# Effect of System Capability Verification on Conflict, Trust, and Behavior in Automated Vehicles

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With automated driving, vehicles are no longer just tools but become teammates, which enable an increasing space of new interaction possibilities. By changing the relationship between the drivers and the automated vehicles (AV), conflicts regarding maneuver selection can occur. Conflicts can lead to safety-critical takeovers by the drivers. Current research mainly focuses on information requirements for takeovers, only a few works explored the factors necessary for automation engagement. Therefore, a fix-based driving simulator study with N=28 participants was conducted to investigate how verifiable information influences automation engagement, gaze behavior, trust, conflict, criticality, stress, and interaction perception. The results indicate, if drivers can verify the information given by the system, they perceive less conflict and more trust in the system, leading to a lower rejection frequency of an overtaking maneuver performed by an AV. The results indicate that systems that aim to prevent drivers initiated interventions should provide verifiable information.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**.

Additional Key Words and Phrases: HMI; Automated Vehicles; Information Verification; Trust; Conflict; Eye-Gaze; Driver-Vehicle Interaction.

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## 1 INTRODUCTION

Visions for the future of mobility mainly include self-driving vehicles that take over the driving task completely [42]. Based on anticipated benefits such as reduced accidents [1], reduced carbon dioxide emissions through platooning [53], improved traffic flow [53], improved driving quality, and freed time for passengers to enjoy non-driving related activities such as reading or even sleeping [50], both research and industry invest significant efforts into the development of automated vehicles (AVs).

Despite the rapid development, technical limitations remain, especially under challenging conditions [56]. Thus, it is unclear when an AV will be capable to operate under all circumstances possible. Therefore, take-over requests (TORs) [8, 30, 60] or cooperative approaches [5, 59, 62] for reaching the end of an operational driving domain (ODD; e.g., end of a highway) are expected to shape the transition phase to fully automated driving. Albeit there was no longer a need for drivers to take over the driving task from a technical point of view, AVs will continue to provide the possibility for drivers to intervene manually (e.g., see BMW's VISION NEXT [19]). As long as the possibility of taking control is given, it will continue to be used, especially when drivers do not agree with the AV's behavior [64]. Furthermore, both vehicle-initiated TORs and spontaneous, driver-initiated, and uninformed takeovers introduce several problems, the main being the "out-of-the-loop effect" [61]. Drivers are out-of-the-loop if they do not perform the primary driving tasks (e.g., steering, braking, acceleration) and are not aware of the status of the vehicle and traffic situation [41]. Removing drivers from the control loop can result in skill loss (over time) and reduced situation awareness. These factors are related to a decreased driving performance and, thereby, reduced safety [13]. Several studies indicate that switching from automated to manual driving leads to safety-critical driving behavior like worse reaction times, higher accelerations, and more crashes [17, 18]. Additionally, after a successful takeover, post-automation effects degrade drivers' lane-keeping ability [40]. Consequently, the automation, within its capabilities, should remain engaged [24]. However, current work mainly focuses on the information requirements for successful takeovers, and only a few works explored the factors necessary for automation engagement [24]. For example, in the context of automation engagement, Woide et al. [64] could show that although the situation is objectively entirely manageable by the automation (overtaking in foggy conditions), drivers takeover manual control due to information only available to the AVs but missing to the drivers. Thus, for sufficient driver-vehicle interaction, AVs need to communicate transparent information to achieve a shared situation representation [12]. However, the information given by the AVs can only be transparent if the drivers can compare it with the environment [12].

To investigate how (1) verifiable information influences the drivers' rejection frequency of an overtaking maneuver performed by an AV, compared to (2) information that is equal in content but not verifiable and (3) without any information presentation, a fixed-based simulator study (*N*=28) was conducted. Additionally, the influence on conflict perception, trust, criticality, stress, gaze behavior, and interaction perception was examined. A Human-Machine Interface (HMI) with and without a bird's-eye view served as information presentation, and oncoming traffic (yes/no) served as information verification, resulting in a fully-crossed $2 \times 2$ between-subject design.

The results reveal that only information the drivers can verify increases the trust in the system, reduces the conflict, and reduces rejection frequency. Moreover, the results indicate that if the drivers cannot verify the given information, the system does not provide any benefit compared to a system without information presentation. Besides, it is demonstrated that a system with non-verifiable information is rated even worse regarding trust and conflict compared to a system without information presentation. This study provides evidence that systems that aim to prevent drivers initiated maneuver rejection, or takeovers should provide verifiable information.

*Contribution Statement:* This work provides: (1) Authentic conflicting situations between driver and AV leading to driver-initiated takeovers. (2) A visualization to reduce driver-initiated takeovers in conflicting situations. A (3) comparison of verifiable information and non-verifiable information on the takeover frequency. (4) Results of a fix-based driving simulator study (*N*=28) showing the necessity for automation verification.

## 2 RELATED WORK

The development of automated driving comes with many changes in the previously static hierarchy between driver and vehicle. For example, in driving task allocation, responsibility, the shift of power, and interface designs [65]. This far-reaching change in the dynamics between driver and vehicle results in an increasing space of interaction possibilities and, therefore, in more dynamic relationships and interactions between drivers and AVs. With changing dynamics between driver and vehicle, the perception of the interaction also changes [65] and AVs are considered as cooperation

Table 1. Description Dimensions Interdependence Theory

| Dimension | Description |
|---|---|
| Power | Describes the degree of control drivers perceive over the outcome of a situation. |
| Conflict | Describes the extent drivers perceive to which the desired outcome is in correspondence or in conflict with the desired outcome of the AV. |
| Mutual Dependence | Describes the extent drivers perceive to which the situation's outcome depends on the individual behavior of both partners. |
| Information certainty: System to Human | Describes the driver's perception of how informed the AVs are about the driver's preferred outcomes. |
| Information certainty: Human to System | describes the driver's perception of the degree to which the drivers are informed about the AV's preferred outcomes. |
| Future Interdependence: System to Human | Describes a drivers perception of whether the behavior of the AV in a future interaction is influenced by the driver's behaviors in the current situation |
| Future Interdependence: Human to System | Describes the driver's perception of whether the driver's future interaction with the AVs will be influenced by the outcome of the current situation. |

partners or team player [27, 62, 65]. Moreover, with an increasing level of autonomy, the human-machine interaction is increasingly perceived as a social interaction [15] since people tend to treat technology as a social actor [46]. In line with these findings, the Computers Are Social Actors (CASA) framework, and the Media Equation Theory, reveal that humans apply social norms, dynamics, and attitudes from human-human interaction to human-computer interaction [45–47, 51]. Therefore, it seems reasonable to transfer the characteristics of social interactions to the driver-vehicle interaction. Woide et al. [65] showed that the same dimensions of human-human interaction as proposed in the interdependence theory (conflict, power, mutual dependence, information certainty, and future interdependence) are perceived and taken as a rationale for action in driver-vehicle interaction. The dimensions referring to Gerpott et al. [16], Woide et al. [65] are described in Table 1.

### 2.1 Conflict in Driver-Vehicle Interaction

Conflict is an essential factor influencing behavior. For example, situations with conflicting interests can generate negative emotions and cognition and lead to less cooperative behavior [31, 44, 57]. These findings are accompanied by the results of a driving simulator study by Woide et al. [64].

Woide et al. [64] were able to show that if the AV performed a maneuver based on information that is not accessible by the drivers, the drivers perceive a conflict between them and the AV. This conflict results in an uninformed, inappropriate, and safety-critical takeover. Therefore, it can be concluded that drivers should have all information used by the automation to reduce the conflict between the driver and the vehicle. This is in line with the idea of shared situation representation [12, 61], that for a successful interaction between driver and AVs, each team member needs to possess the same information and thus same situation awareness [12]. What remains open is the question: What preconditions must be met so that the presented information helps to generate a sufficient shared situation representation to reduce the drivers' perceived conflict?

### 2.2 Explaining Visualizations in Automated Vehicles

In the context of AVs, numerous works have explored different information types to either enhance TORs or provide information about the AV's state. This included information about decisions [9, 38], detections [6, 7, 9, 10, 20, 36, 63], destination, regulation, and navigation [10, 54]. While some work proposed that augmented reality windshield displays work best [6], a comparative study by Colley et al. [9] showed that no futuristic visualization is necessary and current Head-Up Displays provide sufficient information. When comparing different levels of information abstraction for takeovers, Colley et al. [8] found that visual stimuli were preferred and that additional information increased subjective variables, whereby the objective situation awareness was not improved significantly. Regarding visualizations to encourage automation to remain engaged, Hock et al. [24] compared three feedback conditions: without, with a computer-generated voice, and, additionally to the voice, a humanoid avatar on the co-driver's seat. They found that their anthropomorphic feedback approach persuaded participants to let the automation remain engaged longer when following a slow lead vehicle.

In general, Koo et al. [28] found, when investigating *how* and *why* information for semi-AVs, that explanatory information led to the highest trust. The combined messages, however, led to the safest driving behavior [28]. As previously mentioned, there are different approaches to pursuing different information and goals in the design of interfaces. To design an interface, which supports drivers during an overtaking maneuver, information about the course of the route and distance to the vehicles ahead should be provided. The modality precision hypothesis assumes that the modality which is more accurate for the task being performed will dominate when performing a task [3]. Since vision is usually the most accurate modality for spatial tasks [3], it can be concluded during an overtaking maneuver drivers will benefit from a visual presentation of the course of the route and distance to the vehicles ahead. In the conducted study, this was realized with a bird´s-eye view Figure 2. However, it will not be enough for the system to simply present the information. Drivers must also be able to verify the information to determine the capability of the system and calibrate their own trust in the system and information [29, 61].

### 2.3 Trust in Automated Vehicles

Trust is of focal interest for understanding human decision-making and behavior regarding human-machine interaction as it is a predictor of reliance on automation use (e.g., [4, 21, 32, 33]). Studies show first indications that people rely on the automation they trust, for example, by monitoring it less and preferring it over manual control [22, 43]. Lee and See define trust "as the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" [34, p. 51]. Trust is influenced by the information the user receives from the system [34], and previous studies indicate that transparent systems lead to higher trust in automation [2, 25]. Therefore, it can be assumed that the system should present the information in a transparent, comprehensible, useful, and verifiable form for the drivers. However, the presented information can vary with different HMI designs, and thus the trust in the AV can change.

Based on the research and theories presented, the following hypotheses were formulated:

(1) H1: Conflict is lower if drivers can verify the information given by the bird's-eye view through oncoming traffic than if they can not verify the information given by the bird's-eye view.
(2) H2: Trust is higher if drivers can verify the information given by the bird's-eye view through oncoming traffic than if they can not verify the information given by the bird's-eye view.
(3) H3: The number of rejections of the performed overtaking maneuver is lower if drivers can verify the information given by the bird's-eye view through oncoming traffic than if they can not verify the information given by the bird's-eye view.

In addition to the specific hypotheses, the following general research questions were investigated:

(1) RQ1: How does the verification of the information given by the bird's-eye influence perceived stress, criticality, and intention to use?
(2) RQ2: How does the verification of the information given by the bird's-eye influence mutual dependence, information certainty, power, and future interdependence?

(3) RQ3: How does the verification of the information given by the bird's-eye influence eye gaze behavior?

To answer the hypotheses and research questions, a fixed-based driving simulator study was conducted.

## 3 EXPERIMENT

### 3.1 Participants

The participants were recruited personally, via social media, and at Ulm University. All participants had to be at least 18 years old, possess a driver's license, and speak German at a native level. Due to technical malfunctions, six participants were excluded from the analysis. One participant was excluded due to simulator sickness. One further participant was removed from the analysis due to conspicuous response patterns. The final sample consisted of *N*=28 participants. Of these, 54% were female and 46% male with an average age of 26.89 years (*SD*=9.68) ranging from 19 to 55 years. About 46% of the participants owned their own car, and 25% stated that they share the use of a car. The driving experience of the participants varied from driving daily or several times a week (43%) to less than once a month (18%). On average, the participants held their driving license for 9.36 years (*SD*=9.50), ranging from two to 37 years. 32% of the test persons stated that they already had previous experience with driving simulators. The participants were compensated with 20 Euros or 1.5-course credits. An ANOVA found no significant differences between the participants in the four conditions in terms of propensity to trust ($F(3, 11.74) = 0.96$, $p$=.44).

### 3.2 Study Design

The study intended to examine the influence of *system transparency* and *information verification* on conflict, trust, and behavior. In order to investigate these research questions, a $2 \times 2$ repeated measurements design with the between-subject factors system transparency and information verification and four measurement points were used, resulting in four conditions. Each condition included *n*=7 participants.

*System Transparency:* System transparency was operationalized by two different representations of the HMI (see Figure 2). The representations differed in the availability of additional information. In the visual condition, participants obtained a bird's-eye view that provided the driver with information about the course of the route and oncoming traffic. In contrast, participants in the non-visual condition received no bird's-eye view and therefore no information about the course of the route and oncoming traffic from the system.

*Verification:* Information verification was manipulated by combining the bird's-eye view (1) with oncoming traffic and (2) without oncoming traffic. In the condition of information verification, the participants received a bird's-eye view with oncoming traffic. In the condition of no information verification, the participants received a bird's-eye view without oncoming traffic. By performing the entire drive with 50m visibility, the participants in the verification condition were able to verify whether the representation on the bird's-eye view was correct by verifying whether a vehicle displayed on the birds-eye view appeared in the fog at the expected time. Whereby, in the no verification condition was no oncoming traffic. Therefore, verifying whether a vehicle displayed on the bird's-eye view appeared in the fog at the expected time was not possible.

*Conflict and Measurement Points:* To enable conflicting situations, visibility was set to 50m via fog, and the AV performed an overtaking maneuver. This method is in line with the proposed study design by Woide et al. [64] to create conflicts between drivers and vehicles in a driving simulator. In total, the AV overtook a leading vehicle four times.

Fig. 1. The driving simulator used. 50m visibility range.

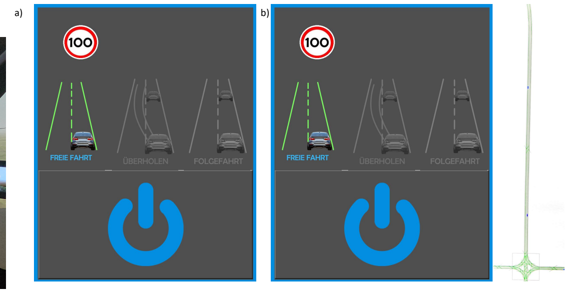



Fig. 2. The HMIs used for the different conditions of system transparency. a) depicts the interface without a bird's-eye view. b) shows the interface with a bird's-eye view.

### 3.3 Apparatus and Materials

*3.3.1 Driving simulator.* The study was conducted in the static driving simulator at Ulm University. The driving simulator consisted of three 1920 x 1200px video projections onto three screens of 3.3 x 2.1m providing a viewing angle of 200°. All essential car interior elements were contained in the vehicle mock-up. Moreover, a 17" touch display (1024 x 1280px) was located in the center console, enabling interaction with the automation. The driving simulator was equipped with an automatic transmission. The simulation software SILAB 5.1 [14] was used to program the simulator.

*3.3.2 Automation.* The automation used was able to accelerate and decelerate by itself, follow the road course, and overtake slower vehicles ahead. Furthermore, the automation used a simulated radar system to detect other road users and see through the fog. When possible, the automation maintained a constant speed of 100 km/h and avoided accidents at all times. Moreover, the automation used had a fall-back strategy. If the automation could not complete the overtaking maneuver, it had a strategy to cancel the maneuver safely. This strategy involved braking sharply and reeving behind the slower vehicle. The automation used corresponds to SAE Level 4 [55].

*3.3.3 Human-Machine Interface.* In the center console, a display was located containing information about the traffic rules and the current maneuver (free ride, overtaking, following) (see Figure 2). Free ride was displayed when the vehicle was not performing an overtaking maneuver or following the vehicle in front. Overtaking was displayed as soon as the vehicle was 175m behind the vehicle in front. The following ride was displayed when the overtaking maneuver was rejected, and the vehicle was following the vehicle in front. In addition, the button to activate the automation was placed in the lower section of the display. Furthermore, in the two conditions with the bird's-eye view, additional visual information about the course of the route and oncoming traffic was shown on the right side of the display. This HMI enabled the drivers to monitor the status of the automation. To abort the planned overtaking maneuver, participants had to press the brake pedal until a sound was heard. The automated system then aborted the overtaking maneuver, pulled in behind the following vehicle, and continued driving behind the following vehicle.

*3.3.4 Driving Scenario.* The driving track was designed as a two-lane rural road with a 100 km/h speed limit. The experimental drive was subdivided into five sections, whereby an intersection indicated the end of each section with a stop sign. Each section consisted of two straight sections and two curves. The order of the straight sections and the curves, and the sequence of the four sections were presented in randomized order. Except for the baseline drive at the beginning of the experiment, a slower lead vehicle appeared within each section. The automation overtook this lead vehicle by default. The overtaking maneuver always took place on one of the two straight sections of the track. The baseline drive did not include a lead vehicle. Therefore, no overtaking maneuver was performed on the baseline drive. Each section of the experimental drive lasted about 1.5 minutes.

*3.3.5 Eye-Tracking.* Head-mounted Ergonners' Dikablis 3 Glasses measured eye movement and gaze direction at 60Hz.

*3.3.6 Questionnaires.* After each driving scenario, the participants repeatedly answered several questionnaires. After the last experimental drive, the demographic questionnaire was additionally raised. The questionnaires were conducted via the survey platform Unipark.
*Maneuver Rejection*: The maneuver rejection was measured binary: 0 rejected the overtaking maneuver 1 did not reject the overtaking maneuver.
*Situational Interdependence*: The situational interdependence during driver-vehicle interaction was measured using the Human-Machine-Interaction-Interdependence (HMII) questionnaire [65]. The HMII assesses the dimensions of power, conflict, mutual dependence, information certainty (human to system + system to human), and future interdependence (human to system + system to human) on a five-point Likert scale. *Stress*: Stress was measured using the single item "How stressed/nervous were you in the situation you just experienced?" with scale endpoints ranging from 1 (not stressed/nervous at all) to 100 (very stressed/nervous) [11, 37].
*Criticality*: Situational criticality was assessed with the item "How do you evaluate the situation you just experienced?" with scale endpoints ranging from 0 (nothing noticed) to 10 (not controllable) [48].
*Trust*: Trust was measured using the single item "How much did you trust the autonomous system in the situation you just experienced?" ranging from 0 (I do not trust the system at all) to 100 (I fully trust the system) [23].
*Intention to use*: Intention to use was measured on a five-point Likert scale [49, 58].
*Demographics*: The demographic questionnaire assessed the participants' gender, age, education, and driving characteristics, (e.g. duration of holding a driver's license, frequency of car use).

### 3.4 Procedure

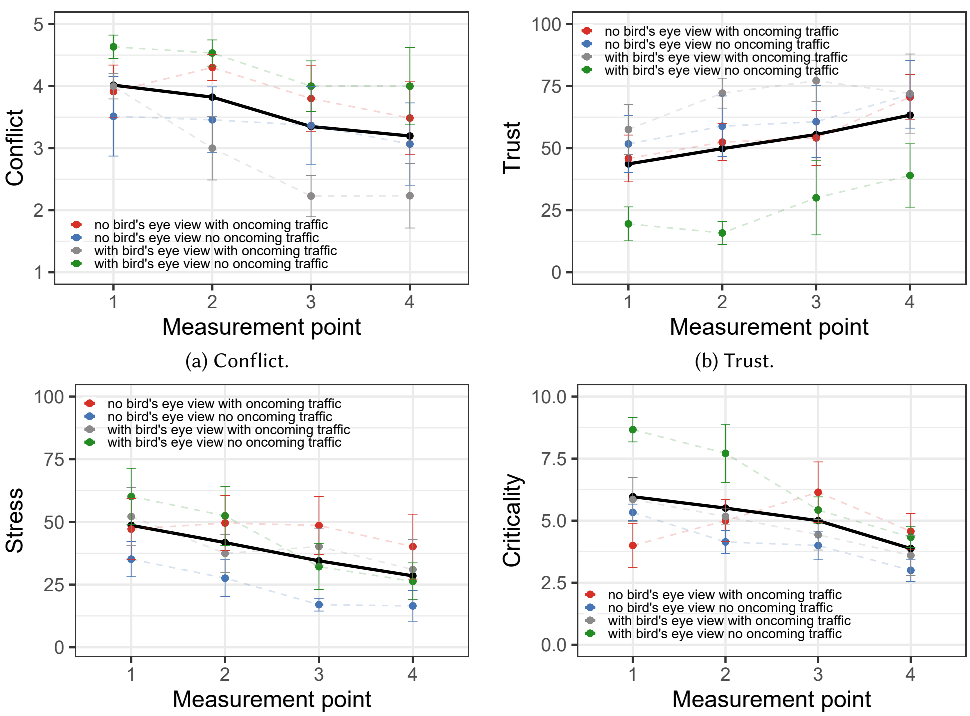
The participants were welcomed, their vaccination status regarding SARS-CoV-2 was checked, and participants could prove a negative test not older than 24h. After reading the participant information and agreeing to the privacy statement and informed consent, the participants were randomly assigned to one of the four conditions. Following this, it was checked whether the participants fulfilled the inclusion criteria regarding age (18 and older), possession of a driver's license, and native language (German). No participant had to be excluded due to not fulfilling the inclusion criteria. Next, the driving simulator and the interface were introduced. In order to ensure a standardized procedure of the study, the explanations of how the automation works and the interaction possibilities with the automation were presented in text form (see Appendix A). In addition, the participants were introduced to the task of intervening whenever they feel uncomfortable or unsafe with the overtaking maneuver. Finally, three comprehension questions were asked to ensure that the participants understood their task and the given information (1. I can command the automation to perform an overtaking maneuver. 2. "Free ride" means overtaking the vehicle in front. 3. Within its field of view, the automated system can detect traffic ahead and oncoming traffic, regardless of the visibility condition.). The participants then conducted a 10 minutes test drive without traffic to familiarize themselves with the driving simulator. Before the experimental drive, the eye tracker was calibrated. Additionally, the participants were asked to reread their tasks. Subsequently, the baseline drive was conducted, followed by four experimental drives. At the end of the baseline drive and each experimental trial, the participants answered several questionnaires on a tablet. After the last experimental drive, the demographic questionnaire was additionally raised. In the end, the participants were thanked for their participation and compensated with 20€. Overall, the study lasted 1.5 hours.

## 4 RESULTS

### 4.1 Data Analysis

Before every statistical test, the required assumptions (normal distribution and homogeneity of variance assumption) were tested. Observations that were 1.5 IQR below the first quartile or 1.5 IQR above the third quartile were excluded from the analysis [35]. For the factorial analysis of non-normal data, the non-parametric ANOVA (NPAV) as implemented by Lüpsen [39] was used. The participants were included as a random intercept for the four measurement repetitions. We always used Dunn's test with Bonferroni correction for post-hoc tests. The alpha level was 0.05. R in version 4.2.0 and RStudio in version 2022.02.0 was used. All packages were up to date in April 2022.

### 4.2 Descriptive Description of Conflict, Trust, Stress, Criticality




(a) Conflict. (b) Trust. (c) Stress. (d) Criticality.

Fig. 3. Temporal trend for conflict, trust, stress, and criticality.

Figure 3a and Figure 3b show descriptively that in the condition with a bird's-eye view and no oncoming traffic, the system is less trusted than the conditions without a bird's-eye view and the system with a bird's-eye view and with oncoming traffic. A similar pattern emerged in the evaluation of conflict. In the condition with a bird's-eye view and no

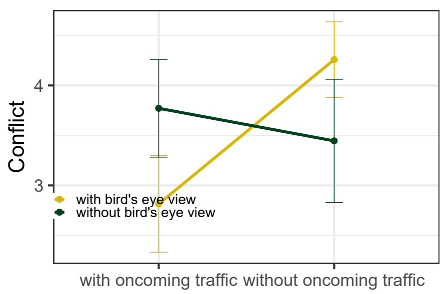



Fig. 4. IE on conflict.


Fig. 5. IE on trust.

oncoming traffic, a higher conflict was perceived than in the condition without a bird's-eye view and the system with a bird's-eye view and with oncoming traffic. In the case of criticality, the situation in condition with a bird's-eye view and no oncoming traffic was perceived most critically at the first two measurement time points. At measurement time points 3 and 4, all conditions converged in their criticality ratings. In the case of stress, no differences between the conditions were apparent. After the description, the results on the hypotheses and research questions are described.

### 4.3 Hypothesis Testing on Conflict, Trust and Rejection

*Conflict:* In hypothesis 1, it was assumed that conflict is lower if drivers can verify the information given by the bird's-eye view through oncoming traffic than if they could not verify the information given by the bird's-eye view. The NPAV found a significant interaction effect (IE) of *traffic* × *transparency* on conflict ($F(1, 23) = 6.14$, $p$=.021; see Figure 4). With oncoming traffic, a bird's-eye view led to low conflict. However, without traffic, the bird's-eye view led to higher conflict than not having the bird's-eye view. Therefore hypothesis 1 can be supported.

*Trust:* In hypothesis 2, it was assumed that trust is higher if drivers can verify the information given by the bird's-eye view through oncoming traffic than if they can not verify the information given by the bird's-eye view.

The NPAV found a significant main effect of *measurement point* on trust ($F(3, 69) = 9.60$, $p$<.001; see Figure 3b). The NPAV found a significant IE of *traffic* × *transparency* on trust ($F(1, 23) = 4.72$, $p$=.040; see Figure 5). While trust remained almost equal for traffic levels without a bird's-eye view, trust was significantly reduced when there was a bird's-eye view but no traffic. Therefore hypothesis 2 can be supported.

In hypothesis 3, it was assumed that the number of rejections of the performed overtaking maneuver is lower if drivers can verify the information given by the bird's-eye view through oncoming traffic than if they can not verify the information given by the bird's-eye view. A logistic mixed model (estimated using ML and Nelder-Mead optimizer) was calculated to predict rejection with transparency and traffic (formula: rejection transparency * traffic). The model included the participant as a random effect (formula: 1 | code). The model's total explanatory power is substantial (conditional $R^2$=0.53), and the part related to the fixed effects alone (marginal $R^2$) is 0.27. The model's intercept, corresponding to transparency = without bird's-eye view and traffic = without oncoming traffic, is at 1.17 (95% CI [-0.30, 2.64], $p$=.119). Within this model:

- The effect of transparency [with bird's-eye view] was statistically non-significant and positive (beta=0.03, 95% CI [-1.95, 2.01], $p$=.976; Std. beta=0.03, 95% CI [-1.95, 2.01])

- The effect of traffic [with oncoming traffic] is statistically non-significant and negative (beta=-0.12, 95% CI [-2.11, 1.87], *p*=.907; Std. beta=-0.12, 95% CI [-2.11, 1.87])
- The IE of traffic [with oncoming traffic] on transparency [with bird's-eye view] is statistically significant and negative (beta=-3.09, 95% CI [-6.04, -0.15], *p*=.040; Std. beta=-3.09, 95% CI [-6.04, -0.15])

Standardized parameters were obtained by fitting the model on a standardized version of the dataset. 95% Confidence Intervals (CIs) and p-values were computed using the Wald approximation. Due to the significant IE, and as only a reduction of the rejection occurs when a bird's-eye view is combined with oncoming traffic, hypothesis 3 is supported.

A chi-square test with subsequent Dunn's test ($chi^2(3, n=28)=21.53$, $p<.001$) showed that compared to all other conditions in the condition with a bird's-eye view and oncoming traffic the overtaking maneuver was rejected significantly less often (18%). There were no significant differences between the other conditions (*M*=68%) (see Figure 7).

### 4.4 Findings Research Questions

*4.4.1 Stress, Criticality, Intention to Use.* The first research question dealt with how the verification of the information given by the bird's-eye influences perceived stress, criticality, and intention to use?

*Stress:* The NPAV found a significant main effect of *measurement point* on stress ($F(3, 67) = 18.22$, $p<.001$). Post-hoc tests showed that stress in the first measurement point (*M*=48.04, *SD*=28.67) was significantly higher than in the fourth (*M*=23.72, *SD*=18.48; $padj$=.009).

*Criticality:* The NPAV found a significant main effect of *transparency* on criticality ($F(1, 18) = 7.29$, $p$=.015). With a bird's-eye view (*M*=5.46, *SD*=2.22), criticality was rated significantly higher than without (*M*=4.23, *SD*=1.82). The NPAV also found a significant main effect of *measurement point* on criticality ($F(3, 61) = 17.79$, $p<.001$). A post-hoc test showed that the first (*M*=5.93, *SD*=2.59; $padj$=.02) and second (*M*=5.15, *SD*=2.26; $p<.001$) *measurement point* was rated as significantly more critical than the fourth (*M*=3.55, *SD*=0.91).

*Intention to Use:* Intention to use was measured after every trial. For the comparison, the average of these four values was compared condition-wise (the four between-subject conditions). An ANOVA found no significant differences between the four conditions ($F(2, 11.99) = 0.73$, $p$=.50). Intention to use ranged from *M*=2.29 (with bird's-eye view with **no** oncoming traffic) to *M*=3.21 (with bird's-eye view with oncoming traffic).

*4.4.2 Mutual Dependence, Information Certainty, Power, Future Interdependence.* The second research question dealt with, how the verification of the information given by the bird's-eye view influences mutual dependence, information certainty, power and future interdependence?

*Mutual Dependence:* The NPAV found no significant effects on mutual dependence. Mutual dependence was highest with no bird's-eye view with oncoming traffic (*M*=3.02, *SD*=1.11) and lowest with bird's-eye view with oncoming traffic (*M*=2.91, *SD*=1.08). The values, however, were very close.

*Future Interdependence:* The NPAV found no significant effects on future interdependence-system to human. Future interdependence-system to human was highest with no bird's-eye view with oncoming traffic (*M*=2.37, *SD*=0.95) and lowest with bird's-eye view with oncoming traffic (*M*=2.11, *SD*=0.88).

The NPAV found a significant main effect of *measurement point* on future interdependence-human to system ($F(3, 16) = 5.55$, $p$=.008). However, a post-hoc test found no significant differences. Future interdependence-human to system was highest for no bird's-eye view no oncoming traffic (*M*=3.93, *SD*=0.87) and lowest for with bird's-eye view no oncoming traffic (*M*=3.73, *SD*=0.94).

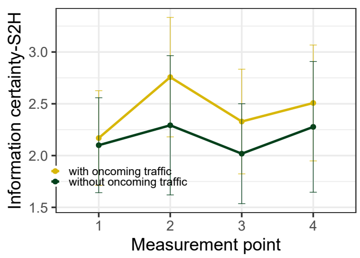



Fig. 6. IE on information certainty-system to human.

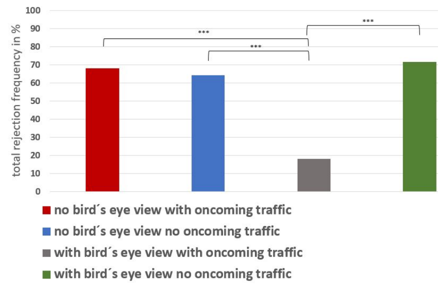



Fig. 7. Total rejection frequency.

*Power:* The NPAV found a significant main effect of *measurement point* on power ($F(3, 40) = 6.71$, $p$<.001). Post-hoc tests showed that power was significantly higher in measurement point two ($M$=3.06, $SD$=0.11) compared to measurement point one ($M$=3.00, $SD$=0.00; $padj$=.024), measurement point three ($M$=3.00, $SD$=0.00; $padj$=.014), and measurement point four ($M$=3.00, $SD$=0.00; $padj$=.016). The NPAV found a significant IE of *transparency* × *measurement point* on power ($F(3, 11) = 6.19$, $p$=.010).

*Information Certainty:* The NPAV found a significant IE of *traffic* × *measurement point* on information certainty-system to human ($F(3, 64) = 2.99$, $p$=.037; see Figure 6). Without oncoming traffic, information certainty-system to human was always rated lower than with oncoming traffic. However, this uncertainty difference was very low in the first trial but increased, and then remained approximately equal for the second to the fourth measurement point.

The NPAV found a significant main effect of *measurement point* on information certainty-human to system ($F(3, 65) = 4.05$, $p$=.011). However, post-hoc tests found no significant differences. The lowest value was in measurement point one ($M$=4.06, $SD$=0.68), the highest in measurement point three ($M$=4.30, $SD$=0.56).

*4.4.3 Eye-Tracking.* The third research question dealt with how the verification of the information given by the bird's-eye view influences eye gaze behavior? Due to technical issues caused by the mandatory of wearing a mask during the experiment, only eye gaze data from three participants in the condition with a bird's-eye view with oncoming traffic and five participants in the condition with a bird's-eye view no oncoming traffic (i.e., both conditions with interfaces) could be analyzed. The total fixation of the HMI during the overtaking maneuver from the announcement to the actual overtaking maneuver (total x milliseconds) was summed up for comparison. The NPAV found no significant effects on interface glances (with oncoming traffic: $M$=6781.67, $SD$=3110.83; without oncoming traffic: $M$=5617.70 ms, $SD$=5635.02).

## 5 DISCUSSION

This study investigated how the possibility of verifying the presented information of the AV affects the drivers' interaction perception, rejection frequency, conflict, trust, stress, criticality, and gaze behavior. A fix-based driving simulator study with $N$=28 participants was conducted. The results indicate that additional information via a bird's-eye view only reduces the conflict and the rejection frequency and increases trust significantly if drivers can independently verify the correct functioning of the information system beforehand. Additionally, the perception of the interaction regarding power, information certainty, and future interdependence was influenced by the measurement points, system transparency, and verification. The results, the practical implications, and limitations are discussed below.

In the presented study, both conditions with a bird's-eye view have the same system with identical visualizations on the interface (displaying oncoming traffic, traffic on the own lane, road course, and maneuver). Nevertheless, the results show that the drivers in the condition with a bird's-eye view but without oncoming traffic rejected the overtaking by the automation significantly more often than in the bird's-eye view condition with oncoming traffic. A possible explanation is that the drivers in the condition without oncoming traffic did not pay attention to the display. However, this is contradicted by the average fixation time of the HMI during the overtaking, which does not differ between the bird's-eye view conditions with and without oncoming traffic. Even though the average fixation time of the HMI did not differ in the two conditions, there is a difference in rejection frequency. Therefore, it can be assumed that they have a different understanding of how the AV works and, therefore, different mental models. This assumption is supported by the fact that drivers need to be able to map the systems' capabilities presented through the HMI towards their goals, to develop an accurate mental model of the functionality of the system [12]. Participants in the condition with a bird's-eye view and without oncoming traffic did not have the opportunity to verify the systems' capabilities to detect oncoming traffic. Therefore, the drivers form a mental model that the AV is apparently unable to detect oncoming traffic and, thus, safely perform an overtaking maneuver. Whereas the drivers in the conditions with a bird's-eye view and oncoming traffic seem to build up a mental model about the AV in which an overtaking maneuver is safe and possible. These different mental models could explain the different observed rejection frequencies. However, it must be considered that in both conditions with the bird's-eye view, the vehicle in its own lane was correctly displayed. Therefore, in both conditions with a bird's-eye view, it is possible to verify the traffic in the own lane. Nevertheless, this verification of the traffic in the own lane does not seem to influence the mental model regarding oncoming traffic used during the overtaking maneuver. Therefore, before starting the critical overtaking maneuver, the possibility should be given to building up an adequate model of the oncoming traffic. In practice, a bird's-eye view should always be displayed to build up an adequate model by the drivers. If the bird's-eye view is only switched on during a critical overtaking maneuver, no adequate mental model would have been built up by then. Consequently, the system would not adequately support the drivers, resulting in dangerous takeovers.

### 5.1 Trust, Conflict, Social Interaction

Trust is an important predictor of reliance in, and thus use of, automation (e.g., [4, 21, 22, 32, 33, 43]). Trust is influenced by the information the user receives from the system [34]. Our results show that trust is even lower in the condition with a bird's-eye view and without oncoming traffic than in the conditions without a bird's-eye view. However, with the possibility of verifying the given information, the trust in the condition with a bird's-eye view is significantly higher than in the condition with a bird's-eye view and without oncoming traffic. The results of this study reveal that the given information alone is not appropriate to increase trust. Hence, if systems provide verifiable information trust increases. The assumption that the properties of the system influence trust is strengthened by the fact that the participants in the different conditions did not differ in trust during the baseline measurement. Besides trust, conflict is another crucial factor for automation engagement [64].

Woide et al. [65] stated that by changing the relationship between the drivers and the AVs, disagreement regarding the maneuver choice can occur. Our results of the conducted study support this assumption, as we showed that conflicts between driver and vehicle are perceived during an overtaking maneuver. Furthermore, the study showed that the possibility of verification reduces conflict significantly. Additionally, the results indicate that the conflict occurs because either the drivers lack information that the automation has or the given information is not verifiable. This, in turn, means that verifiable information makes the systems‘ behavior understandable and thus reduces conflict. Furthermore, the results show that the different conditions change the perception of human-vehicle interaction regarding power, future interdependence, and information certainty. These results support the assumption that the interaction's perception will change when the relationship between the drivers and the AVs change. As the perception of interaction is a strong predictor of behavior [26, 52], attention to the perception of human-vehicle interaction is crucial to understanding how system design and the situation are perceived and how the interaction is actively influenced.

### 5.2 Practical Implications

The findings show that providing additional information via a bird's-eye view only reduces rejection frequency and conflict, and increases trust significantly if the drivers can independently verify the information displayed by the AV. Therefore, we conclude that systems that fail to provide verifiable information will fail to support the driver's needs. Consequently, future systems must provide information verification possibilities to enable adequate mental models and, in consequence, appropriate trust. These adequate mental models allow reaping the benefits of automation engagement and avoiding error-prone takeovers. Moreover, to build adequate mental models, future systems should avoid showing information in a specific situation that could not be verified before. This design recommendation is crucial in safety-critical and high-conflict situations. Otherwise, drivers make spontaneous, uninformed, and safety-critical control takeovers. Therefore, systems that only selectively share unverifiable information do not provide any benefit or may even reduce trust in the system. In addition, the study points out that conflicting situations between drivers and AVs can occur in the future. Furthermore, the change in the relationship between drivers and AVs will lead to changes in the interaction perception (e.g., shift of power, future interdependence, information certainty) between drivers and AVs.

### 5.3 Limitations

The experiment provides insights into the importance of information verification in driver-vehicle interaction. Nevertheless, the study has its limitations: One limitation is the group size per condition ($n$=7). Due to technical malfunctions, simulator sickness, and conspicuous response patterns, eight participants were excluded from the analysis. Additionally, only a few eye-tracking data could be used due to the mandatory wearing of a mask during the experiment because of SARS-CoV-2. One additional limitation is the external validity. Even if actual behavior was observed in the driving simulator, conclusions about the natural behavior during automated driving should be strengthened by further experiments. The last limitation is the use of one presentation form in the HMI. More research is needed on how other modalities and HMIs behave regarding information verification and rejection frequency.

## 6 CONCLUSION

The presented fixed-based driving simulator study ($N$=28) investigated how the possibility of verifying the presented information of the AVs affects automation engagement and the perception of the interaction with AVs. The results show that if drivers can verify the information provided by the AV, automation engagement is supported. Furthermore, the findings reveal that the drivers' perception of the interaction with AVs influences the drivers' behavior (rejection frequency) towards the AVs. To conclude, to take advantage of AVs and avoid takeovers, it is not a question of how well the AVs can perform. Instead, what matters is how drivers perceive the interaction with AVs since the drivers' perception is crucial for their behavior. Besides these first insights, more research is necessary to investigate how the design of AVs influences the drivers' perception of the interaction and, consequently, the automation engagement.

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# A INSTRUCTIONS

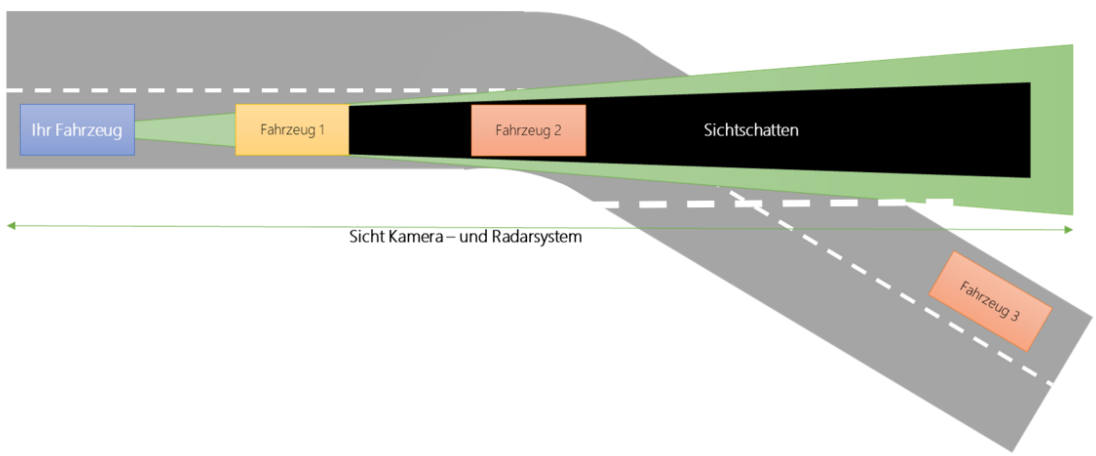
The instructions were given in the native language German, therefore, the figures still are shown with German text.

## A.1 Functionality

You are about to drive an automated vehicle in the driving simulator. Once the automation system is activated, the vehicle is controlled automatedly. I.e.:

- The vehicle accelerates and decelerates by itself and can overtake.
- The vehicle recognizes the road, traffic signs, and other road users.
- The vehicle is able to find the way to the destination programmed into the navigation system on its own.
- The vehicle adheres to the currently valid traffic regulations and the legal safety distance. The vehicle manages the aforementioned tasks with the help of various sensors.
- The vehicle has a camera system to read signs, for example.
- The vehicle has radar technology to be able to detect obstacles regardless of the visibility condition.
- The vehicle has a map system that has stored the geographical data as well as the applicable traffic rules.

## A.2 Functionality field of view




The schematic diagram above shows the vehicle's field of vision when the automation is activated.

In principle, the field of view spreads out in a cone shape to the front (and rear). Due to the blocking of the field of view by vehicle 1, road users in the shadow of the field of view (here vehicle 2) cannot be detected directly by the system. Vehicle 3 is still outside the field of view and is only detected when it enters the field of view.

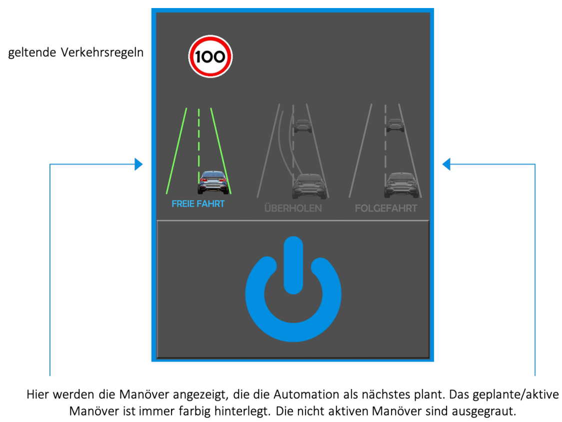
## A.3 Functionality of driving behavior

The vehicle decides on a particular maneuver with the highest possible degree of safety within the limits of its capabilities. If the automated system decides to overtake, it will only do so if it has a fallback strategy. This means that if the automation cannot complete the overtaking maneuver, it has a strategy to safely cancel the maneuver. These strategies usually involve hazard braking, sudden lane changes, or narrowly reeving. This is not desirable.

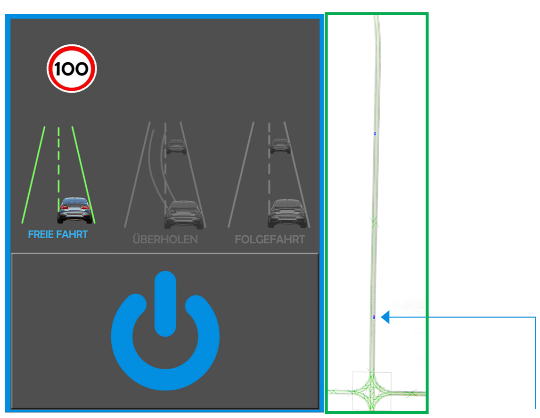
## A.4 Explanation of the interface

*A.4.1 Display of maneuvers.* The maneuvers that the automation is planning next are displayed here. The planned/active maneuver is always highlighted in color. The inactive maneuvers are grayed out.

Free ride: no obstacle within the sensor range of the vehicle. Overtake: The vehicle will overtake the obstacle. Follow drive: The vehicle will not overtake the obstacle, but will follow it at an adapted speed.




*A.4.2 The bird's-eye view (framed in green).* Shown in blue on the right side you see your ego-vehicle.



### A.5 Interaction with the vehicle

Actuation of the brake

By braking, the overtaking maneuver can be rejected and a follow-up maneuver can be initiated. Press and hold the brake until you hear a signal tone and the maneuver is cancelled. Only after the signal tone sounds can you release the brake and automatically follow the vehicle in front.

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