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"Watch out!": Prediction-Level Intervention for Automated Driving

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ABSTRACT

It seems that autonomous driving systems are substituting human responsibilities in the driving task. However, this does not mean that vehicles should not interact with their driver anymore, even in case of full automation. One reason is that the automation is not yet advanced enough to predict other road user's behavior in complex situations, which can lead to sub-optimal action choices, decrease comfort and user experience. In contrast, a human driver may have a more reliable understanding of other road users' intentions which could complement that of the automation. We propose a framework that distinguishes between four levels for interaction with automation. Based on the framework, we introduce a concept which allows drivers to provide prediction-level guidance to an automated driving system through gaze-speech interaction. Results of a pilot user study show that people hold a positive attitude towards prediction-level intervention as well as the gaze-based interaction method.

CCS CONCEPTS

• **Human-centered computing** → Human computer interaction (HCI); HCI theory, concepts and models; Human computer interaction (HCI); HCI design and evaluation methods; User studies.

KEYWORDS

Cooperative driving, automated driving, gaze interaction, human-machine interaction

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1 INTRODUCTION

The development of autonomous driving technology commonly assumes a transition of control and responsibility from the human driver to an autonomous system. However, this does not mean that in the highly autonomous conditions the vehicles will not interact with their driver anymore. There are still many scenarios where the driver may want to spontaneously influence the behavior of the autonomous driving system (Non-critical Spontaneous Situations, NCSSs [63, 69]) such as adjusting the driving style to the current preference of the driver.

More importantly, there are still many situations that the autonomous driving system cannot handle well, which may increase the risk of automated driving. The number of factors that must be considered for achieving the driving task is still a challenge for automated driving systems [5, 10, 29]. As a consequence, even in SAE L4/5 [54] automation, inappropriate behavior of the system may lead to low efficiency and an uncomfortable driving experience. This might, in particular, be the case in situations in which the system's predictions about other road user's behavior are inappropriate or wrong. Humans on the other hand are often capable of making predictions based on multiple factors in complex and even novel situations. For example, if there is a van parking on the shoulder lane with an open door, a human driver may feel more conscious about someone exiting the car. For an automated system, however, the van is nothing more than a standing vehicle. Since presumably trivial tasks such as detecting an open door are already a challenge [59], advanced reasoning about situations and making adequate predictions is even more difficult given the increasing dimensionality of the feature space [64].

One approach to tackle this problem is to hand over the control back to the driver, which has been investigated extensively [21, 38, 41, 46]. However, there are several issues regarding this approach [47]. Although human drivers might be more sensitive to the occurrence of abnormal events, they may lack awareness of the overall situation which would be necessary for taking over in automated driving conditions [77] and people's driving performance after taking over may be negatively affected by the automation [43]. Another approach to cope with the shortcomings of autonomous vehicles is to introduce maneuver-level intervention or shared control [19, 56, 67]. However, if the driver can only select among different maneuver plans provided by the system, without informing the system about the reasons for his selection, this might lead to other problematic situations.

Here we summarize previous research on human-vehicle cooperation and categorize different levels of cooperation between people and automated driving systems according to a framework of autonomous driving systems. Inspired by this, we suggest a concept which directly merges human prediction-level interventions into the automation. Furthermore, we propose a multimodal interaction paradigm that combines human gaze- and speech input to conduct the intervention.

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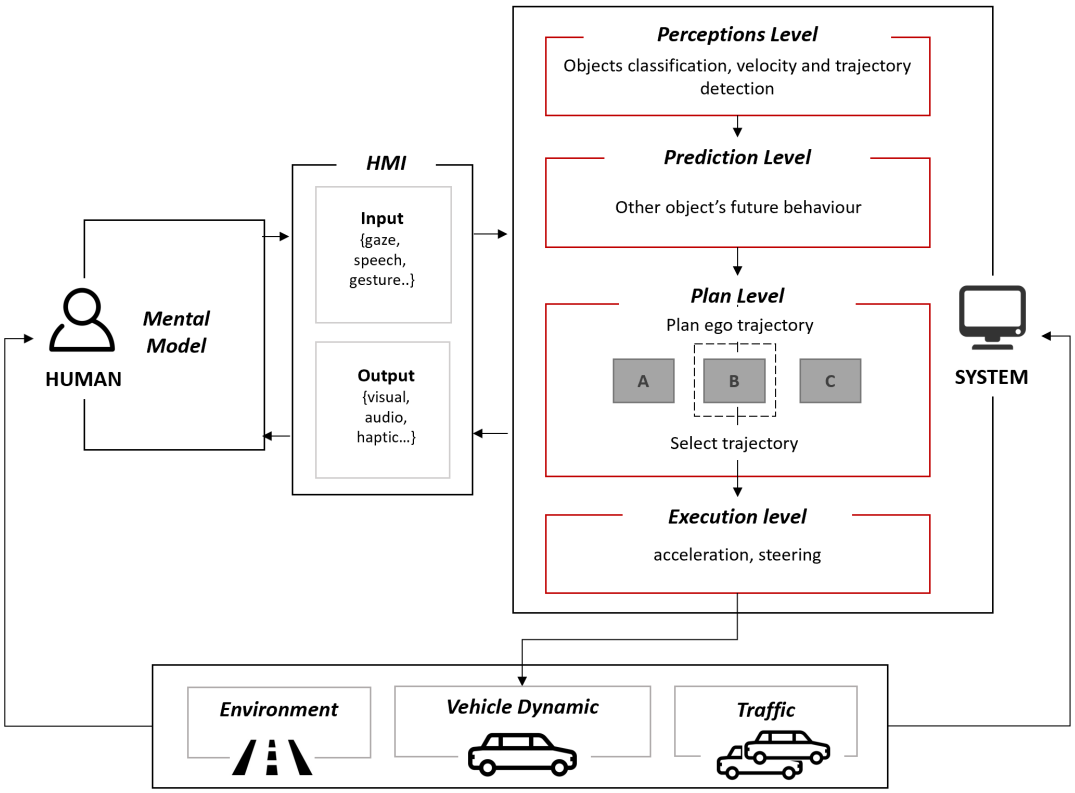


Figure 1: Framework of cooperative driving (based on [69]).

To gain first insights about the subjective utility of this approach, we prototyped the concept in a Wizard-of-Oz driving simulator pilot experiment which allows us to investigate the following hypotheses:

H1: Prediction-level cooperative automated driving is perceived as useful.

H2: Gaze-speech interaction can provide a high usability in prediction-level cooperation.

H3: Prediction-level cooperation in automated driving has a positive influence on system trust.

2 RELATED WORK

2.1 Cooperative driving framework from a system perspective

In the automotive domain, several frameworks of shared control between human and automation have been proposed [7, 9, 18, 34, 57, 66]. However, there is no clear pipeline of applying these frameworks to a concrete human-machine interface. One reason is that there is a gap between human factors research and the technical implementation of autonomous systems. Therefore, we switch our perspective to the side of the automated driving system. Based on previous research [23, 30, 76], the processing flow of an automated driving system can be separated into four steps:

1. Perception level: The system collects data by different sensors, such as camera, radar or LIDAR to classify objects and calculate their trajectories.
2. Prediction level: The system predicts the future behavior of nearby objects. The earlier the system has knowledge about the future behavior of other vehicles, the smoother it can react to it [76].
3. Trajectory plan level: Different future trajectory options are generated. After optimization, the best trajectory is selected, considering safety, comfort and utility of the trajectory.
4. Execution level: The system controls the vehicle according to the selected plan.

Merging the four levels into the human-vehicle cooperation framework proposed by Wang [69], a refined framework which can guide concrete implementation of cooperative HMI's was created (Figure 1). According to this framework, cooperative autonomous driving can be seen as the interaction between human and automated driving system in these four levels. In the following, we summarize examples of related work accordingly.

2.2 Human-vehicle cooperation

2.2.1 Perception level. The recognition of many object categories is still challenging [40], which creates opportunities for human-vehicle cooperation. Presently, few studies have investigated human intervention at this level. One reason may be that in this phase,

vehicles normally move fast. There is little time for humans to provide much information online. Nevertheless, some studies tried to tackle this limitation by HMI design. For example, Walch et al. [65] proposed the *CooperationCaptcha* concept, which enables humans to label traffic signs on-the-fly by speech input. It should be pointed out that: another study by Walch et al. [68] allows the driver to cancel an autonomous overtaking maneuver, when they notice contraflow before the system does. It is a plan level intervention which addresses a perception-level problem.

2.2.2 Prediction level. Algorithms of behavior predictions have widely been investigated in autonomous driving research [5, 10, 29, 36]. However, there are not many studies of human-vehicle cooperation at this level. In a recently published patent, Miriam et al. [45] proposed a sensory system which can track drivers' gaze movement. By analyzing the gaze pattern, a driver's perception of abnormal traffic can be detected, and corresponding measures can be taken to avoid accidents.

2.2.3 Plan level. There is a large body of previous work related to this level [22, 75, 80], also regarding human-vehicle cooperation. *Conduct-by-Wire* is a vehicle guidance paradigm, by which a human driver can control an automobile by maneuver commands [56]. Under this paradigm, Kauer et al. [28] proposed a user interface which allows a person to send a plan level request to the system, such as "lane change right", "follow lane" or "park the vehicle", through a modified steering wheel and a graphical user interface.

2.2.4 Execution level. The concept of "shared control" is a typical case of human-vehicle cooperation at the execution level. It can be defined as allowing "both the human and the [automation] to exert forces on a control interface, of which its output (its position) remains the direct input to the controlled system" [13]. Based on this concept, Abbink et al [1] implemented haptic feedback in a traditional steering wheel to assist the driver to control the vehicle. Instead of a steering wheel, Terken et al.[61] proposed a six degree-of-freedom stick to communicate with the autonomous vehicle.

2.2.5 Cooperation at multiple levels. One representative for cooperation at multiple levels is the *H-Mode* [19]. Through a haptic-visual interface, the driver is able to switch between a *secured rein* mode, where the automation is fully in control and the driver is out of the loop, a *loose rein* mode, where the driver provides plan level guidance, and a *tight rein* mode, in which the system only acts with low forces on a haptic interface.

2.3 Opportunities of cooperative prediction-level intervention

Cooperation concepts between humans and automated systems have been mainly proposed on the plan- and execution-level. However, a focus on human intervention at the prediction level has received less attention. Meanwhile, prediction of surrounding traffic behavior remains a difficult problem for autonomous driving. Multiple methods were proposed to address this problem including model-based frameworks that take into account the road infrastructure, risk level and traffic rules [14, 16, 52]. Besides, statistical approaches were suggested [2, 53, 55, 76], which base predictions on previously collected data that consider the position, velocity and maneuver cost of the vehicle.

Nevertheless, in the real world, automated driving systems only consider pre-defined factors for making predictions, potentially ignoring important information that was not anticipated in the design of the system, due to the limited capability of the sensor, computing workload or dataset for training. In contrast, experienced human drivers are usually well capable of estimating the intention and future behavior of other traffic participants based on multiple dimensions of information and experiences that can be retrieved from memory. Besides, a driver might have a different perception of a situation leading to different conclusions compared to the system. Such a mismatch between driver and vehicle may decrease the user experience. Thus, cooperation at this level could enhance the usability and acceptance of automated driving systems.

3 CONCEPT AND SYSTEM DESIGN

3.1 A concept for cooperative prediction-level intervention

In this section, we introduce the concept of prediction-level cooperation with an example and explain the advantages of this type of interaction.

Imagine a big truck is driving on the right lane of the ego vehicle (Figure 2A). The system perceives the scenario by various sensors and recognizes different objects. It predicts the behavior of each object based on the velocities, traffic rules and road information etc. The system may arrive at the conclusion that the truck is just driving on the right lane and will stay on its lane. Based on the evaluation of the situation, the system generates two maneuver plans (A, changing lane; B, keeping current speed) and chooses plan B. However, a human driver might have a different perception of the situation. He could conclude that the big truck wants to change to the left lane, but might not have found an appropriate slot yet. The human driver predicts that the truck has a high probability of cutting-in later. If this was the case, the ego-vehicle would have to decelerate dramatically, which is dangerous and uncomfortable.

Thus, the driver might want to proactively intervene by means of informing the system that the truck may cut in (Figure 2B). The system receives the intervention and therefore increases the probability of the truck being a potential issue. Multiple factors can thereby be considered, such as comfort or risk of the driver [17, 51, 76], to adjust the value of possible trajectories. Finally, the system selects the optimized trajectory, Plan C (newly generated), reducing speed.

Previous research mostly focused on the intervention in the planning or controlling phase, i.e. directly letting the human driver select a plan. However, since in the automated driving mode, a driver's situational awareness is likely to be low [39, 44, 77], such a shift of responsibility could be inappropriate. For example, in the scenario shown in Figure 2B, a driver who intervenes at the plan level may just select Plan A – change lane – to avoid the big truck. This would not be an optimal choice as the driver may not notice the approaching vehicle on the left lane (Figure 2B left). Instead, in case of prediction-level intervention, the driver only needs to point out the risk of the truck to cut in but let the automated vehicle

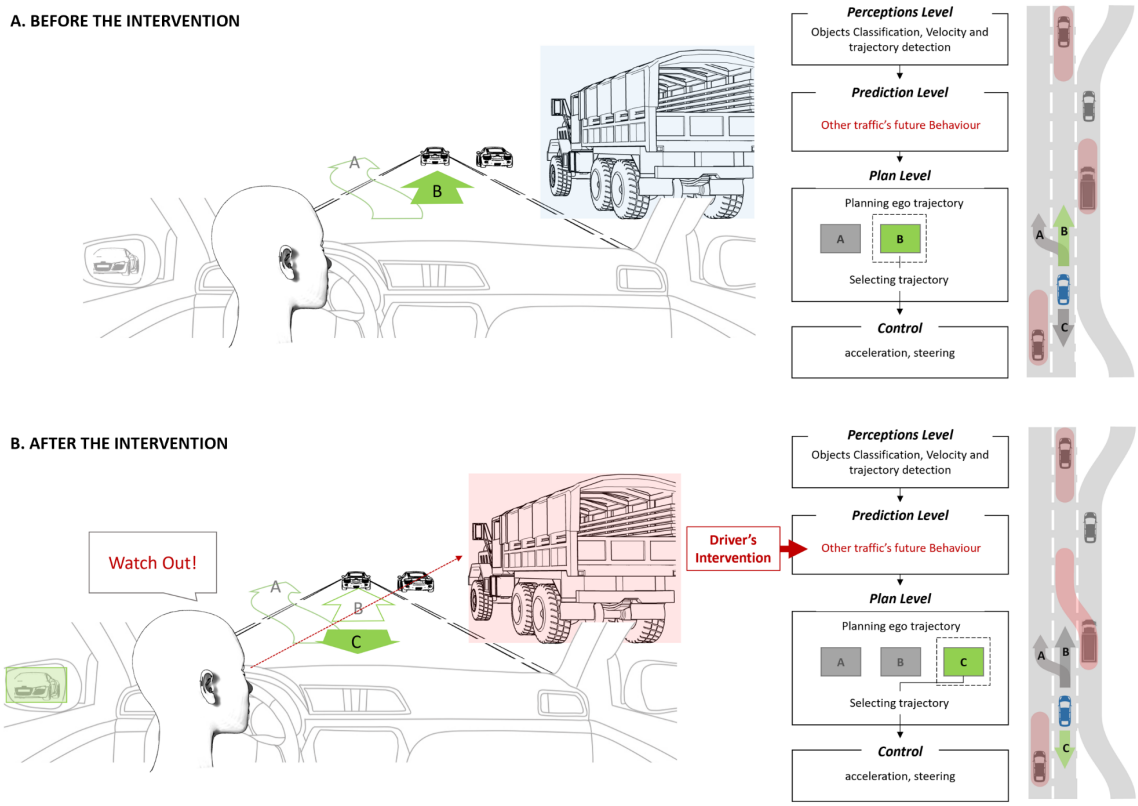


Figure 2: Before the prediction-level intervention (A) and after the intervention (B)

adapt its subsequent choices accordingly on its own, which may reduce the driver's workload and enhance safety.

3.2 Gaze-speech input for prediction-level intervention

One key element of the prediction-level cooperation is to communicate the user's intention to the system. Precisely referencing an object of interest in the environment within limited time requires an intuitive and responsive interface.

One promising interaction means for this concept is gesture-based interaction, which is a natural way to refer to physical items in the environment (deictic gestures) as well as a way to express meanings (iconic gestures) [42]. In a series of studies on social driving [12, 71–74], Wang et al proposed an interaction system which enables a driver to select a surrounding vehicle and deliver rich information at the same time through one gesture. However, they reported that the gesture interaction increased the driver's workload and needed some effort for stretching their arms [70].

Another promising interaction method is gaze-based interaction. Through gaze, a user can interact with the system from a distance without physical contact [58]. In the automotive domain, eye gaze is widely investigated as an explicit cue for human-machine interaction in vehicles. However, most of the gaze-based interaction systems focus on the operations of in-vehicle entertainment. For example, Poitschke et al. [50] proposed a concept which utilized gaze as an object-selection tool for multi-modal interaction in vehicles. Recently, some studies utilized gaze not only to point to objects outside the vehicle but also as guidance for automated driving. Jiang et al [27] proposed a gaze-based system that enables the driver to indicate to the autonomous vehicle where to go.

Here we propose a gaze- and speech based interaction for prediction-level intervention, which takes advantage of gazing speed for referencing an object [26, 49, 60] and the potential richness of the speech input [3, 4]. In this pilot study, we only investigated one kind of prediction-level input. However, the speech input could provide much more information in principle. To evaluate our proposed concept of prediction-level intervention and the gaze-speech interaction design, we conducted a pilot user study which aimed at testing the acceptance and usability of the concept.

4 METHODS

4.1 Evaluation setup

4.1.1 Participants. A within-group experiment involving 8 participants was conducted (7 male). Participants were required to have a valid driving license and corrected-to-normal vision. All participants gave written informed consent before taking part in the study. Participants were divided into two groups for counterbalancing the experimental conditions and to avoid learning effects.

4.1.2 Experimental setup. A static driving simulator running SILAB 5.1 (WIVW GmbH) with real-vehicle controls for steering, braking and accelerating was used. Three display panels (50-inch diagonal, Resolution: 3 x 1080p, 60 Hz) were arranged to provide approximately 160-degree field of view and showed the front, side- and rear-view mirror views of the driving scene. A wearable 120 Hz monocular eye-tracker (Pupil Labs GmbH, see [56]) was used for gaze recording.

An experimenter acted as Wizard operating the automated driving system. He controlled the simulated ego- vehicle remotely using a second steering wheel and pedals connected to the simulation software. A curtain was used to prevent participants from seeing the experimenter and the remote driving equipment (Figure 3). Participants wore the head-mounted eye tracker while sitting in the driving simulator. A screen displayed the eye-tracking world camera video stream of the participant with the respective gaze location. Based on this, the experimenter could tell where participants were looking and which object they were referring to.

4.1.3 Implementation of the gaze-speech interaction design. The interaction flow of the gaze- and speech interaction was separated into three steps:

1. Activating speech input: Participants could press any of the black buttons on a Logitech input device to activate speech input (Figure 3A, top right). The system provided audio feedback and showed a microphone icon on the dashboard (Figure 3A, top center) for confirmation. In case of mis-triggering the activation button, participants could press a red button to deactivate the speech-input mode (Figure 3A, top right).
2. Referring to object: Participants were told to look at an object and say, "watch out", if they perceived it to be risky. The experimenter received the user's input and pressed a confirmation button which triggered a second audio feedback and the disappearance of the microphone icon.
3. Adapting behavior: Based on the participant's request, the experimenter adapted the driving behavior according to a pre-set protocol.

4.1.4 Protocol of the driving behavior of the experimenter. For comparability of experimental runs, we used a protocol to systematize driving behavior in each segment of the trip (see supplementary material), including adjusting speed according to traffic signs and overtaking slow vehicles. The basic logic of the driving behavior is introduced in the section 4.2.

4.2 Scenarios and events

A highway scenario including curves, parking areas, entrance and exit ramps, and a road surrounded by forest along with a low density of traffic was created for testing. The total duration of the scenario was 15 minutes. In the scenario, fifteen segments were defined (Figure 3B) and one of three types of events could occur (Figure 3C) :

4.2.1 Five "Cut in or not" events (in segment 3, 5, 7, 11 and 13). A vehicle is driving out of a parking area on the right lane of the ego-car. Around 800 m ahead, the road diverges (Figure 3C left). This is an ambiguous situation since the vehicle may drive along the lane and leave the highway or change lane to remain on the highway. Therefore, the pre-defined driving behavior presents the limitation of predicting the cutting in behavior of the right lane vehicle. When it cuts in, the system must brake suddenly. In contrast, if the user intervenes, it can keep either distance to the right lane vehicle or change lane according to the situation. The pre-set driving behavior was as follows:

Algorithm 1 *Driving behavior for "Cutting in or not" events*

```
if right lane vehicle is referred to:
    if there is no vehicle on the left lane:
        change to left lane
    else if there is vehicle on the left lane:
        if distance to the right vehicle is
            approximately more than 100 m:
            keep 100 m distance to the right-lane vehicle
        else if distance to the right vehicle is between
            50-100 m:
            release pedal to establish 100 m distance
            to the right-lane vehicle
        else if distance to the right vehicle is less than
            50 m:
            break to establish 100 m distance to the
            right-lane vehicle
else if right lane vehicle is not referred to:
    if right lane vehicle cuts in (in this event, the vehicle will cut
        in very near distance):
        hard break
    else:
        keep speed according to traffic signs
```

In segment 3, 7, 11 and 13, vehicles were merging in, in segment 5 the vehicle was exiting the highway. In segment 7, 11 and 13, there were overtaking vehicles on the left lane of the ego-car. Different types of vehicles were used including a truck (segment 3, 5 and 11); a passenger car (segment 7); and a van (segment 13). All participants experienced the same order of events.

4.2.2 One "Construction road" event (in segment 8). The ego-vehicle changes to the left lane to overtake a slower vehicle on the right lane (Figure 3C middle). However, as the right lane is blocked by a construction site several hundred meters away, the slow vehicle on the right lane has to cut in. It has been shown that construction roads are challenging for the perception and decision making of automated driving vehicles [2, 15, 40]. To represent this limitation, the driving behavior is set as follows:

4.2.3 Three "Boars on the side" events (in segment 9). Three groups of wild boars appear respectively at distinct points of this segment (Figure 3C right). One of the boars in the first group enters the road and runs towards the other side of the road. For the other two groups, some of the boars move randomly, but do not enter the road. For a system it is hard to realize that an unknown object standing still can be dangerous [15, 79]. Accordingly, the driving behavior is set as follows in this event:

Algorithm 2 *Driving behavior for "Construction road" event:*

```
if right lane vehicle is referred to:
    if distance to the front vehicle is approximately more than 100 m:
        keep 100 m distance to the right-lane vehicle
    else if distance to the right vehicle is between 50-100 m:
        release pedal to keep 100 m distance to the right-lane vehicle
    else if distance to the right vehicle is less than 50 m:
        break to keep 100 m distance to the right-lane vehicle
else if right lane vehicle is not referred to:
    if right lane vehicle cuts in (the vehicle will cut in very near distance):
        hard break
```

Algorithm 3 *Driving behavior for "Wild boar jumping into the road" event*

```
if boar is referred to:
    if there is no vehicle on the left lane:
        change lane to the left
    else if there is a vehicle on the left lane:
        break to reduce speed to 30 km/h and pass the boar
else:
    if boar enters the road:
        hard break
    else:
        keep speed according to the sign
```

4.3 Experiment procedure

At the beginning of the experiment, participants filled out an informed consent form as well as a short questionnaire regarding demographic data. Next, a familiarity session according to guidelines specified by Hoffmann and Buld [25] was conducted to avoid simulator sickness. Afterwards participants attended two experimental conditions. The order of the conditions was counter-balanced.

Baseline session: The participant passively experienced the highway scenario described in section 4.2. The automated vehicle always behaved according to the pre-set plan. Afterwards, participants were asked to fill the trust of automation questionnaire [37].

Intervention session: Before the intervention session, a training session was conducted to familiarize the participants with the interaction mode of the system. In this session, the ego-vehicle drove on a German highway with vehicles appearing in front of the ego-car and overtaking from the left side. Participants practiced the gaze- and speech interaction (pressing the voice input button, looking at certain objects and saying, "watch out!") up to 20 times. If participants felt comfortable with the use of the intervention mode, the training session was ended and the intervention drive was started. The scenario of the intervention session was the same as for the baseline. However, participants were able to influence the system by gaze and speech input. After this session, participants were asked to fill out the questionnaires.

Before each session, the eye tracker was calibrated and gaze data were collected during the drive. After all driving sessions and filling out the questionnaires, participants were asked questions about their subjective experience of the system.

4.4 Experiment design and dependent measures

The experiment aimed at evaluating the proposed concept of prediction level intervention based on a gaze- and speech interface. One factor was varied throughout the experiment which was the availability of the intervention system. To assess the acceptance and usability of the system, questionnaire data were obtained as well as responses from a semi-structured interview. To evaluate the overall acceptance of the intervention system, the Van-der Laan scale [35] was used that obtains usefulness and satisfaction scores. Besides, the System Usability Scale (SUS) [11] was used for evaluating the usability of the gaze-speech interface. Both questionnaires were only filled out with respect to the intervention drive. In addition, the trust of automation questionnaire was applied [37] to compare the perceived trust between baseline and intervention drive.

Besides the subjective data, we examined the number of interventions with respect to the different experimental segments, as well as measures of the driving behavior between baseline and intervention mode in an exploratory analysis.

5 RESULT

5.1 Driving validity analysis

Because vehicle control was carried out by an experimenter (wizard), we investigated whether the driving was sufficiently consistent to ensure comparability across participants. For this purpose, we developed a hierarchical validity analysis which evaluates the consistency of several driving variables: Longitudinal velocity, longitudinal acceleration, and lateral velocity. The overall median for each of these variables at the respective driving course position was taken as reference value.

At the first level, the differences between these variables and the reference values were computed for every sampling step (60Hz). For a sample to be classified as valid, differences should not exceed any of ±5 m/s for longitudinal velocity, ±2 m/s/s for longitudinal acceleration and ±1 m/s for lateral velocity.

At the second level, the percentage of valid samples per driving course segment was used as an indicator for segment validity. Thereby periods of 400 meters following user intervention were excluded to avoid falsification of results by expected deviations from the reference values. We set the threshold for acceptance of a segment to a sample validity of 80%.

At the third level, the percentage of valid segments was used as an indicator for participant validity. We set the threshold for acceptance of a participant to a segment validity of 80%.

Figure 4 (top-left and top-right) illustrates for each segment individually how often it was classified as invalid and valid for the baseline and the intervention conditions. We found that for all participants the segment validity was above 82% (mean: 93, SD: 6) and for all except one participant above 91%. Overall, 93% of segments in the baseline condition and 93% of segments in the intervention condition were classified as valid. Therefore, we conclude that conditions were sufficiently comparable across participants.

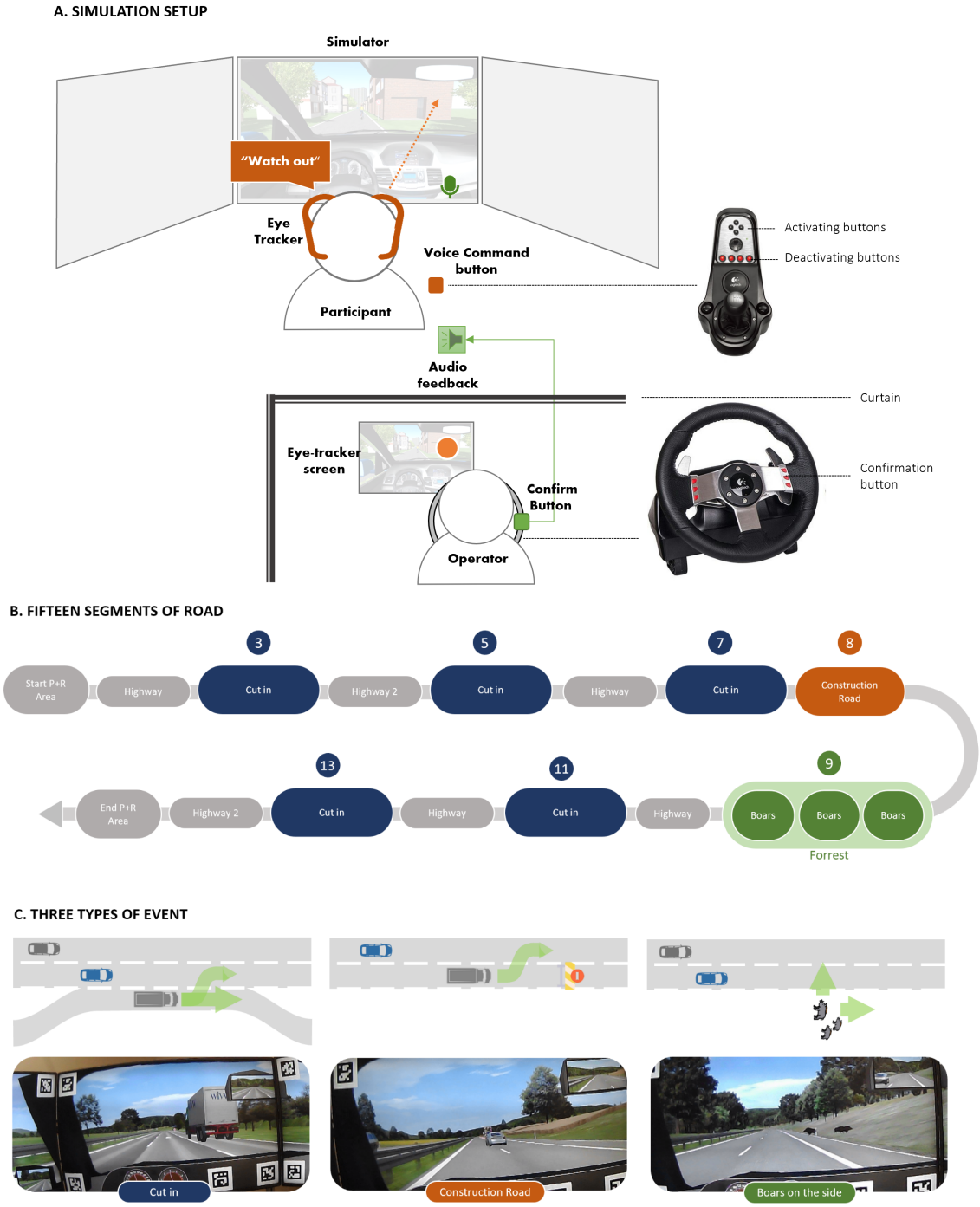


Figure 3: A: Concept implementation in a driving simulator. B: Fifteen road segments. C: Three types of event.

5.2 System usage

Although multiple situations were designed to evoke uncertainty in the participants, the use of the intervention system was voluntary and thus determined entirely by the participants and their momentary subjective evaluation of a situation. Here we report statistics on system usage with respect to specific periods of interest.

We found that in total participants interacted with the system between four and nine times for all segments classified as valid. Thereby the frequency of interaction varied between segment categories (Figure 4 bottom-left). On average, participants triggered the system in 70% (SD: 21%) of the cut-in situations, and in 100% (SD: 50%) of cases in which no cut-in would occur. This outcome

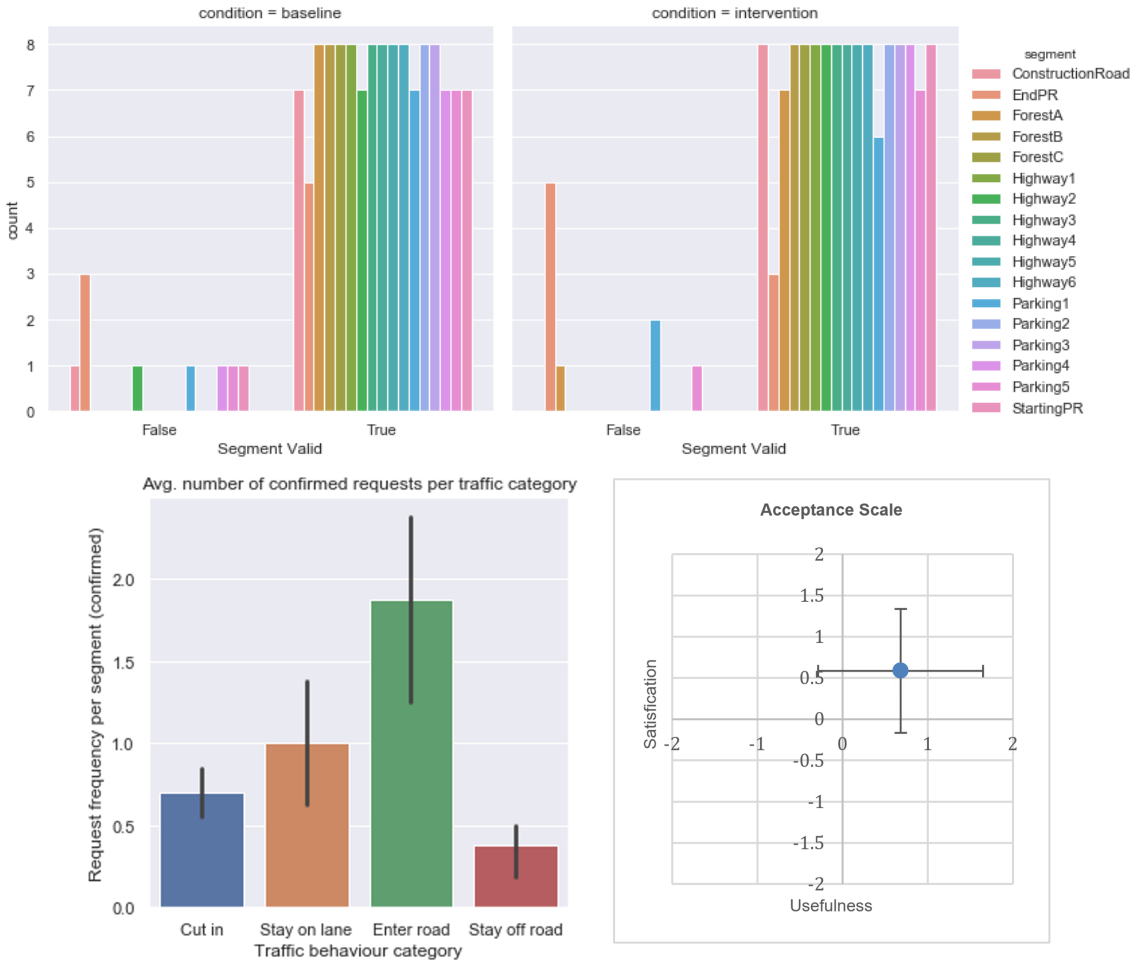


Figure 4: Top-left: valid segment in baseline; Top-right: valid segments in intervention group; Bottom-left: Average number of confirmed requests for each traffic behavior category; Bottom-right: Van-der-Laan scale (acceptance) results.

suggests that participants were unable to predict the behavior of the respective vehicles of interest.

For situations in which a boar entered the road, participants triggered the system on average more than once (187%, SD: 83%), whereas subsequent appearances of boars outside the road only led to interventions in 37.5% (SD: 23%) of the cases.

Overall, the usage of the system lets us conclude that scenario manipulations successfully evoked an urge to interact with the driving system and that a basis for a subjective evaluation should exist.

5.3 Trust of automation

A Wilcoxon signed-rank test was applied to the data of the trust questionnaire in order to compare perceived trust in the autonomous driving system between the baseline and the intervention drive. The result revealed no statistically significant difference between the two groups.

5.4 Acceptance

Results of the Van-der-Laan scale showed that on average both the usefulness (Mean=0.68, SD= 0.97) and the satisfaction score (Mean=0.58, SD= 0.75) were positive (Figure 4 bottom-right). We were interested in how subjective reports of system acceptance were supported by actual differences in the driving behavior following an intervention. The driving protocol should have led to such differences. However, the size and the impact of these changes which presumably would affect the overall perception of the intervention system, could only be assessed post-hoc. Therefore, we investigated measures of velocity and temporal distance.

The orange curve on the left side of Figure 5 shows the average velocity during the first 400 meters following user input. The orange curve shows the velocity in the intervention condition. The blue curve shows the velocity for the same segments in the baseline condition (the starting point is the same location where participant intervened in the intervention condition). Due to individual variance of the input location, the baseline curve fluctuates stronger.

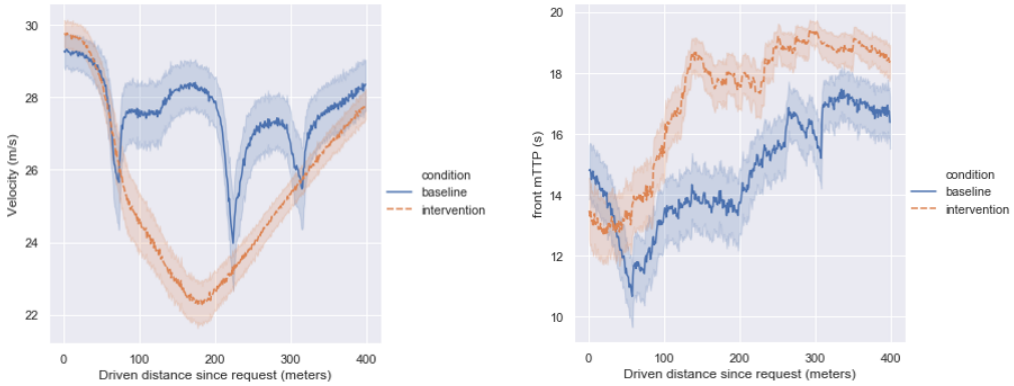


Figure 5: Left: Average velocity (95% CI) during periods after user input. Right: Average TTP (time to passing).

But we can still see that the brake point in the baseline is later than in the intervention condition, which indicates that the safety distance to the cutting in vehicle is shorter. The following measure should illustrate this relationship:

A measure that we hypothesize to relate to driving comfort and thus possibly also acceptance ratings of the proposed system is the temporal distance to other vehicles [16, 31–33]. Thereby a large average temporal distance should correlate with a higher acceptance state whereas short temporal distances might reduce acceptance. While the temporal distance is commonly quantified by a time to collision (TTC), here we evaluate it in terms of a time to passing (TTP) instead. The TTP between two vehicles (a, b) describes the time it would take for one vehicle (b) to overtake another (a) without requiring the two to be on a collision trajectory:

$$TTP_{ba} = \begin{cases} \frac{Dist_{ab}}{Vel_b - Vel_a} & if \quad Vel_b > Vel_a \\ \\ \infty & else \end{cases}$$

The outcome of a low TTP is not necessary as dangerous as that of a low TTC but it is more suitable for our data due to a lack of imminent collision risks in most segments.

Analogous to the acceleration on the left side of Figure 5, the right side shows the average TTP (front direction) development during periods that follow user input. We can see that the TTP is considerably larger in the intervention condition than in the baseline condition during most times. This result is directly related to the use of the prediction-level intervention and might have supported the positive acceptance ratings.

5.5 System Usability Scale (SUS)

The mean system usability score for the intervention mode was 71.25 (SD = 15.27). This result indicates that the usability of the concept is "acceptable" [6, 8].

5.6 Interview results

In order to get further feedback about the proposed system, semi-structured interviews were conducted. Three questions were asked in the interview: 1) "Do you think the concept is useful? And why?" 2) "Do you think the prediction-level intervention would increase trust in the automated driving system?" 3) "What do you think about the gaze-speech interaction system?" Remarks concerned the following topics and are summarized in the following:

1) Acceptance. Most participants reported that the prediction level intervention for the automated driving system was useful. However, two participants argued that it would have been better if they could have also intervened on the maneuver level or even temporarily takeover, since then they could have had more control over the vehicle's behavior. Another issue raised by participants is that the scenario setup could have been more reasonable. "The automated system worked very well; it can overtake slow cars. But why can't it see that the right lane is closed in front and the right car has to merge in." Furthermore, five participants argued that the function might be more suitable for an urban area, since there are usually more ambiguous situations than on a highway.

2) Trust. Most of the participants reported that the human intervention system does not increase trust. One participant said: "After my suggestion, it (the system) drove better. However, I felt less safe when I provided guidance to the system." Another participant argued that he felt "stressed" when giving input to the system.

3) Usability. Many participants noted a lack of "transparency". They wanted to know the plan of the driving behavior after the intervention. "From the audio, I know it received my command, but I don't know how it would react (to the situation)." It was even more confusing when the vehicle did not change its behavior. Participants also wanted to know the limitations of the system in order to decide whether they would need to provide guidance. One participant stated, "Some AR (augmented reality) interface can be helpful to see whether the system mis-judged the situation."

People also asked for visual feedback of the deictic gazing on an object. Besides visualizing the maneuver plan, some participants also wanted to know the reason of the behavior. "I wondered why it did not change to the left lane after I pointed to a truck, until the left lane vehicle passed me."

Most of the participants reported that the gaze- and speech input was easy to use, but some participants mentioned that it might not be quick enough for the intervention. "Sometimes it was already too slow when I said, 'watch out', I would expect that when I press a button the system can understand my intent (without speaking)."

6 DISCUSSION

In this study, we expanded a framework on human vehicle cooperation and derived a concept for prediction-level intervention in autonomous driving. The concept was prototyped in a driving simulator and evaluated in a Wizard-of-Oz pilot study.

6.1 Acceptance of the system

Questionnaire data and interview results revealed that most participants considered the prediction-level intervention to be useful. However, many participants indicated that the use case is not very complex. This indicates that the perceived benefit of the intervention feature might be different in urban environments. Urban environments contain many ambiguous conditions and social interactions [62, 79]. Thus, human intervention could significantly enhance safety and efficiency here.

Another finding is that the satisfaction with the concept was related to the transparency of the automated driving system. This result is in line with recent findings in the domain of explainable AI [20, 62]. Participants wanted to know what the system recognized, predicted and planned in order decide whether to intervene or not. Participants could only estimate the capability of the automated system based on the current driving behavior or past mistakes in order to decide whether they need to intervene.

The multimodal input was rated favorably, but there is room for improvement. For pointing at an object by gaze, there was no visual feedback to inform participants whether the correct object was selected, which was confusing to some participants and reduced the input speed. Although participants were reportedly familiar with pressing buttons to activate speech input like in many in-vehicle entertainment systems [78], this step might not be necessary. By analyzing user's gaze direction and speech input, the system could infer to which object the driver is referring to outside at the expense of the privacy advantage provided by a button solution.

6.2 Recognition of user intention

Due to the general complexity of expressing prediction-level information, speech input was utilized. However, there was just one kind of prediction-level input in the present study. Therefore, one confirmation button was suggested to replace speech by some participants, as it would be faster and more convenient. Even though there are more kinds of predictive information that need to be delivered in other scenarios, "one-button" input can be considered.

Besides, the personalization of driving behavior was also suggested by participants. Driver interventions should be remembered by the system, so it could independently deal with similar situations next time.

6.3 Trust in the system

The results do not indicate that the system with the intervention feature positively influenced perceived trust. Many participants even reported that although the driving behavior felt better with the intervention, they felt less trust in the system. Previous research suggests that take-over requests by automated driving systems lowered the trust, as it was perceived as a form of automation failure [24, 48]. The reason behind the trust result in this study seems similar. The intervention feature highlighted the limitation of the automated driving system. An autonomous system should however also not induce overtrust. One role of interfaces for such systems is to calibrate the trust to an appropriate level by being transparent enough to provide a more accurate understanding of the system's capabilities.

6.4 Limitations

Many insights were generated through the study. However, there are several limitations in our experiment: Due to COVID-19 restrictions, only a limited number of participants could be included in this study. As the automated driving system was operated by an experimenter, not the same level of consistency in behavior could be achieved as with a fully determined system. Furthermore, the use of a static driving simulator may have changed effects of driving behavior on peoples' perception of comfort.

7 CONCLUSION

In this paper, we introduced and investigated a concept for creating prediction-level cooperation between humans and an automated driving system, to overcome the system's limited capability of predicting other road user's intentions. A Wizard-of-Oz prototype experiment which integrated a gaze-speech interaction design was implemented in a driving simulator. Three hypotheses were evaluated:

H1 is supported by both quantitative data and interview results: Participants gave positive scores both in usefulness and satisfaction dimensions of the acceptance questionnaire. Most of the participants showed a positive attitude towards the concept.

H2 is not supported. Questionnaire result showed the usability is only "acceptable"; and the interview result also revealed a limitation of the input speed and lack of system transparency

H3 is also not supported by the result. According to the trust in automation questionnaire, there is no significant difference between the condition with the intervention and without. The interview results also revealed that the participants did not feel more trust when they could interact with the system.

However, various insights to increase the usefulness and user experience of the prediction-level cooperation were generated. For example, prediction-level intervention may have only advantages in certain scenarios. A transparent interface which enables users to understand the recognition, prediction and maneuver plan of the system could enhance the usability.

In this research, we also extended a framework which categorizes cooperative driving into four levels. This framework is based on the operation process of automated driving systems, which creates clear boundaries for classifying different kinds of cooperative driving. By analyzing previous studies in light of this framework, the potential of the prediction-level intervention was discovered, implemented and evaluated. The result confirmed the usefulness of the intervention at this level and the feasibility of conveying predictive information by gaze. In the future, we plan to further develop this concept by exploring use cases in urban scenarios, enhancing the transparency of system's intention and evaluating the possibility to provide richer information by speech.

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