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Keeping the driver in the loop in conditionally automated driving: A perception-action theory approach ☆

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ABSTRACT

In this paper we investigated if keeping the driver in the perception–action loop during automated driving can improve take-over behavior from conditionally automated driving. To meet this aim, we designed an experiment in which visual exposure (perception) and manual control exposure (action) were manipulated. In a dynamic driving simulator experiment, participants (n = 88) performed a non-driving related task either in a head-up display in the windshield (high visual exposure) or on a head-down display near the gear shift (low visual exposure). While driving, participants were either in an intermittent control-mode with four noncritical take-over situations (high manual control exposure), or in a continuous automation-mode throughout the ride (low manual control exposure). In all conditions, a critical take-over had to be carried out after an approximately 13 min ride. Measurements of take-over behavior showed that only high visual exposure had an effect on hands-on reaction time measurements. Both visual exposure and manual control exposure had small to medium sized main effects on time to system deactivation, the maximum velocity of the steering wheel, and the standard deviation of the steering wheel angle. The combined high visual – and high manual control exposure condition led to 0.55 s faster reaction time and 37% less steering variability in comparison to the worst case low visual – and low manual control exposure condition. Together, results corroborate that maintaining visual exposure and manual control exposure during automated driving can be efficacious and suggest that their positive effects are additive.

1. Introduction

The development and implementation of increasingly automated vehicles will remain relevant for the coming decades (Chan, 2017; Fagnant & Kockelman, 2015). As long as automation is not fully continuous and robust (e.g. SAE Level 4/5), humans will remain an integral part of the human-vehicle-environment system (Hoffman, Hayes, Ford, & Hancock, 2002; Parasuraman & Wickens, 2008). Automating a task increasingly takes the human out of the task's perception–action control loop (Merat et al., 2018; Mole et al., 2019; Sheridan & Verplank, 1978). In conditional vehicle automation the driver may fully delegate the driving task to the automated vehicle (AV), but the intended function of such a systems requires the driver to be

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capable of taking back control rapidly and adequately when prompted to do so by the vehicle (SAE, 2014; 2018). In the current study, we aim to investigate if keeping the driver in the loop during automated driving can improve take over behavior.

1.1. The out-of-the-Loop problem

A considerable body of research is currently pointing out that the out-of-the-loop problem in this design of automation can lead to performance decrements in the speed and quality of reclaiming manual control (Gold, Damböck, Lorenz, & Bengler, 2013; Louw et al., 2017; Louw & Merat, 2017; de Waard, Van Der Hulst, & Hoedemaeker, 2010). The loop in vehicle control has been defined on several levels from strategic to tactical, operational and recently executional levels taking place on different time-scales (Abbink et al., 2018; Michon, 1985). In studies where performance decrements are discovered in taking back control under time pressure (Gold et al., 2013; Merat, Jamson, Lai, Daly, & Carsten, 2014; Zhang, de Winter, Varotto, Happee, & Martens, 2019), these decrements appear to be specific to control on the level of operational and executional loops (Mole et al., 2019). Being out of the loop has been defined as a lack of motor processes and perception/monitoring of the driving scene (Merat et al., 2018). Therefore, it is of interest how drivers' take-over performance can be improved by maintaining gaze patterns and motor calibration while driving with conditionally automated vehicles (Mole et al., 2019).

1.2. The perception-action approach

According to the perception–action framework, manual driving behavior emerges as the driver interacts with the environment through loops of perception and action (Bootsma, 1998; Fajen, 2005; 2007;; Fajen & Devaney, 2006; Harrison, Turvey, & Frank, 2016; Mathieu, Bootsma, Berthelon, & Montagne, 2017). For example, the optical expansion of a stop sign is perceived by drivers and guides their braking actions towards it (DeLucia et al., 2016; Lee, 1976; Morando, Victor, & Dozza, 2016). In turn, the action of braking changes the optical expansion of the stop sign relative to driver, thereby closing the perception–action loop. When the driver is in the loop, perception entails the driver's visual attunement to the task-relevant information, such as the looming of the stop-sign for braking (Fajen & Devaney, 2006). For an adequate action to result, the drivers action must be well-calibrated (Brand & de Oliveira, 2017), that is, applying the right amount of pressure to the brake given the current context.

1.3. A perception-action approach to keeping the driver in the loop

It has been found that in-the-loop gaze patterns and motor-calibration are disrupted when the AV takes over the full driving task (Mole et al., 2019). Although there are AV designs which maintain either drivers' gaze on the road (Radlmayr, Brüch, Schmidt, Solbeck, & Wehner, 2018) or motor-calibration (Russell et al., 2016), it is unclear which role combinations have on take-over time and adequacy (Mole et al., 2019). Studies of gaze in manual curve driving have suggested that drivers look ahead approximately 1–2 s (Land & Lee, 1994). Inversely, the extent that eyes are taken off the road or the degree of foveal visual eccentricity have been shown to lead to slower hazard detection (Lamble, Laakso, & Summala, 1999) and decreased reaction time (Summala, Lamble, & Laakso, 1998). However, when transferred to automated driving, maintaining one's gaze near the road by the using a Head-Up-Display has not been found to improve take-over performance (Radlmayr et al., 2018).

Maintaining gaze on the road during automated driving has, to our knowledge, not been combined with AV designs that maintain motor-calibration or action. This might be crucial observation, as being in control has been stated to change what is perceived (Wilson, 2004). Considering motor-calibration, relieving the driver from physical control through automated driving has been shown to increase variability in evasive take-over maneuvers from automation (Navarro, François, & Mars, 2016), In contrast, naturalistic vehicle studies have shown that providing the same take-over situation improves motor-calibration or steering variability in take-overs (Russell et al., 2016). Thus it appears that while driving with automation reduces motor-calibration, this decay may be ameliorated by recurring take-overs to manual control. This conjecture is supported by several studies incorporating recurring take-overs in conditionally automated driving (Bourrelly et al., 2019; Feldhütter, Gold, Schneider, & Bengler, 2017; Meratet al., 2014). Previous research has raised legitimate questions regarding drivers acceptance of AVs with intermittent manual control (Merat et al., 2014). However, empirical data on take-overs shows that acceptance might be higher than expected (Körber, Prasch, & Bengler, 2018). Therefore, further research is necessary to understand the effect of manual control exposure and visual exposure on acceptance. Aside from acceptance, it is necessary to study motor-calibration in take-overs within the same take-over time-budget as shorter time budgets have been shown to lead to higher steering wheel variability (Gold et al., 2013). A further advantage studying take-over situations with a small time budget is that it pressures participants to react immediately and reduces interpersonal variation in reaction preferences (Zhang et al., 2019).

1.4. The present study

The purpose of this paper is to study if the perception–action approach towards keeping the driver in the loop while driving with conditional automation can improve take-over behavior. We hypothesize that maintaining drivers' *visual exposure* to the road improves reaction times when they need to take back control from the AV (H1). To maintain action or motor-calibration the effects of recurring take-overs to manual control on steering variability were found to be relevant. Our hypothesis is that recurring take-overs, henceforth referred to as *manual control exposure*, increase the stability of the take-over as manifested by lower steering variability (H2). We also examined the combined effect of visual – and manual control exposure on take-over behavior. Our hypothesis is that a condition in which both factors are high would show most improvements in reaction time and steering stability, as opposed to any other factor combinations (H3). Finally we explored whether acceptance differed between the possible combinations of visual and manual control exposure AV design.

2. Method

2.1. Participants

For the current study 140 participants were recruited to participate via the internal BMW employee participant pool. Before the study informed consent by all participants was attained, and the study complied with the American Psychological Association Code of Ethics. Participants needed to have at least 50,000 km driving experience, normal or corrected to normal eye-sight, and did not work in the field of vehicle automation. The participants were randomly divided into four conditions. For the 140 participants data were rigorously analyzed to ensure the rides were valid and no spurious system failures occurred. This led to the exclusion of 41 participants due to errors in the simulation software. An additional 11 participants were excluded because the manipulation of visual exposure did not work in their condition. This led to 52 participants being excluded. The final data set consisted of n = 88 participants (*mean age* = 31 Years (*SD* = 9.6 years), 11 Female, *Average lifetime driving experience* = 155 000 km) divided approximately evenly across conditions (see Table 1).

Given a power analysis showing that a small-to-medium effect requires 80 participants this sample was deemed sufficient for an 80% chance of rejecting the null hypothesis at an alpha of 0.05.

2.2. Experimental setup

This study was performed in a dynamic driving simulator (see Fig. 1a), comprising a full BMW 5 Series mockup with automatic transmission (see Fig. 1b). The hydraulic hexapod had six degrees of freedom with the capacity for 7 m/s^2 transitional – and 4.9 m/s^2 continuous acceleration. BMW's Spider simulation environment calculated sound, scenario handling and communication between the computers. A 240° horizontal and 45°vertical frontal field of view was provided by seven 1080p, 50 Hz, projectors. Two additional projectors with the same specifications and one LCD Display in the back of the vehicle respectively served as left, right and rearview mirror. Furthermore eye-movements were recorded at 50 Hz via a Dikablis Essential glasses optical eye-tracking system with D-Lab Software (D-Lab 2.5, 2013).

Table 1
Distribution of participants across conditions.

Variable	Intermittent Control		Continuous Automation	
	HUD	HDD	HUD	HDD -
Number of Participants	24	19	25	20
Number of Females	1	5	2	3
Mean Age	31(11)	29(5)	32(10)	30(9)

Note. Standard deviations are presented in parentheses.

a b

Fig. 1. Exterior view of the dynamic simulator (a) and interior view (b).

2.3. Experimental design

A two by two factorial between-subject design was developed to measure the influence all combinations of visual exposure (high / low) and manual control exposure (high / low) on take-over behavior (See Fig. 2).

2.3.1. Independent variable: visual exposure

The manipulation of visual exposure was achieved by placing a visual non-driving-related (NDRT) task in either a Head-Up-Display (HUD) with virtually no eccentricity to the road center, or a Head-Down-Display (HDD) tablet, at high visual eccentricity (approximately 60°, as illustrated in Fig. 2). The purpose of the NDRT was to require constant foveal attention on the NDRT location. The rapid-serial-visual response task (RSVP) which has previously been adapted to for the current research purpose (Wiedemann et al., 2018) was used for this. The participant's task was to attend to symbols occurring every second and click a button near the gear shift when numbers were shown in between distractor letters (Broadbent & Broadbent, 1987; Wiedemann et al., 2018). The researcher monitored the participants NDRT engagement and prompted participants to engage in the NDRT if they missed three numbers. Eye-tracking was used to confirm that this manipulation of focal visual attention succeeded.

2.3.2. Independent variable: manual control exposure

To manipulate manual control exposure, the automated system drove with either continuous automation or posed vehicle-initiated take-overs to manual control intermittently (see Fig. 2). These intermittent take-overs led to deactivation of the automated system after five seconds forcing the drivers to take back control. The system was then deactivated for 30 s forcing the driver to drive manually until automation became available again. These take-overs occurred at four instances in following traffic situations: (1) curved empty road, (2) slower vehicle ahead, (3) while overtaking a slower vehicle, and (4) while being overtaken. Once automation became available drivers reactivated the automated system or were prompted to do so 10 s after the system became available.

In all conditions, the route that was driven consisted of a highway route with three lanes and moderate traffic (Radlmayr, Gold, Lorenz, Farid, & Bengler, 2014). The AV kept a constant speed of 130 km/h, provided lateral and longitudinal guidance and overtook slower vehicles. The speed limit was chosen in line with the common 130 km/h on German highways. Hence, for the participants in the intermittent manual control exposure condition this was a natural speed to maintain. However, drivers speed could differ around 130 km/h, leading to slight differences in the elapsed time until the take-over at the end of the ride (see Table 2).

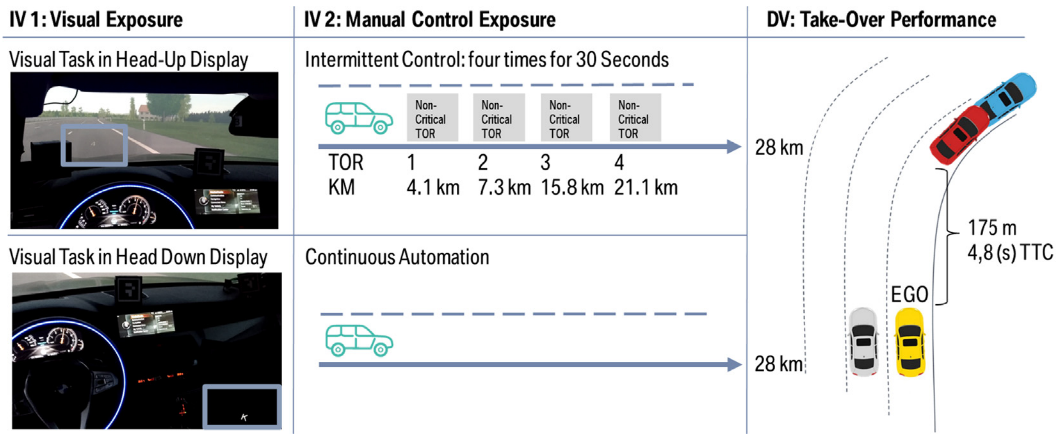

Fig. 2. Schematic presentation of the experimental design. Note. The figure shows the experimental manipulations with independent variables visual exposure (IV 1) and manual control exposure (IV 2) followed by the dependent variable take-over performance (from left to right). Regarding visual exposure the head-up display corresponds to the high exposure and the head-down-display corresponds to the low exposure. In regard to manual control exposure continuous automation corresponds to low exposure whereas intermittent control corresponds to high exposure.

Table 2
Elapsed time at the critical take-over situation.

Variable	Intermittent Control		Continuous Automation	
	HUD	HDD	HUD	HDD -
Mean Time to Tor (Min.)	13.03(0.03)	13.03(0.05)	13.00(0.01)	13.00(0.03)

Note. Standard deviations are presented in parentheses.

2.3.3. Dependent variable: critical take-over

At the end of each session a vehicle initiated critical take-over was programmed, which was identical for each participant (see Fig. 2). To demarcate the effect of perception and action manipulations on take-over performance, the situation needed to be critical enough to avoid floor effects in which all participants maneuvered the situation adequately. According to previous research a five-second time-to-collision meets this goal (Gold et al., 2013). The critical take-over occurred in a curve by means of two crashed vehicles appearing behind a curve at 175 m distance at 4.8 s time-to-collision. A vehicle on the middle lane that drove at 130 km/h created a medium traffic complexity scenario (Radlmayr et al., 2014) without interfering with the participants avoidance maneuver. To bring the take-over to a safe ending, participants had the opportunity to change lanes, brake and change lanes, or remain in the lane and brake. Given the curvature of the road, not changing the lane still forced participants to steer. The NDRT was discontinued when the take-over-request was issued.

2.4. Procedure

Participants signed an informed consent and a demographic questionnaire. The NDRT was explained and drivers were instructed to engage in it whenever possible while ensuring that they arrived safely. The activation of automation was then explained, and drivers were shown that the human–machine-interface consisted of an illuminated steering wheel, sound, and icons in the speedometer display (see Fig. 3).

The system could be inactive while driving manually or display the automation-related status (1) automation available, (2) automation active, (3) non-critical take-over and (4) critical take-over. Each take-over was accompanied by a unique pulsating sound that was designed to be critical or lightly critical. The critical take-over was not shown to participants so as to invoke a first contact experience (Hergeth, Lorenz, & Krems, 2017).

Then, we explained the experimental procedure. Participants were instructed to imagine it was two years later than today, they have picked up the vehicle from the airport and would get to know most of the automation function during the ride. Subsequently, we started the experiment, which consisted of three trials.

2.4.1. Practice trial: Familiarization with manual and automated driving

Participants performed standardized acceleration, lane change and emergency braking maneuvers. Next, they activated the automation feature and performed the NDRT before being instructed to deactivate the system by pressing the "AUTO" button, steering, braking or accelerating. The ride took approximately 5 min which is a common time span for a first practice ride (Gold, Naujoks, Radlmayr, Bellem, & Jarosch, 2018).

2.4.2. Practice trial: Noncritical takeovers from automation

In order to ensure that all participants had the same experience in taking back control from automation independent of the continuous automation/ intermittent control condition, the four non-critical take-over scenarios, performed in the

Fig. 3. The visual interface modalities in the speedometer and the illuminated steering wheel.

experimental trial were performed by all participants. Participants were instructed to drive with automation whenever possible and the NDRT was available on the tablet or HUD depending on the condition. It was instructed as an optional task, allowing participants to naturally acquaint themselves with the automation. This second trial took approximately five minutes and the two practice trials together comprised a ride of 15 km, which would be sufficient for novel drivers to adapt to the driving simulator (Ronen & Yair, 2013).

2.4.3. Data collection trial

For the last trial the participants were instructed to drive with automation whenever possible, and to perform as well as they could on the NDRT while ensuring that they arrived safely. The NDRT was located depending on the condition of perception. Depending on the action condition participants either had to take over at four variably spread noncritical take-over scenarios throughout the route (intermittent control) or never at all. After 28.7 km the critical take-over scenario occurred. After this, participants were asked to drive the vehicle to side of the road and the experiment was concluded. The participants and filled in questionnaires regarding perceived criticality of the situation and were debriefed.

2.5. Measures

2.5.1. Manipulation ***check***

To analyze whether participants' perception manipulation (NDRT in either HUD or HDD) succeeded only participants with valid eye-tracking data comprising at least 90% Pupil recognition were included, leaving a sample of 66 participants. During six 30-seconds timeslots that were comparable across participants, the foveal attention to the HUD and HDD were compared. As a manipulation check for the necessary level of criticality in the critical take-over situations we analyzed the minimum time to collision (TTC) from the middle of the ego vehicles front bumper to the nearest point in the bounding box of the stationary obstacle vehicle. As the take-over took place in a curve and the TTC was calculated for a prospective straight path, the calculated TTC may be several milliseconds lower than the real curvilinear TTC. However, the TTC in the curvilinear trajectory would still be highly critical and the calculation was consistent across all participants allowing for comparability across experimental conditions.

To ensure that steering behavior was displayed in take-over behavior across groups we analyzed the types of maneuver chosen per group.

2.5.2. Drivers reaction time

Drivers' reaction time was measured as duration from the take-over signal to resuming motor readiness by placing hands on the steering wheel (Gold et al., 2013; Zhang et al., 2019). Next, the time until the driver deactivated the automated system was measured, which is a standard reaction time measure (Mole et al., 2019). Deactivation of the system entailed either pressing the auto button, steering over 10° or pressing the brake for at least 10% of the total brake pedal movement range.

2.5.3. Drivers steering stability

Drivers steering adequacy was quantified as the standard deviation of the steering wheel angle which is a standard measure of steering variability (Mole et al., 2019). This measure was complemented with the maximum velocity of the steering wheel, in order to assess the jerkiness of the movements. Both were analyzed in the six seconds after the take-over request that comprised the timespan in which participants either came to halt in the curve or passed the obstacle.

2.5.4. Acceptance

In order to understand in how visual - and manual control exposure affected participants' subjective experience of the automated system, acceptance was measured with a nine item forced choice acceptance scale (Van der Laan, Heino, & De Waard, 1997). This scale results in two scales reflecting usefulness and satisfaction of new technology, respectively. After the experimental ride participants were asked to think of the system they had just experienced while filling in the items.

2.6. Statistical analysis

For the take-over situation we confirmed that the time to collision was critical and drivers maneuver choices included steering behavior. Next, we excerpted the criticality of the take-over situation, reaction time, and steering adequacy with MATLAB (Version R2015b, MathWorks Inc.) and performed statistical analyses with R-Studio (V 3.5.1). To analyze hypotheses 1 and 2 we distinguish main effects of driving- and visual exposure an aligned ranks transformation (ATR) factorial analyses of variance (ANOVA) was performed with a significance level of $\alpha = 0.05$ (Wobbrock, Findlater, Gergle, & Higgins, 2011). This established procedure performs an aligned ranking transfomation for each effect (main and interaction) before an F-test is performed. It was appropriate to apply this analysis to our data, because it is particularly suited for factorial experimental data, that are not normally distributed and not homoscedastic. Additionally the method is not sensitive to the outliers in our take-over response data, which were not due to measurement errors. ATR ANOVA builds on ranking transformations (Conover & Iman, 1981), but adds an additional preprocessing step of alignment step for each effect (Hodges & Lehmann, 1962) which has been shown to make interactions interpretable (Higgins & Tashtoush, 1994; Salter & Fawcett, 1993; Wobbrock et al., 2011).

Although this procedure offers a non-parametric method of detecting main and interaction effects, it does not allow for an overall contrast between the combinations of conditions as the data are ranked separately for each effect. Therefore, it was necessary to perform a separate analysis to test our hypothesis 3 that, overall, the condition with high visual and manual control exposure would show the greatest improvements in take-over behavior (hypothesis 3). Akin to a planned treatment contrast we compared all conditions to the worst case situation, low visual and manual control exposure, which we considered as worst case scenario. This was possible by utilizing a Kruskal-Wallis test for omnibus differences between the cells and then applying a focused comparison method, testing the significance of the mean rank differences between the worst case scenario and all other groups (Field, Miles, & Field, 2012; Siegel and Castellan, 1988).

Due to a layout error acceptance was wrongly collected on a 7-point [−3; 3] instead of a 5-point rating scale during data collection. To ensure comparability of the data with other studies and the original scale, the ratings were linearly transformed into a 5 Point rating scale [−2, −1.33, −0.67, 0, 0.67, 1.33, 2]. Acceptance was then analyzed with a 2-way ANOVAs inspecting the effect of manual control and visual exposure on each of the subscales, usefulness and satisfaction using, an $\alpha = 0.05$ cutoff value.

3. Results

3.1. Manipulation checks

Participants in the HUD condition showed a glance duration at the HUD (and were thereby visually exposed to the road) of 94%. Participants in the HDD condition showed a glance duration at the HDD for 80% of and 10% on the road. Taking into account that the NDRT allowed for quick glances at the road, this confirms that our manipulation worked. In order to detect differences in take-over behavior, the critical take-over was initialized with 4.8 s time-to-collision if no action were taken by the driver. The data show that this led to the expected criticality with drivers displaying a time to collision of *Mdn* = 0.792 s (see Table 3). This confirms that the situation was highly critical (Brookhuis, De Waard, & Fairclough, 2003). Given these non-realistic levels of criticality, which were deliberately constructed in this study to elicit immediate driver reactions, eight crashes occurred which divided approximately evenly across conditions.

The take-over situation confronted participants with a blocked lane and allowed for all participants to act naturally in their response. Therefore, different responses were possible. Most participants braked and changed lanes whereas many changed lanes without braking and few braked without changing lanes (see Fig. 4). However, even participants that did not change lanes had to take on steering action because they were driving in a curve.

Table 3
Minimum Time-To-Collision across conditions.

	Manual Control Exposure					
	Intermittent Control		Continuous Automation		Marginal	
Visual Exposure	M	SD	M	SD	M	SD
HUD	1.10	0.71	0.93	0.61	1.01	0.66
Tablet	0.82	0.44	0.77	0.49	0.79	0.46
Marginal	0.98	0.61	0.86	0.56		

Note. M and SD represent mean and standard deviation, respectively.

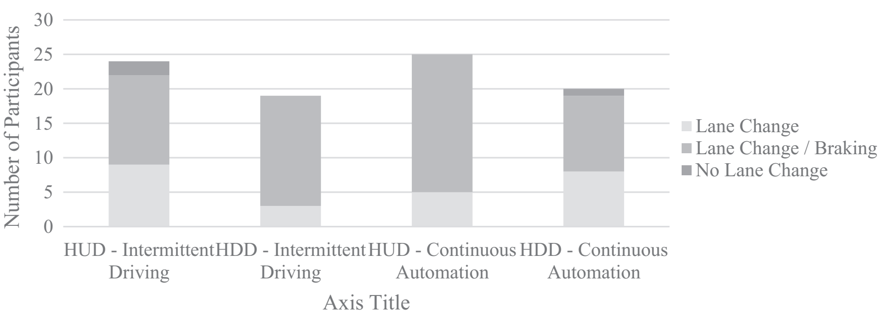

Fig. 4. Choice of maneuver displayed per condition.

3.2. Independent variable: reaction time

We expected that high visual exposure would lead to faster reaction times (hypothesis 1).

For the analysis of the hands on the steering wheel reaction time in the critical take-over situation an additional seven participants were excluded because the sensor was temporally defective.

In line with our expectation, the Hands-On the steering wheel reaction time showed a main effect of visual exposure with a small-to-medium effect size (Cohen, 1988), $F(1, 77) = 4.28$, $p = .041$, $\eta_p^2 = .052$. Manual control exposure did not have a significant impact, $F(1, 77) = 0.82$, $p = .365$, $\eta_p^2 = .010$, and the ANOVA revealed no significant interaction, $F(1, 77) = 1.35$, $p = .248$, $\eta_p^2 = .017$.

Regarding time to system deactivation, both visual exposure, $F(1, 84) = 4.28$, $p = .041$, $\eta_p^2 = .048$, and manual control exposure, $F(1, 84) = 4.79$, $p = .031$, $\eta_p^2 = .054$, had a main effect with small-to-medium effect sizes. The ANOVA revealed no significant interaction, $F(1, 84) < 0.01$, $p = .99$, $\eta_p^2 < 0.01$ (see Fig. 5). It appears that the combination of visual – and manual control exposure has an additive effect as both factors have significant main effects and the interaction is insignificant.

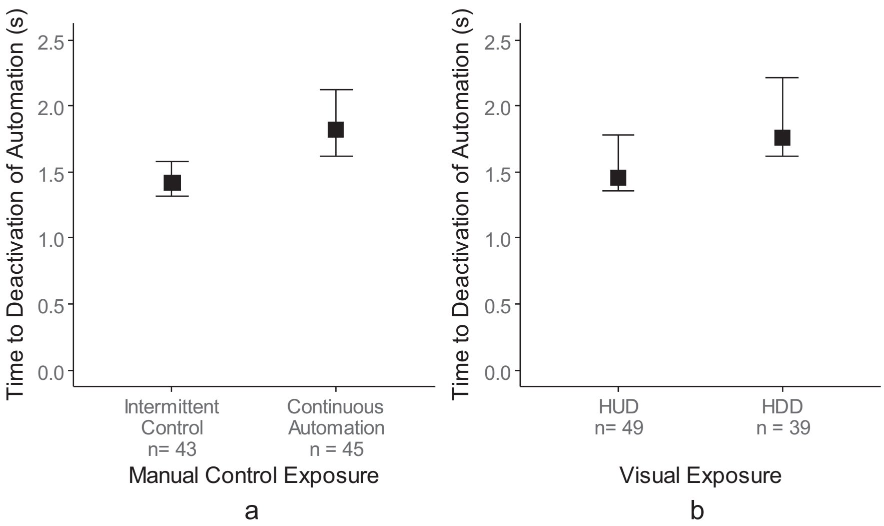

Fig. 5. Medians with 95% confidence intervals for the main effects on time to system deactivation. Note. Medians with bootstrapped 95% confidence intervals (Carpenter & Bithell, 2000) for the main effects of (a) factor manual control exposure (high = Intermittent Control, Low = Continuous Automation) and (b) factor visual exposure (high = Head-Up Display and low = Head-Down Display) on time to system deactivation.

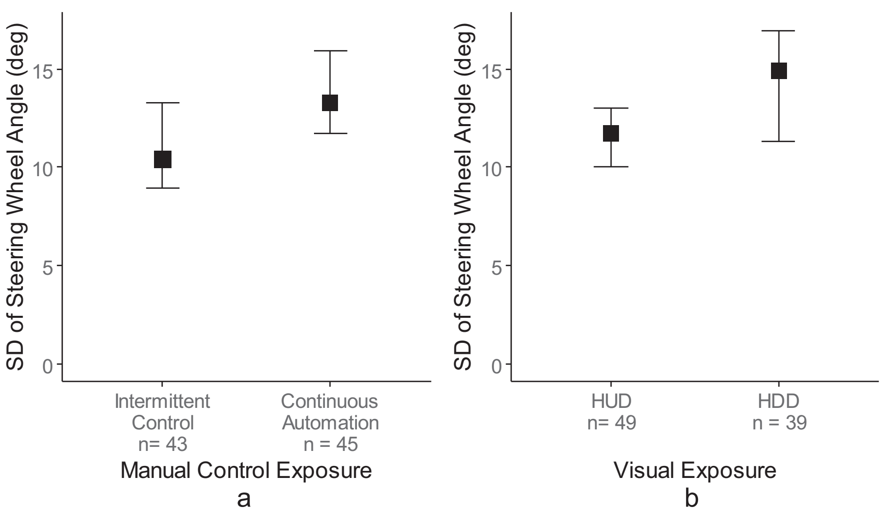

Fig. 6. Median with 95% confidence intervals for the main effects on SD of the steering wheel angle. Note. Medians with bootstrapped 95% confidence intervals (Carpenter & Bithell, 2000) for the main effects of (a) factor manual control exposure (high = Intermittent Control, Low = Continuous Automation) and (b) factor visual exposure (high = Head-Up Display and low = Head-Down Display) on the standard deviation of the steering wheel angle.

Table 4
Minimum velocity during the critical take-over for all experimental conditions.

Variable	Intermittent Control		Continuous Automation	
	HUD	HDD	HUD	HDD -
Mean Minimum Velocity (km/h)	98(29)	93(27)	92(26)	95(29)

Note. Standard deviations are presented in parentheses.

3.3. Independent variable: take-over steering stability

In hypothesis 2 we expected that manual control exposure would have an effect on steering variability. Regarding the maximum steering wheel velocity, manual control exposure showed a main effect with a small-to-medium effect size, $F(1, 84) = 4.84$, $p = .037$, $\eta_p^2 = .050$, whereas the effect of visual exposure manipulation did not reach the $\alpha = 0.05$ cutoff but showed a similar effect size, $F(1, 84) = 3.74$, $p = .056$, $\eta_p^2 = .042$. The interaction effect was not significant $F(1, 84) = 0.25$, $p = .612$, $\eta_p^2 = .003$.

Similarly, the standard deviation of the steering wheel angle was influenced by manual control exposure, $F(1, 84) = 5.13$, $p = .025$, $\eta_p^2 = .057$, and visual exposure also had an influence, $F(1, 84) = 4.19$, $p = .043$, $\eta_p^2 = .047$ (see Fig. 6), both with small-to-medium effect sizes. There was no significant interaction $F(1, 84) = 0.78$, $p = .37$, $\eta_p^2 = .009$. Taking into account the significant main effects of both factors on the standard deviation of the steering wheel angle, as well as their non-significant interaction, it again appears that the combination of the factors had an additive effect.

Finally, the standard deviation of the steering wheel angle is related to the minimum speed of the vehicle, which was also the case our data $r_s = -0.44$, however no minimum velocity differences were found between the experimental conditions, $H(3) = 1.91$, $p = .59$ (see Table 4).

3.4. Planned comparisons

The ANOVA analysis showed that the effect of maintaining visual and manual control exposure is additive. This is in line with our expectation that high visual exposure plus high motor control exposure would show the largest improvements in take-over behavior (hypothesis 3). However, the significance of this difference between the combined experimental conditions could not be tested with the method used above. Therefore planned comparisons of all conditions to the expected worst case condition, HDD and continuous automation were performed in a nonparametric fashion. For a comparison of time to hands-on the steering wheel an omnibus Kruskal-Wallis test was performed, $H(3) = 6.84$, $p = .076$, $\eta^2 = 0.057$, which did not justify comparisons at the $\alpha = 0.05$ significance level. For time to system deactivation an omnibus Kruskal-Wallis test, $H(3) = 9.95$, $p = .018$, $\eta^2 = 0.093$, allowed for planned comparisons. In line with hypothesis 3, this analysis showed that only the combination of high visual – and manual control exposure showed significantly faster system deactivation times than the worst case scenario (*difference* = 24.0, *critical difference* (at $\alpha = 0.05$, corrected for number of tests) = 18.51). Indeed Fig. 7) shows that participants in the HUD / Intermittent control manipulation were faster (*Mdn Difference* = 0.55 s or 29% faster)

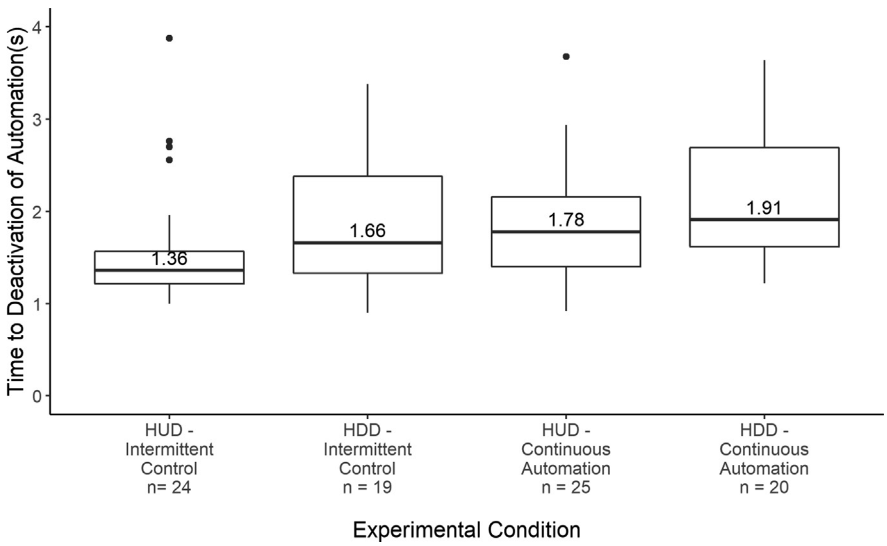

Fig. 7. Boxplot of the time to system activation for all experimental conditions.

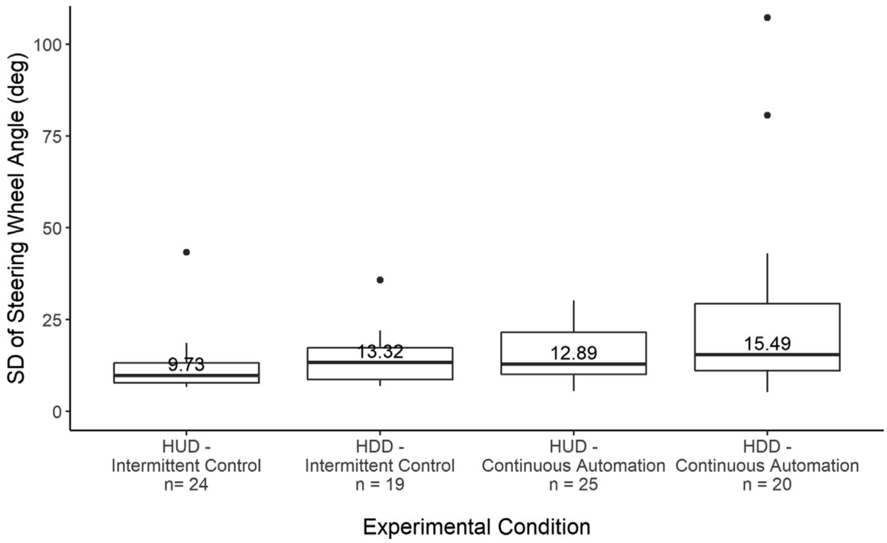

Fig. 8. Boxplot of the standard deviation of the steering wheel angle for all experimental conditions.

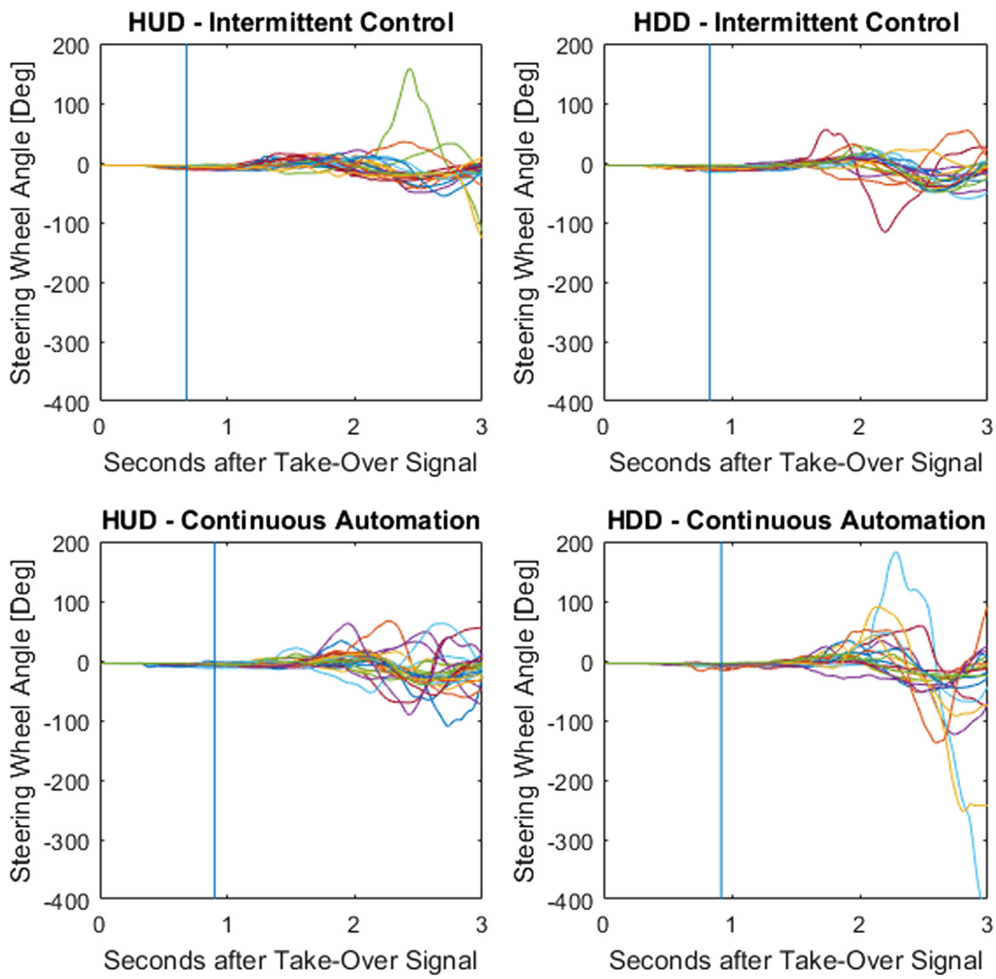

Fig. 9. Individual participant's trajectories of the steering wheel angle. Note. Individual participant trajectories of the steering wheel angle in all conditions in the six seconds following the take-over signal. The median system deactivation time is included (blue line) to facilitate interpretations regarding the relation between take-over timing and steering wheel angle.

Table 5
Means and Standard Deviation for the acceptance subscales satisfaction and usefulness.

Variable	Intermittent Control		Continuous Automation	
	HUD	HDD	HUD	HDD -
Satisfaction	1.09(0.65)	1.43(0.49)	1.37(0.40)	1.22(0.60)
Usefulness	0.82(0.49)	1.15(0.38)	0.89(0.51)	0.95(0.53)

Note. Standard deviations are presented in parentheses.

than worst case scenario. It is also noteworthy that visual inspection of Fig. 7 shows that the spread of time to system deactivation is markedly smaller in the HUD – Intermittent control condition as opposed to all others. In the current study it appears as though only this additive combined effect led to a significant difference in steering stability to the worst case scenario.

The focused comparison of the maximum velocity of the steering wheel was not justified by the Kruskal-Wallis test, $H(3) = 7.13$, $p = .067$, $\eta^2 = 0.093$, at the $\alpha = 0.05$ level. For the standard deviation of the steering wheel angle a Kruskal-Wallis test, $H(3) = 9.24$, $p = .026$, $\eta^2 = 0.085$, permitted planned comparisons. In line with hypothesis 3, this analysis showed only the high visual - and manual control exposure condition was significantly different from the worst case scenario (*difference* = 23.27, *critical difference* (at $\alpha = 0.05$, corrected for number of tests) = 18.51). Furthermore, Fig. 8 shows drivers in the high visual and manual control exposure condition displayed a standard deviation of the steering wheel angle that was lower (*Mdn Difference* = 5.76° or 37% lower) than worst case scenario. The intermediate combinations such as HUD with continuous automation (i.e. high visual and low manual control exposure) or HDD with intermittent control (i.e. low visual – and high manual control exposure) did not differ significantly from the worst case scenario. It is also noteworthy that visual inspection of Fig. 8 shows that the spread of standard deviation of the steering wheel angle is markedly smaller in the HUD – Intermittent control condition as opposed to all others. This is corroborated by the raw steering wheel angle data presented in Fig. 9.

3.5. Acceptance

System acceptance was evaluated with a simple scale with two subscales: satisfaction and usefulness (Van der Laan et al., 1997). According to Van der Laan and colleagues (1997) these subscales can aggregated if *Cronbachs* $\alpha > 0.65$. The results of a reliability analysis suggested that subscales satisfaction (*Cronbachs* $\alpha = 0.81$) and usefulness (*Cronbachs* $\alpha = 0.68$) were sufficient to aggregate and analyze the constructs independently. Regarding satisfaction, a 2-way ANOVA showed that neither visual exposure, $F(1, 83) = 0.61$, $p = .435$, $\eta_p^2 = 0.006$, or manual control exposure, $F(1, 83) = 0$, $p = .62$, *partial* $\eta^2 = 0.002$, had a significant effect. However, the analysis revealed a significant interaction of both factors with a small-to-medium effect size, $F(1, 83) = 4.28$, $p = .041$, $\eta_p^2 = .048$. Visual inspection revealed a cross-over interaction. For high visual exposure (HUD), intermittent control is negatively associated with satisfaction whereas and for low visual exposure (HDD) intermittent control is positively associated with satisfaction. Generally, Table 5 shows, the satisfaction values tend to fall into to the upper part of the scale from -2 to +2.

Analyses of the usefulness scale showed a marginally significant effect of visual exposure, $F(1, 83) = 3.29$, $p = .07$, $\eta_p^2 = .037$, suggesting that participants tended to find the head-down-display condition of visual exposure to be more useful than the head-up-display variant. The effects of manual control exposure, $F(1, 83) = 0.24$, $p = .62$, $\eta_p^2 = .002$, and the interaction, $F(1, 83) = 1.71$, $p = .62$, $\eta_p^2 = .020$, were not significant. Generally, however, the values were relatively high given the scale $[-2, 2]$ (see Table 5).

4. Discussion

The goal of this study was to investigate if maintaining visual exposure and manual control exposure during conditionally automated driving can keep the driver in the perception–action loop, and improve take-over reaction time and stability. We expected that maintaining visual exposure, or foveal vision near the road, would improve reaction time (Hypothesis 1). Support for this hypothesis was found, as both the time to hands-on the steering wheel and time to system deactivation were significantly influenced by visual exposure. This is in line with previous research showing that keeping foveal vision on the road improves reaction time (Summala et al., 1998). Interestingly it also shows an effect of visual exposure on reaction time that was not found in previous research (Radlmayr et al., 2018). This effect might have been detected in this study because previous research did not measure hands-on timing and did not combine visual with manual control exposure in measures of time to system deactivation, as will be discussed below.

In the second hypothesis, we expected that maintaining manual control exposure, or intermittent manual control, would improve the steering stability in take-over situations. As expected the maximum velocity of the steering wheel and the standard deviation of the steering wheel angle were significantly affected by manual control exposure. This result is in line with previous research suggesting that repeated take-overs improve motor-calibration (Russell et al., 2016).

4.1. The effect of maintaining both visual and manual control exposure

A novel contribution of the current paper is the investigation of the combined effect of maintained visual - and manual control exposure in all possible combinations. In the reaction time measures, maintained manual control exposure did not affect the time it took for drivers to take their hands back on the steering wheel. The time to hands-on the wheel is viewed as a preparatory step in regaining driving readiness (Gold et al., 2013; Zhang et al., 2019) and appears to be influenced by visual exposure but not by manual control exposure. In contrast the time until drivers started the driving maneuver by deactivating the system was affected by both visual – and manual control exposure. In fact only the combination of gaze on the road and intermittent control led to a significant 0.55 s faster reactions than in the worst case condition. At 130 km/h this time advantage corresponds to an additional 19.8 m distance from the obstacle at the beginning of the maneuver.

In regard to steering stability, the maximum steering wheel velocity was reduced by manual control exposure and by visual exposure to a slightly lesser extent. Arguably, in our data these two factors appear to have led to less jerky movements. This observation extends to the standard deviation of the steering wheel angle where the data show a comparable main effect of both visual – and manual control exposure was found. Moreover a significant 37% reduction of the standard deviation of the steering wheel angle was only found between the conditions in which manual control and visual exposure were both high and the condition where both were low. In line with research showing that steering wheel variation is lower when driving manually, as opposed to taking back control from automation (Eriksson & Stanton, 2017), we interpret this difference to show that motor calibration was improved in the condition with high manual control and visual exposure. Although these results corroborate the notion that lower steering variability is generally associated with adequate take-over behavior (Mole et al., 2019), the safety benefit in a specific take-over situation depends on the complex interplay of different factors, such as speed, reaction time, and traffic complexity.

Taken together, our expectation that visual – and manual control exposure together have the strongest effect was corroborated. Indeed, only participants assigned to the condition with both visual – and manual control exposure displayed faster time to deactivation and lower standard deviation of the steering wheel angle differing significantly from the worst case scenario. However the interactions for these factors were not significant suggesting that their effects are additive. Adding each measure individually might have an effect, but in the present study – only the combination provided significant improvements to the worst case scenario. This would explain why not effects were found when visual exposure was maintained without manual control exposure in a previous studies (Radlmayr et al., 2018).

Beyond the statistical results, visual inspection showed that a combination of the visual and manual control exposure appeared to reduce variability between participants. This would be invaluable as it would increase the controllability for the breadth of drivers that may be inexperienced with vehicle automation. Finally, previous research has stated that a system with recurring take-overs would not be accepted by drivers (Merat et al., 2014). Our data do not find support for this claim and are in line with previous research suggesting that unexplained take-overs are not necessarily detrimental to acceptance (Körber et al., 2018).

4.2. Limitations and future directions

The results suggest that maintaining visual exposure and intermittent manual control exposure can improve reaction time and steering stability. In drawing conclusions from this study it should be considered that that repeated, vehicle initiated, intermittent take-overs, may habituate drivers to non-meaningful warnings over time. This "cry wolf effect" (Breznitz, 1984; Naujoks, Kiesel, & Neukum, 2016) could render drivers less reactive if critical alarms are activated and should be investigated. Moreover, further research is necessary to create a systematic, situation specific understanding of how steering variability influences the safety of the drivers' take-over behavior. Also, it would also be necessary to extend the results achieved with our visual NDRT to more spacious media, such as a movie (cf. Naujoks, Befelein, Wiedemann, & Neukum, 2018). It should be evaluated if a HUD display covering up optical information in the environment would counteract the desired effect of visual exposure. As the focus of the present study was on take-over situations with high time urgency, it should be studied how the effects of maintaining visual – and manual control exposure extend to take-over situations in which participants have more time to react (Eriksson & Stanton, 2017).

Regarding the acceptance the results showed that ratings were generally on the higher part of the scale. However, these results must be interpreted within the studies limitations. Regarding acceptance the results only to first contact evaluations and applies to BMW Employees who may be biased in judging technology produced by their employer (Radun, Nilsonne, Radun, Helgesson, & Kecklund, 2019). It would be interesting to replicate the results with a participant sample that is not potentially confounded in this manner.

4.3. Conclusion

We conducted a driving simulator experiment to test a perception–action theory inspired approach of keeping the driver in the loop while driving with a conditionally automated vehicle. Maintaining 'perception' inspired the measure of maintaining visual exposure to the road via head-up display. Maintaining the 'action' component of the loop inspired maintained manual control exposure by the means of intermittent manual driving. The study showed that maintaining visual exposure can improve reaction time and steering stability whereas intermittent manual control exposure appears to improve mostly steering stability. However, it was only the condition with both visual- and manual control exposure that led to significant improvements above the worst case condition. A novel implication of this research is that the effect of maintaining visual – and manual control exposure appears to be additive. The acceptance scores for all conditions were generally high, suggesting that this might be promising avenue. Future research should explore the method developed in this paper with other non-driving-related tasks and longer time budgets in take-over situations.

CRediT authorship contribution statement

J. Dillmann: Conceptualization, Methodology, Investigation, Formal analysis, Writing - original draft. **R.J.R. den Hartigh:** Conceptualization, Methodology, Formal analysis, Writing - original draft. **C.M. Kurpiers:** Conceptualization, Methodology, Investigation, Formal analysis, Writing - original draft. **F.K. Raisch:** Conceptualization, Methodology, Writing - review & editing. **D. Waard:** Conceptualization, Methodology, Writing - review & editing. **R.F.A. Cox:** Conceptualization, Methodology, Formal analysis, Writing - original draft.

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