggplot(aes(Semantics, fill=LaneChanged)) +
    geom_bar(na.rm = TRUE) +
    scale_fill_manual(labels = c("Subject did not let the other car in", "
Subject let the other car in"), values = c("gray", "chartreuse4")) +
    ggtitle("Number of lane changes") +
  facet_grid(. ~ HUD)
```




```
# CORRECTED MODEL with logistic scale
```

```
# check if the model has already been created and exists as rda file. If i
t does not, refit it!

if(file.exists("M_1_objective_log.rda")) {

  load("M_1_objective_log.rda") # load the model

} else {

  # model that predicts the lanechanges with HUD, semantics and their inte
raction as fixed effects and HUD and semantics as random slopes that are c
onditional on subject

 M_1_objective_log <- rstanarm::stan_glmer(data = laneChangeData, LaneChan
ged ~ HUD*Semantics + (HUD + Semantics | Subject), adapt_delta = 0.999, fa
mily = binomial(link = "logit"))

  # TODO refit this model so that it holds the data for situation as well.
 (i added it already, but it has not yet been computed)

  save(M_1_objective_log, file = "M_1_objective_log.rda") # save the model
 to a file

}



bayr::fixef(M_1_objective_log) %>% kable()

print(M_1_objective_log, digits = 2)
```

model	type	nonlin	fixef	re_factor	re_entity	center	lower	upper
object	fixef	NA	Intercept	NA	NA	0.92	0.39	1.49
object	fixef	NA	HUDHUD	NA	NA	0.94	0.31	1.67
object	fixef	NA	SemanticsEnhanced semantics	NA	NA	0.45	-0.14	1.08
object	fixef	NA	HUDHUD:SemanticsEnhanced semantics	NA	NA	-0.61	-1.48	0.19

```
print(M_1_objective, digits = 2)
```

```
NaNs wurden erzeugtstan_glmer
 family:  binomial [logit]
 formula: LaneChanged ~ HUD * Semantics + (HUD + Semantics | Subject)
------

Estimates:
                                     Median MAD_SD
```

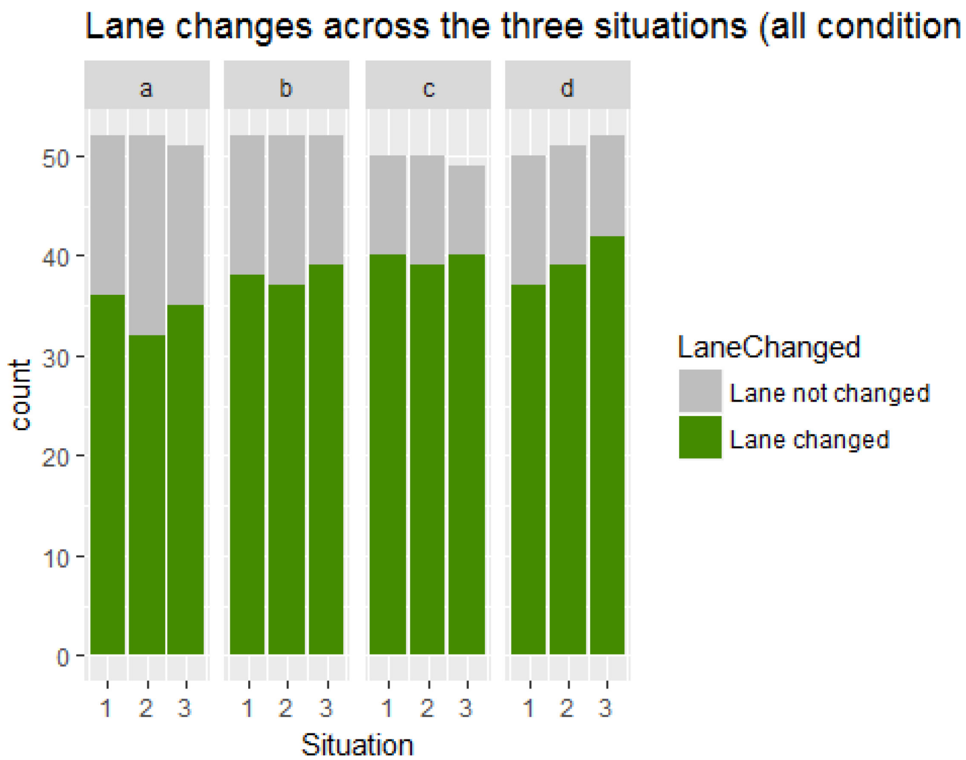
```
(Intercept)                          0.92   0.27
HUDHUD                               0.94   0.34
SemanticsEnhanced semantics          0.45   0.31
HUDHUD:SemanticsEnhanced semantics -0.61   0.43

Error terms:
 Groups  Name                        Std.Dev. Corr
 Subject (Intercept)                 1.326
         HUDHUD                      0.620     0.01
         SemanticsEnhanced semantics 0.641     0.00 -0.37
Num. levels: Subject 52

Sample avg. posterior predictive
distribution of y (X = xbar):
         Median MAD_SD
mean_PPD 0.74   0.02

------
For info on the priors used see help('prior_summary.stanreg').
```

```
 # fit a model to see whether or not there was a learning effect
# check if the model has already been created and exists as rda file. If i
t does not, refit it!
if(file.exists("M_2_objective.rda")) {
  load("M_2_objective.rda") # load the model
} else {
  # also include the situation in the model to see whether there was a lea
rning effect. (e.g. did the subjects let the other car in more often or le
ss often in later trials?)
  M_2_objective <- rstanarm::stan_glm(data = laneChangeData, LaneChanged ~
 HUD*Semantics + Situation, adapt_delta = 0.999)
  save(M_2_objective, file = "M_2_objective.rda") # save the model to a fi
le
}

bayr::fixef(M_2_objective) %>%  kable() # return the fixed effects
```

model	type	nonlin	fixef	re_factor	re_entity	center	lower	upper
object	fixef	NA	Intercept	NA	NA	0.6391076	0.5293946	0.7474789
object	fixef	NA	HUDHUD	NA	NA	0.1347334	0.0361693	0.2282530
object	fixef	NA	SemanticsEnhanced semantics	NA	NA	0.0671447	-0.0304291	0.1631355
object	fixef	NA	Situation	NA	NA	0.0121957	-0.0293147	0.0548846
object	fixef	NA	HUDHUD:SemanticsEnhanced semantics	NA	NA	-0.0944846	-0.2286688	0.0414774

Examining a potential order effect
Within the conditions

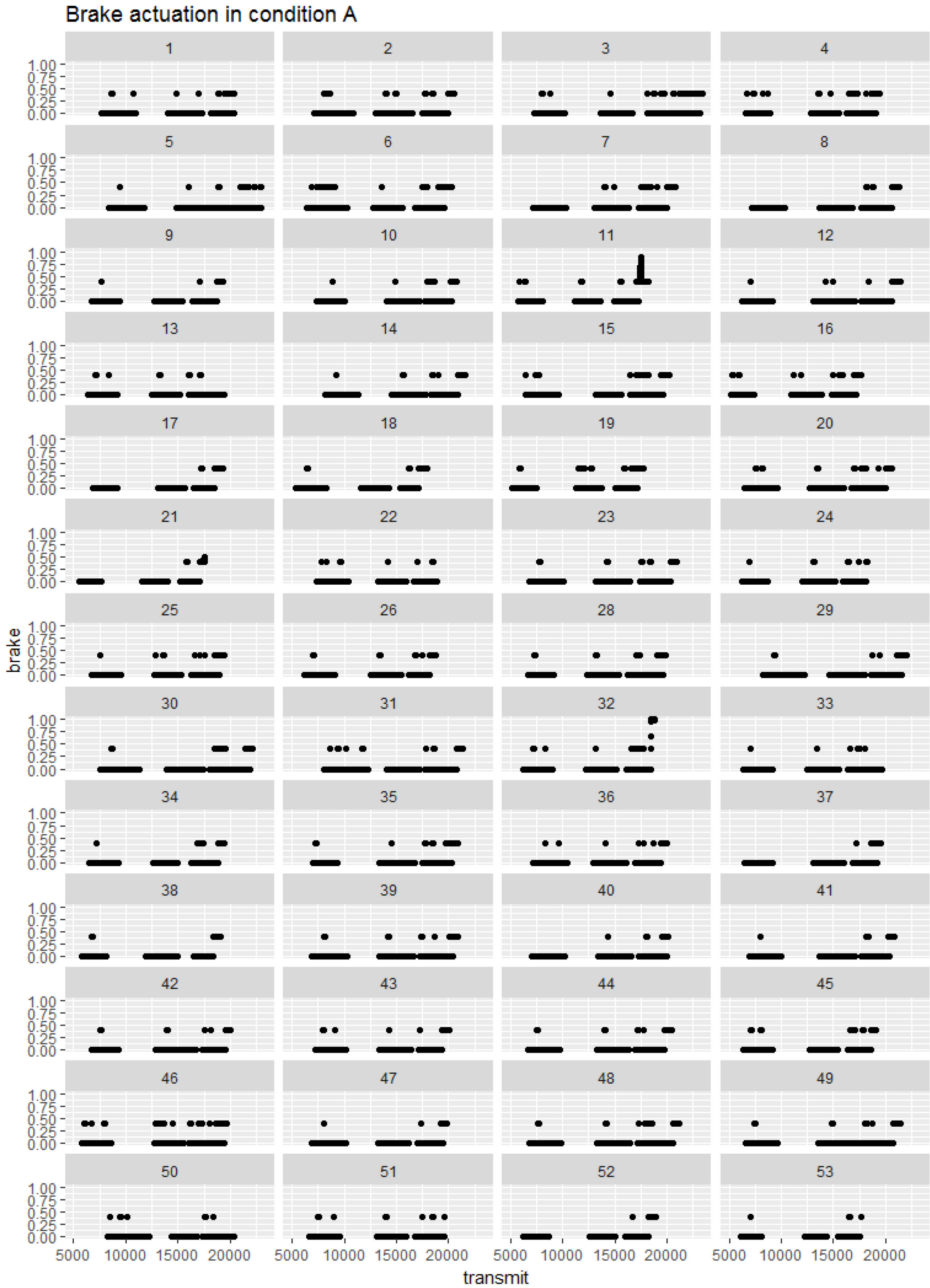
```
# plot for the learning effect

# in general (all situations). plot is divided by condition
subset(laneChangeData, !is.na(LaneChanged)) %>%
    ggplot(aes(Situation, fill=LaneChanged)) +
    geom_bar(na.rm = TRUE) +
    scale_fill_manual(labels = c("Lane not changed", "Lane changed"), valu
es = c("gray", "chartreuse4")) +
    ggtitle("Lane changes across the three situations (all conditions)") +

  facet_grid(. ~ Condition)
```



Braking behavior

Brake actuation of all drivers in condition A**

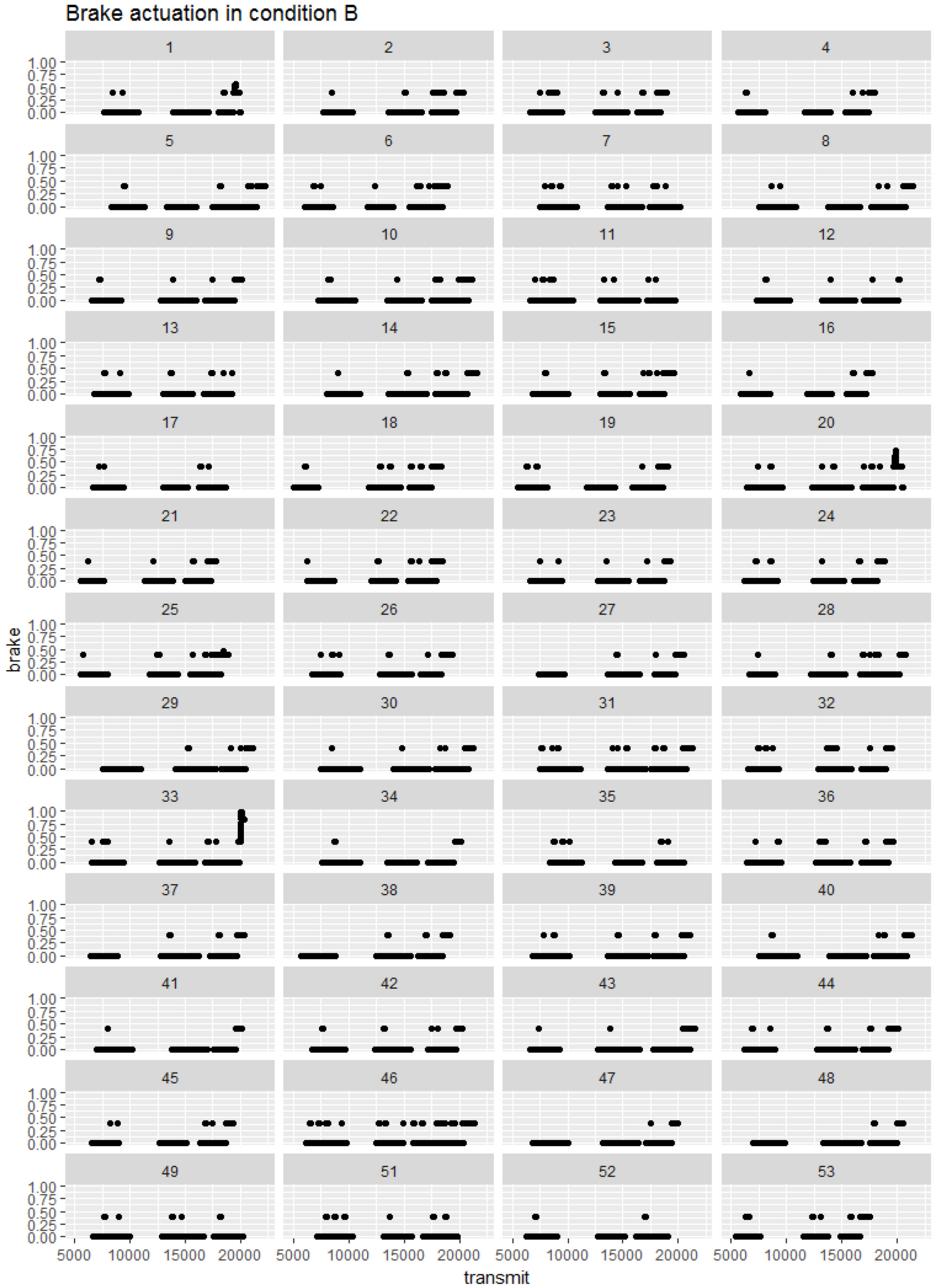
```
# create the individual plots
plot1 <- filteredData %>%
  filter(Scenario == "a" & triggerValue == 1) %>% # filter out anything be
low 70
  ggplot(data = ., mapping = aes(transmit, brake)) +
  geom_point()


  plot1 + facet_wrap( ~ VP, ncol = 4) + ggtitle("Brake actuation in condit
ion A") # 4 plots in each row
```



Brake actuation of all drivers in condition B**

```
# create the individual plots
plot2 <- filteredData %>%
  filter(Scenario == "b" & triggerValue == 1) %>% # filter out anything be
low 70
  ggplot(data = ., mapping = aes(transmit, brake)) +
  geom_point()
```

```
# summarize them in one facet_wrap
plot2 + facet_wrap( ~ VP, ncol = 4) + ggtitle("Brake actuation in conditio
n B") # 4 plots in each row
```



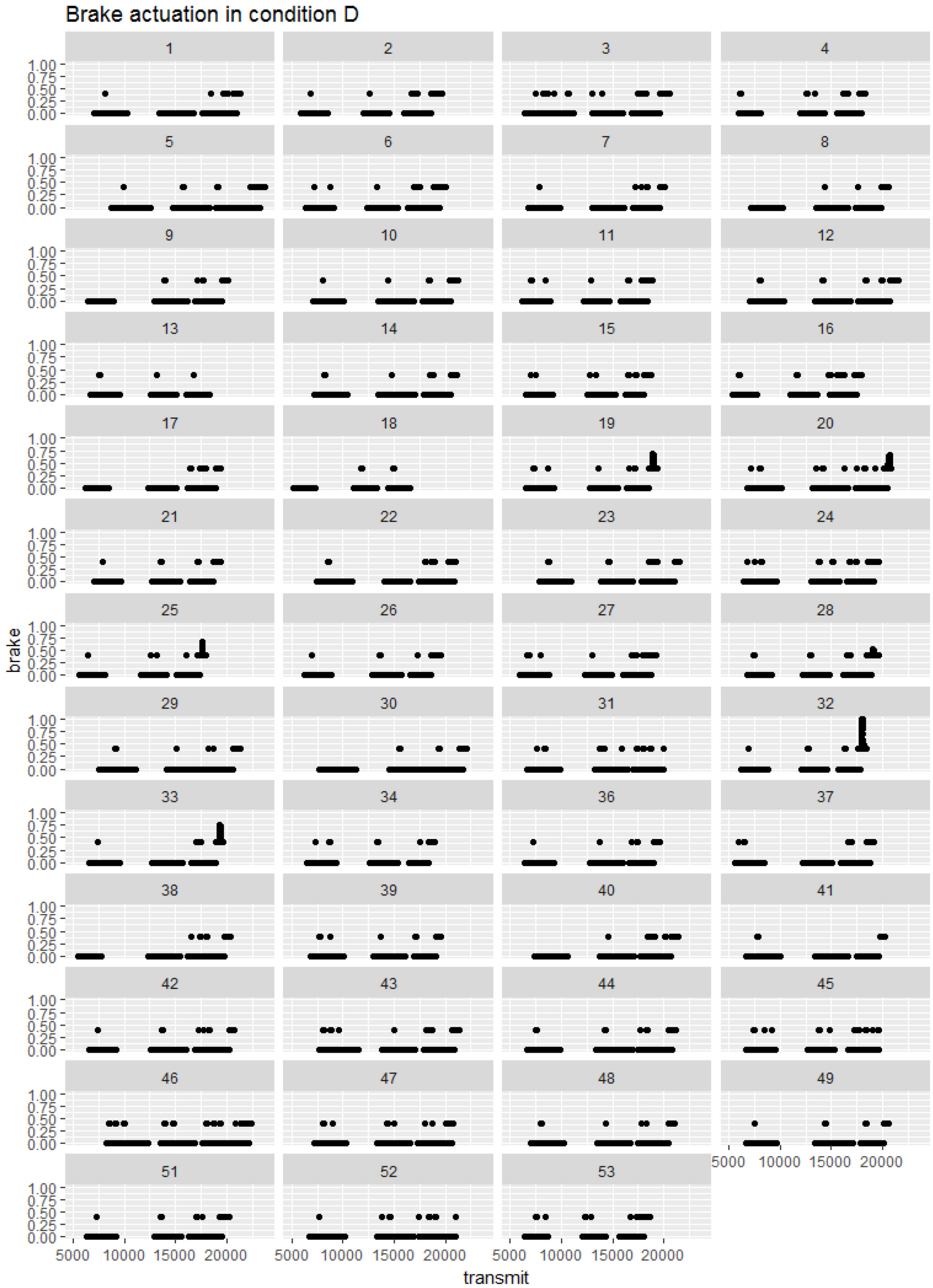
Brake actuation of all drivers in condition C**

```
# create the individual plots
plot3 <- filteredData %>%
  filter(Scenario == "c" & triggerValue == 1) %>% # filter out anything be
```

```
low 70
  ggplot(data = ., mapping = aes(transmit, brake)) +
  geom_point()

# summarize them in one facet_wrap
plot3 + facet_wrap( ~ VP, ncol = 4) + ggtitle("Brake actuation in conditio
n C")# 4 plots in each row
```

Brake actuation of all drivers in condition D**

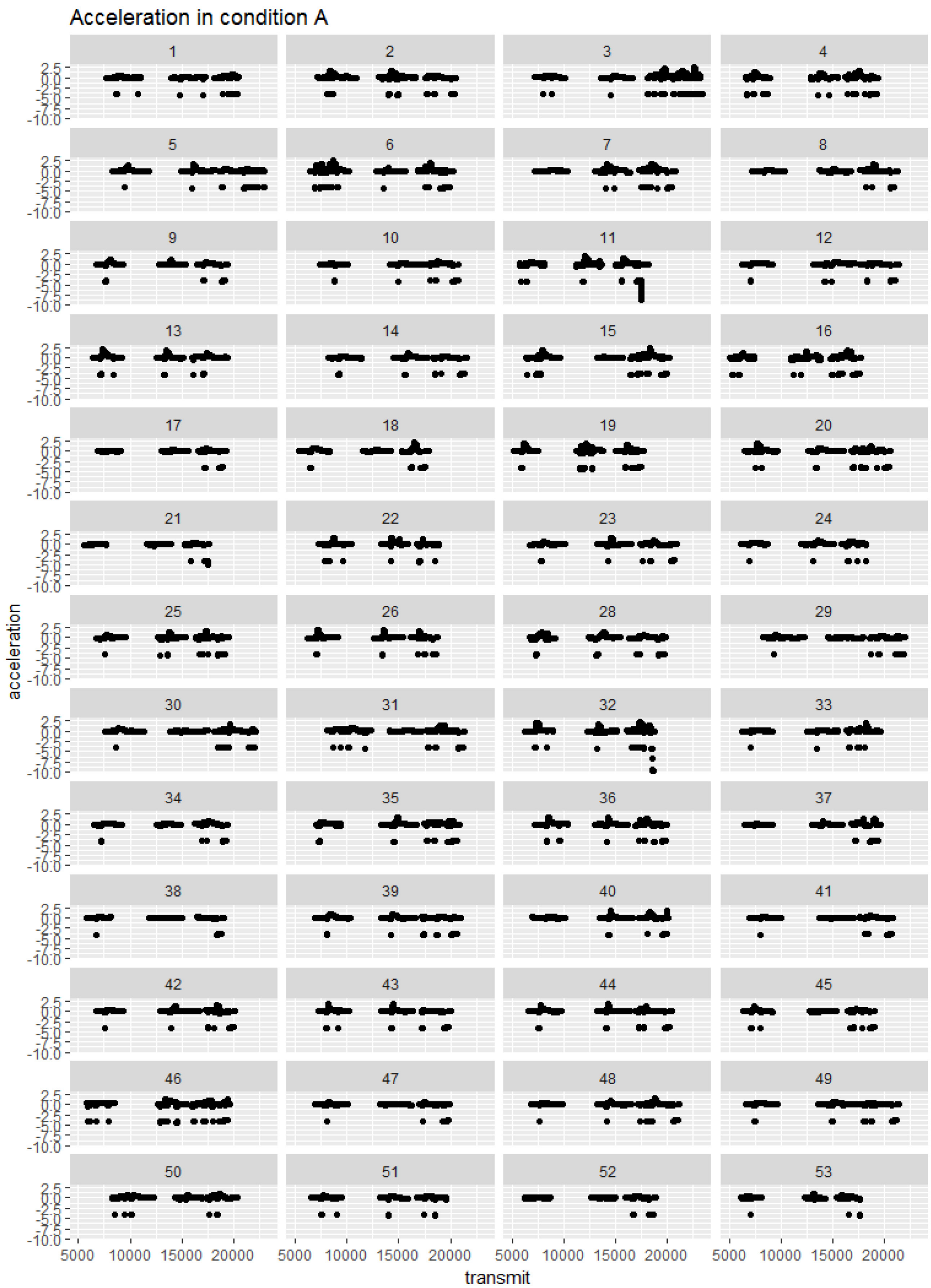
```
# create the individual plots
plot4 <- filteredData %>%
  filter(Scenario == "d" & triggerValue == 1) %>% # filter out anything th
at does not belong to the situations
  ggplot(data = ., mapping = aes(transmit, brake)) +
  geom_point()

# summarize them in one facet_wrap
plot4 + facet_wrap( ~ VP, ncol = 4) + ggtitle("Brake actuation in conditio
n D") # 4 plots in each row
```



Acceleration of all drivers in condition A**

```
# create the individual plots
plot1 <- filteredData %>%
  filter(Scenario == "a" & triggerValue == 1) %>% # filter out anything be
low 70
  ggplot(data = ., mapping = aes(transmit, acceleration)) +
  geom_point()
```

```
  plot1 + facet_wrap( ~ VP, ncol = 4) + ggtitle("Acceleration in condition
A") # 4 plots in each row
```



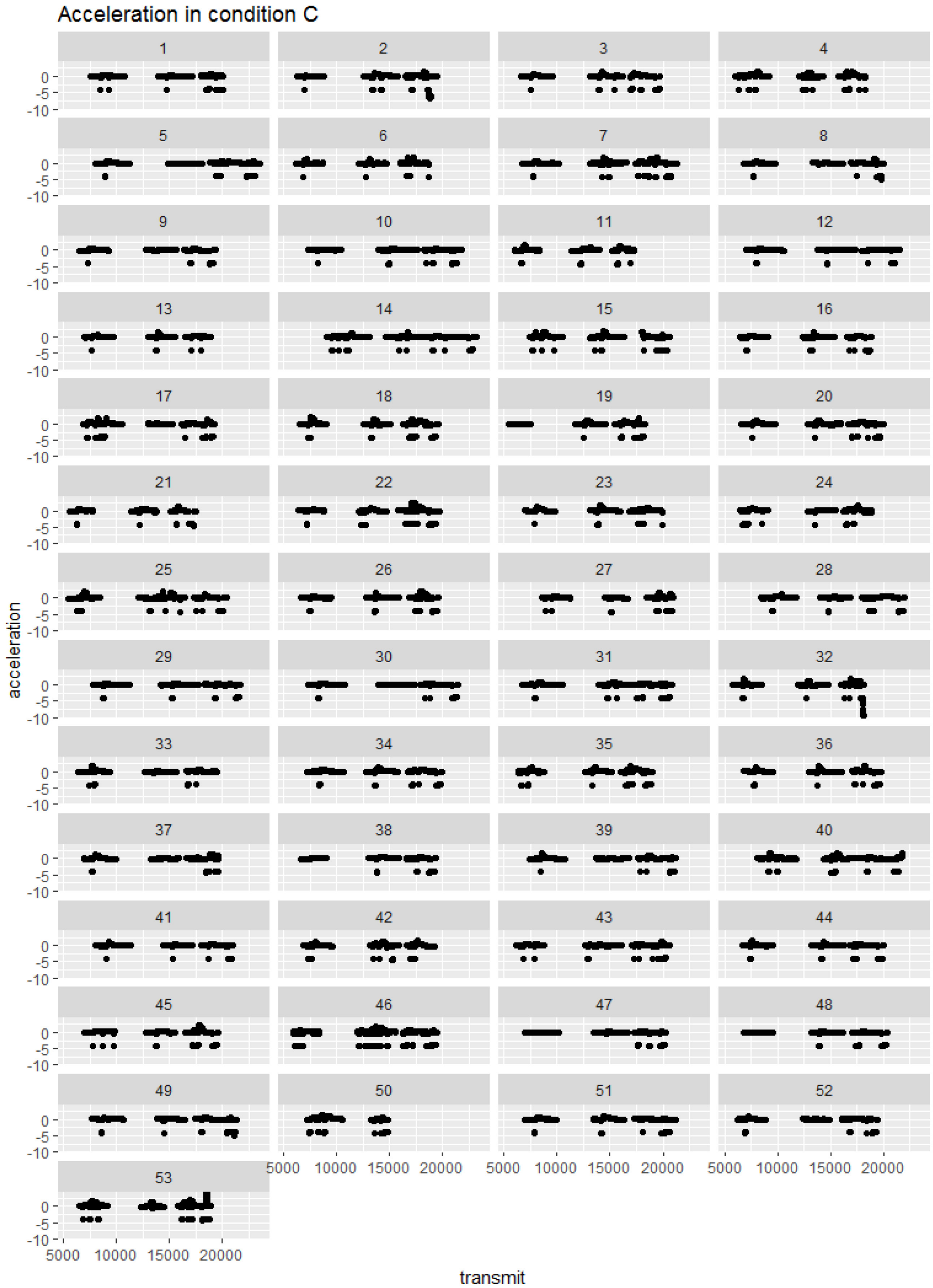
Acceleration of all drivers in condition B**

```
# create the individual plots
plot2 <- filteredData %>%
  filter(Scenario == "b" & triggerValue == 1) %>% # filter out anything be
```

```
low 70
  ggplot(data = ., mapping = aes(transmit, acceleration)) +
  geom_area()

# summarize them in one facet_wrap
plot2 + facet_wrap( ~ VP, ncol = 4) + ggtitle("Acceleration in condition B
") # 4 plots in each row
```

Acceleration of all drivers in condition C**

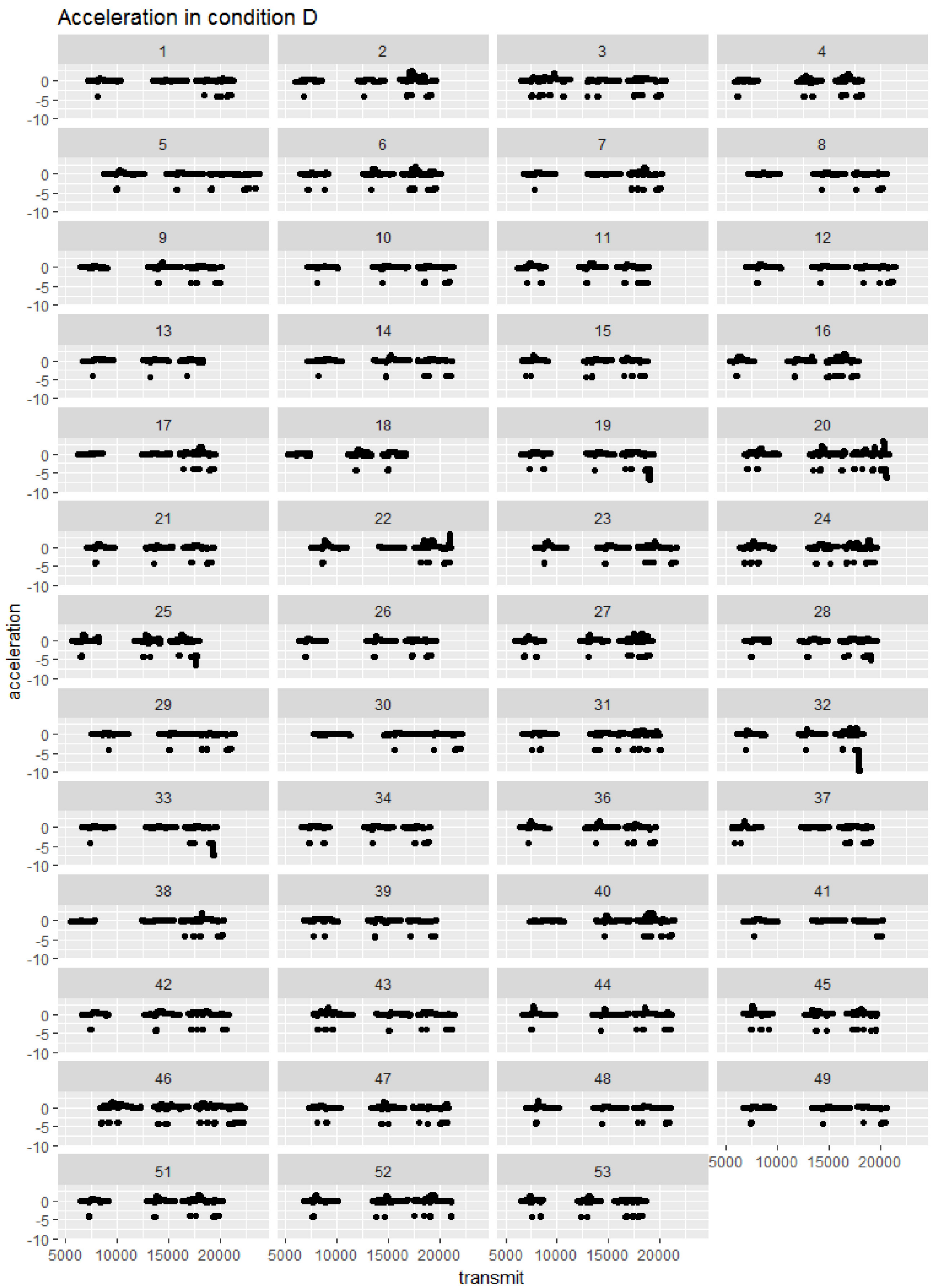
```
# create the individual plots
plot3 <- filteredData %>%
  filter(Scenario == "c" & triggerValue == 1) %>% # filter out anything be
low 70
  ggplot(data = ., mapping = aes(transmit, acceleration)) +
  geom_point()

# summarize them in one facet_wrap
plot3 + facet_wrap( ~ VP, ncol = 4) + ggtitle("Acceleration in condition C
")# 4 plots in each row
```



Acceleration of all drivers in condition D**

```
# create the individual plots
plot4 <- filteredData %>%
  filter(Scenario == "d" & triggerValue == 1) %>% # filter out anything be
low 70
  ggplot(data = ., mapping = aes(transmit, acceleration)) +
  geom_point()
```

```
# summarize them in one facet_wrap
plot4 + facet_wrap( ~ VP, ncol = 4) + ggtitle("Acceleration in condition D
") # 4 plots in each row
```



Visualization of the driving speed within a situation. Speed of all drivers in condition D**

adding a red line

I want to add a red vertical line to the plots at those moments where the rabbit was let in by the drivers. Thus I will use the following condition to detect when the driver let the rabbit in. if ((speed < rabbitSpeed) && (distanceToRabbit > 33) && (rabbitSpeed > 81)) Thus, the line will be drawn at the transmit (X) value at which this condition is satisfied.

I need the transmit value of the row in which the condition is satisfied

filteredData[rowNumber,"transmit"]

In this attempt I am using a for loop. The following data will be exempted from the plotting due to logging failures or other technical failures: Subject 27, Condition A (the drivingdata logging did not work) Subject 27, Condition C (the HUD beamer malfunctioned) Subject 35, Condition D (the drivingdata logging did not work)

```
# this complex construct is required in order to get the line where the ca
r is changing lanes into the diagrams.

# Right now, only condition B will be executed (the rest is commented out)
library(gridExtra)

##
## Attaching package: 'gridExtra'

## The following object is masked from 'package:dplyr':
##
##     combine

# plotListA <- list() # this list will store all the plots
plotListB <- list() # this list will store all the plots
# plotListC <- list() # this list will store all the plots
# plotListD <- list() # this list will store all the plots


for (vpNumber in 1:53) { # for each vpnumber create a plot with the specia
l line

  if (vpNumber == 50) {
    next
  }
    # state the conditions here. they will be used to check whether a line
 should be drawn or not
  # Situation1LaneChanged
  Situation1LaneChanged <- filter(laneChangeData, laneChangeData$Subject==
vpNumber & laneChangeData$Situation == 1)[4] # retrieve the TRUE OR FALSE
value of the laneChanged column
  # Situation2LaneChanged
  Situation2LaneChanged <- filter(laneChangeData, laneChangeData$Subject==
vpNumber & laneChangeData$Situation == 2)[4] # retrieve the TRUE OR FALSE
```

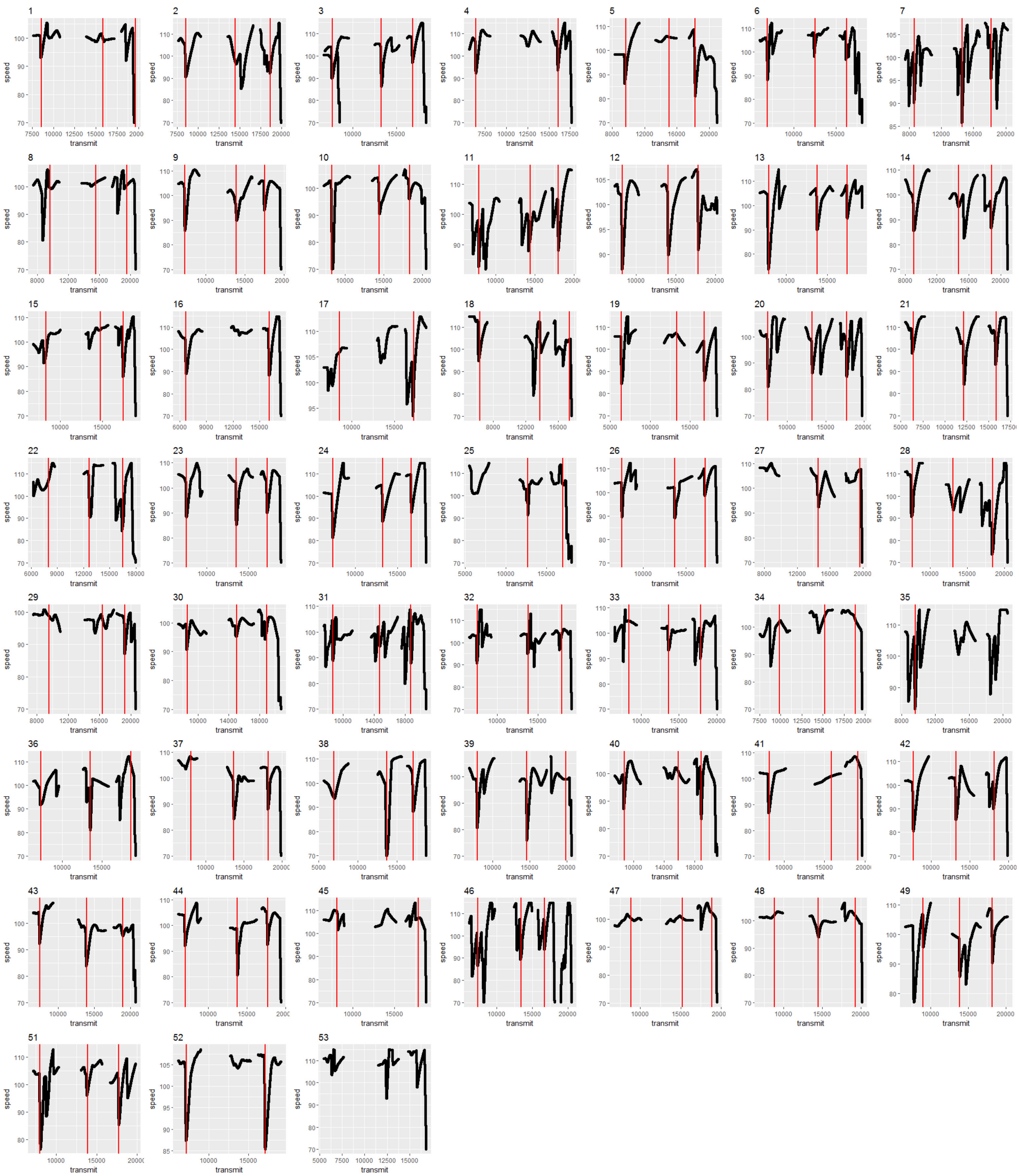
```
value of the laneChanged column
  # Situation3LaneChanged
  Situation3LaneChanged <- filter(laneChangeData, laneChangeData$Subject==
vpNumber & laneChangeData$Situation == 3)[4] # retrieve the TRUE OR FALSE
value of the laneChanged column


  # # the if statements are used to determine whether or not a line should
 be drawn for a specific situation
  # # it will only be drawn if the subject allowed the other car to change
 lanes
  # plotListA[[vpNumber]] <- filteredData %>%
  # filter(VP == vpNumber & Scenario == "a" & speed > 70) %>% # filter out
 anything below 70
  # ggplot(data = ., mapping = aes(transmit, speed)) +
  # geom_point() + ggtitle(as.character(vpNumber))
  #
  # if (!is.na(Situation1LaneChanged[1,1])) {
  #    # add a red line to the plot if the car has changed lanes in the sp
ecific situation
  #   if (Situation1LaneChanged[1,1] == TRUE) {
  #     plotListA[[vpNumber]] <- plotListA[[vpNumber]] + geom_vline(xinter
cept = as.numeric(filter(filteredData %>%
  #                             filter(VP == vpNumber & Scenario == "a" & sp
eed < rabbitSpeed..A6_01. & rabbitDistance..A6_01. > 33 & rabbitSpeed..A6_
01. > 81 & rabbitSpeed..A6_01. < 120))[1,] %>% select(1)), color = "red",
size = 1)
  #   }
  # }
  #
  # if (!is.na(Situation2LaneChanged[1,1])) {
  #
  #   if (Situation2LaneChanged[1,1] == TRUE) {
  #     plotListA[[vpNumber]] <- plotListA[[vpNumber]] + geom_vline(xinter
cept = as.numeric(filter(filteredData %>%
  #                             filter(VP == vpNumber & Scenario == "a" & sp
eed < rabbitSpeed..A6_02. & rabbitDistance..A6_02. > 33 & rabbitSpeed..A6_
02. > 81 & rabbitSpeed..A6_02. < 120))[1,] %>% select(1)), color = "red",
size = 1)
  #   }
  # }
  #
  #
  # if (!is.na(Situation3LaneChanged[1,1])) {
  #
  #   if  (Situation3LaneChanged[1,1] == TRUE) {
  #     plotListA[[vpNumber]] <- plotListA[[vpNumber]] + geom_vline(xinter
cept = as.numeric(filter(filteredData %>%
  #                             filter(VP == vpNumber & Scenario == "a" & sp
eed < rabbitSpeed..A6_03. & rabbitDistance..A6_03. > 33 & rabbitSpeed..A6_
03. > 81 & rabbitSpeed..A6_03. < 120))[1,] %>% select(1)), color = "red",
size = 1)
  #   }
  # }
```

```
  # # the plots for SCENARIO B

   plotListB[[vpNumber]] <- filteredData %>%
     filter(VP == vpNumber & Scenario == "b" & speed > 70) %>% # filter ou
t anything below 70
     ggplot(data = ., mapping = aes(transmit, speed)) +
     geom_point() + ggtitle(as.character(vpNumber))

    # add a red line to the plot if the car has changed lanes in the speci
fic situation
    if (!is.na(Situation1LaneChanged[2,1]) == TRUE) {
      plotListB[[vpNumber]] <- plotListB[[vpNumber]] + geom_vline(xinterce
pt = as.numeric(filter(filteredData %>%
                            filter(VP == vpNumber & Scenario == "b" & spee
d < rabbitSpeed..A6_01. & rabbitDistance..A6_01. > 33 & rabbitSpeed..A6_01
. > 81 & rabbitSpeed..A6_01. < 120))[1,] %>% select(1)), color = "red", si
ze = 1)
    }

    if (!is.na(Situation2LaneChanged[2,1]) == TRUE) {
      plotListB[[vpNumber]] <- plotListB[[vpNumber]] + geom_vline(xinterce
pt = as.numeric(filter(filteredData %>%
                            filter(VP == vpNumber & Scenario == "b" & spee
d < rabbitSpeed..A6_02. & rabbitDistance..A6_02. > 33 & rabbitSpeed..A6_02
. > 81 & rabbitSpeed..A6_02. < 120))[1,] %>% select(1)), color = "red", si
ze = 1)
    }

    if  (!is.na(Situation3LaneChanged[2,1]) == TRUE) {
      plotListB[[vpNumber]] <- plotListB[[vpNumber]] + geom_vline(xinterce
pt = as.numeric(filter(filteredData %>%
                            filter(VP == vpNumber & Scenario == "b" & spee
d < rabbitSpeed..A6_03. & rabbitDistance..A6_03. > 33 & rabbitSpeed..A6_03
. > 81 & rabbitSpeed..A6_03. < 120))[1,] %>% select(1)), color = "red", si
ze = 1)
   }

  # # the plots for SCENARIO C
#
#    plotListC[[vpNumber]] <- filteredData %>%
#    filter(VP == vpNumber & Scenario == "c" & speed > 70) %>% # filter ou
t anything below 70
#    ggplot(data = ., mapping = aes(transmit, speed)) +
#    geom_point() + ggtitle(as.character(vpNumber))
#
#    # add a red line to the plot if the car has changed lanes in the spec
ific situation
#    if (!is.na(Situation1LaneChanged[3,1]) == TRUE) {
#      plotListC[[vpNumber]] <- plotListC[[vpNumber]] + geom_vline(xinterc
ept = as.numeric(filter(filteredData %>%
#                            filter(VP == vpNumber & Scenario == "c" & spe
ed < rabbitSpeed..A6_01. & rabbitDistance..A6_01. > 33 & rabbitSpeed..A6_0
1. > 81 & rabbitSpeed..A6_01. < 120))[1,] %>% select(1)), color = "red", s
```

```
ize = 1)
#    }
#
#    if (!is.na(Situation2LaneChanged[3,1]) == TRUE) {
#      plotListC[[vpNumber]] <- plotListC[[vpNumber]] + geom_vline(xinterc
ept = as.numeric(filter(filteredData %>%
#                              filter(VP == vpNumber & Scenario == "c" & spe
ed < rabbitSpeed..A6_02. & rabbitDistance..A6_02. > 33 & rabbitSpeed..A6_0
2. > 81 & rabbitSpeed..A6_02. < 120))[1,] %>% select(1)), color = "red", s
ize = 1)
#    }
#
#    if  (!is.na(Situation3LaneChanged[3,1]) == TRUE) {
#      plotListC[[vpNumber]] <- plotListC[[vpNumber]] + geom_vline(xinterc
ept = as.numeric(filter(filteredData %>%
#                              filter(VP == vpNumber & Scenario == "c" & spe
ed < rabbitSpeed..A6_03. & rabbitDistance..A6_03. > 33 & rabbitSpeed..A6_0
3. > 81 & rabbitSpeed..A6_03. < 120))[1,] %>% select(1)), color = "red", s
ize = 1)
#    }

  # # the plots for SCENARIO D
#
#    plotListD[[vpNumber]] <- filteredData %>%
#    filter(VP == vpNumber & Scenario == "d" & speed > 70) %>% # filter ou
t anything below 70
#    ggplot(data = ., mapping = aes(transmit, speed)) +
#    geom_point() + ggtitle(as.character(vpNumber))
#
#    # add a red line to the plot if the car has changed lanes in the spec
ific situation
#
#    if (!is.na(Situation1LaneChanged[4,1]) == TRUE) {
#      plotListD[[vpNumber]] <- plotListD[[vpNumber]] + geom_vline(xinterc
ept = as.numeric(filter(filteredData %>%
#                              filter(VP == vpNumber & Scenario == "d" & spe
ed < rabbitSpeed..A6_01. & rabbitDistance..A6_01. > 33 & rabbitSpeed..A6_0
1. > 81 & rabbitSpeed..A6_01. < 120))[1,] %>% select(1)), color = "red", s
ize = 1)
#    }
#
#    if (!is.na(Situation2LaneChanged[4,1]) == TRUE) {
#      plotListD[[vpNumber]] <- plotListD[[vpNumber]] + geom_vline(xinterc
ept = as.numeric(filter(filteredData %>%
#                              filter(VP == vpNumber & Scenario == "d" & spe
ed < rabbitSpeed..A6_02. & rabbitDistance..A6_02. > 33 & rabbitSpeed..A6_0
2. > 81 & rabbitSpeed..A6_02. < 120))[1,] %>% select(1)), color = "red", s
ize = 1)
#    }
#
#    if  (!is.na(Situation3LaneChanged[4,1]) == TRUE) {
#      plotListD[[vpNumber]] <- plotListD[[vpNumber]] + geom_vline(xinterc
ept = as.numeric(filter(filteredData %>%
#                              filter(VP == vpNumber & Scenario == "d" & spe
```

```
ed < rabbitSpeed..A6_03. & rabbitDistance..A6_03. > 33 & rabbitSpeed..A6_0
3. > 81 & rabbitSpeed..A6_03. < 120))[1,] %>% select(1)), color = "red", s
ize = 1)
#    }

}

# # clean the plotLists of the missing values. else the grid arrange metho
d will throw an error
# plotListD[35] <- NULL # remove number 27 and number 50 (i put 49 because
 removing the 27 will move the 50 to 49)
# plotListD[49] <- NULL

plotListB[50] <- NULL

# this combines the plots into one plot
# do.call(grid.arrange,plotListA)
#do.call("grid.arrange", c(plotListA, ncol = 4))
#arrangeGrob(plotListA, ncol = 4)

# do.call(grid.arrange, plotListB)
# do.call(grid.arrange, plotListC)
do.call(grid.arrange, plotListB)

## Warning: Removed 1 rows containing missing values (geom_vline).

## Warning: Removed 1 rows containing missing values (geom_vline).

## Warning: Removed 1 rows containing missing values (geom_vline).

## Warning: Removed 1 rows containing missing values (geom_vline).

## Warning: Removed 1 rows containing missing values (geom_vline).

## Warning: Removed 1 rows containing missing values (geom_vline).

## Warning: Removed 1 rows containing missing values (geom_vline).

## Warning: Removed 1 rows containing missing values (geom_vline).

## Warning: Removed 1 rows containing missing values (geom_vline).

## Warning: Removed 1 rows containing missing values (geom_vline).

## Warning: Removed 1 rows containing missing values (geom_vline).

## Warning: Removed 1 rows containing missing values (geom_vline).
```

Speed of the individual participants in condition A. The moments in which the participants allowed the partner car to change lanes are marked with a red line.



Speed of the individual participants in condition B. The moments in which the participants allowed the partner car to change lanes are marked with a red line.

Speed of the individual participants in condition C. The moments in which the participants allowed the partner car to change lanes are marked with a red line.

Speed of the individual participants in condition D. The moments in which the participants allowed the partner car to change lanes are marked with a red line.