An Approach to Adapting Automated Vehicle Behaviour to Real-Time User Trust: A Driving Simulator Study

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Abstract

With progressively advancing technological developments in automated driving, automated vehicles (AVs) hold significant potential in improving traffic safety and efficiency. However, these benefits can only be realized if people accept AVs. One of the main factors currently hindering acceptance of AVs is trust. Trust needs to be calibrated to achieve a level which is corresponding to the capabilities of the vehicle. This study investigated a form of adaptive automation, testing whether personalized speed could lead to higher trust in AVs for initially low-trusting people. To test that, a driving simulator study was conducted, using a between-subjects design, where 45 participants were divided into three groups (one experimental, two control groups). For the experimental group, speed changed according to real-time trust as indicated by using a trust slider during the 15-minute simulated driving session. Additionally, Electrodermal Activity (EDA) was measured using a wristband and pre- and post-questionnaires were utilized to analyse the change in trust. Even though trust increased significantly after having experienced the AV in all three groups, the adaptive speed did not influence trust. This was also reflected in EDA measures and trust slider values, which did not differ between the groups. Thus, the study did not find a proper way to incorporate adaptive automation according to trust levels. Nevertheless, future studies could improve technical limitations of the current study to build upon the recommendations on how adaptive automation could be realized.

Keywords: automated vehicles, trust in automation, trust calibration, adaptive automation, personalized speed

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Introduction

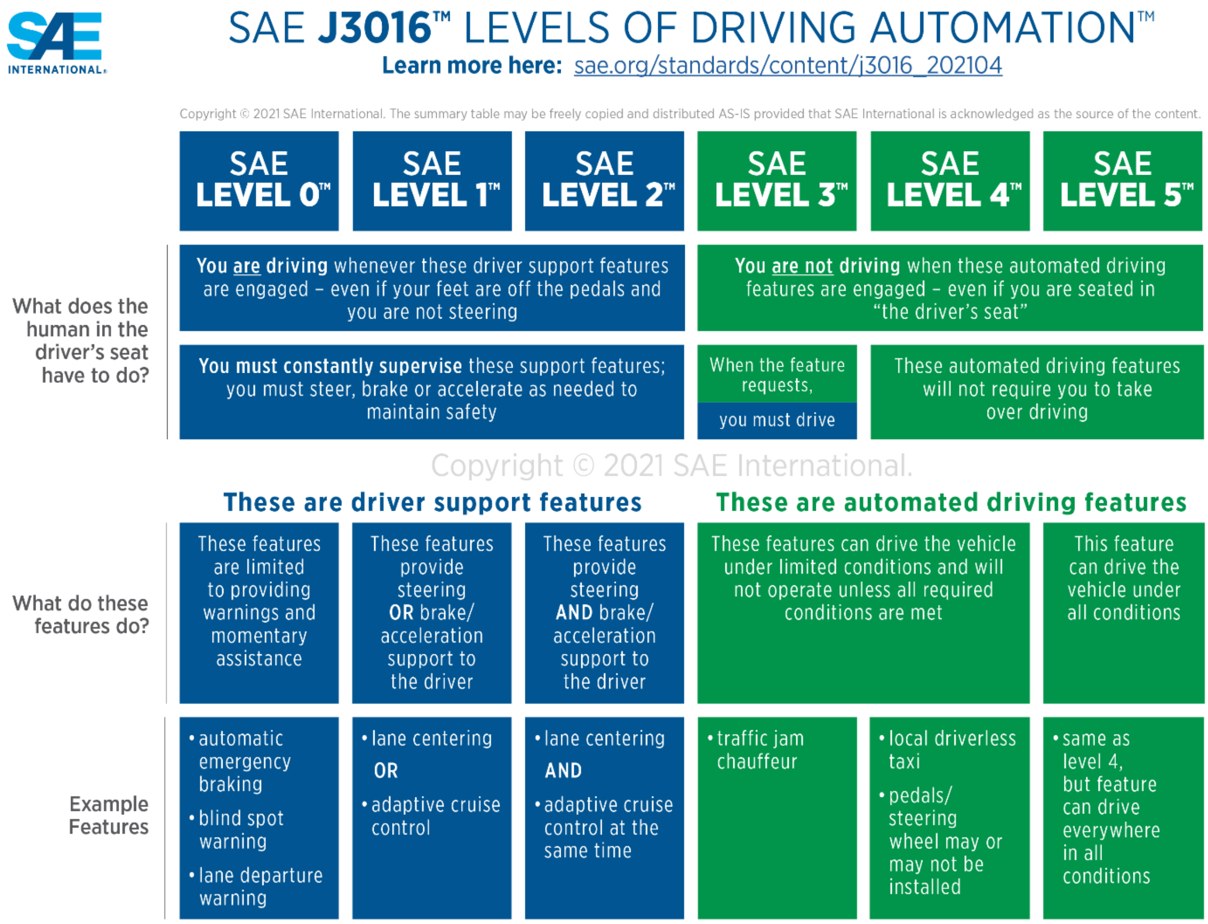
Automated Vehicles

With increasing technological developments in automated driving, the role of the driver is progressively shifted towards a rather passive one. Automated vehicles (AV) promise a decrease in traffic density, which is expected to result in a lower number of traffic accidents and a lower number of collisions in general (Ondruš et al., 2020). This benefit should not be disregarded considering that traffic accidents currently are reported to be one of the leading causes of death around the world, with about 1.3 million deaths each year (World Health Organization, 2022). Furthermore, Hopkins and Schwanen (2021) point out that moving towards AVs would also result in advantages in the environmental, economic, and social sectors.

AVs are characterized by different levels of automation and thus, the degree of involvement of the driver. The Society of Automotive Engineers (SAE, 2021a) provides a taxonomy, explaining six levels of automation (Figure 1). Level 0 is defined as entailing no automation at all, while Level 5 includes full automation. Currently, advancements are at Level 2 of automation, which still involves the driver to constantly monitor advanced driver assistance systems (ADAS) and intervene appropriately if necessary. ADAS are various systems incorporated into the car aimed at supporting the driver (Walker et al., 2018). Such ADAS are for instance lane keeping assistance (LK) or adaptive cruise control (ACC) (Boelhouwer et al., 2020). Thus, the driver still has an active role, but gets assistance from the ADAS while driving. From Level 3 to 5, a transition is happening in take-over possibilities (SAE, 2021a). Take-over describes the process of the driver taking back control of the vehicle after a critical incident (Zhang et al., 2019). This might be initiated by a take-over request from the system or based on self-observation. While take-over can be requested in Level 3, automated driving systems will not require a take-over in Level 4 and 5 (SAE, 2021a). Thereby, Level 4 can drive only under a specific set of conditions, while a Level 5 AV is supposed to be driving autonomously under all conditions (SAE, 2021a).

Figure 1

Taxonomy Including 6 Levels of Automation, as Provided by the SAE (2021a)



As the current study will involve an AV equipped with Level 4 automation, their functionalities will be briefly outlined. In Level 4, there is no need for the passenger to supervise the performance of the car. Vehicles are fully responsible for the driving task and can autonomously perform it. However, the car can only navigate under specific conditions and on specific routes (SAE, 2021b). Outside of those specific conditions, the car cannot operate autonomously. An example of Level 4 automation is a driverless taxi, as a specific route will be planned, and the AV can fulfil this without any need for intervention. In Level 4 already, AVs do not necessarily need to include pedals or a steering wheel (SAE, 2021a). While technological advancements are steadily being made towards higher levels, barriers regarding the uptake of ADAS and AVs might hinder realizing their potential (Feldhütter et al., 2016; Zhang et al., 2020). Particularly trust-related user experience barriers (UX) need to be addressed (Lee et al., 2021). Therefore, it is important to involve end-users in all stages of development to address critical barriers in the adoption of AVs.

Trust in Automated Vehicles

Governmental institutions, lawyers and car manufacturers are currently involved in the process of developing AVs (Hopkins & Schwanen, 2021). However, if the end users do not accept and trust the automated systems, AVs will not reach their desired rate of adoption (Feldhütter et al., 2016). Acceptance refers to "the attitude towards, or the willingness for use (or non-use), that an individual has of an advanced system" (Kaye et al., 2021, p.353). To promote acceptance, trust was found to be crucial in the relationship with automated systems. Trust can be defined as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (Lee & See, 2004, p. 51). In the context of AVs, trust entails accepting vulnerability to the system and the lack of control (Holthausen et al., 2022). Fostering trust, thereby increasing acceptability, is pivotal for the adoption of AVs. However, trust factors should be strategically addressed and reinforced to increase acceptability, rather than simply aiming for an increase in trust (Holländer et al., 2019). In subsequent sections, the nuanced aspects of trust in the context of adoption of AVs will be explored.

It is important to find a balance between undertrust and overtrust. Undertrust may lead to *disuse* of a system as it is characterized by the driver not completely utilizing the AV's capabilities (Azevedo-Sa et al., 2020). Overtrust may lead to *misuse* of the system when users are not aware of technological limitations when trusting the AV, which would lead to them using automated systems in inappropriate situations (Holländer et al., 2019). Both disuse and misuse might result in safety issues (Azevedo-Sa et al., 2020; Walker et al., 2018). For disuse, potential benefits of automated systems might not be realized, while for misuse, dangerous situations might arise in traffic. Dangerous situations entail trusting the AV under conditions it should not be used in, such as in heavy fog in certain levels of automation. To manage trust levels appropriately, trust calibration is essential (Lee & See, 2004; Walker et al., 2018). Trust calibration is defined as the alignment between trust towards the system and the system's capabilities and limitations (Holländer et al, 2019; Lee & See, 2004; Walker et al., 2018). Only then, if trust is calibrated accordingly, a higher adoption of AVs can be expected (Lee & See, 2004; Qu et al., 2023; Walker et al., 2018; Wintersberger et al., 2021).

Recent research suggests that trust calibration might be especially critical in lower levels of automation, where the user still has supervisory control over the automation (Chiou & Lee, 2021). Chiou and Lee (2021) propose that higher levels of automation require a different perspective on how to create and maintain trust in AVs. This is attributed to the altering control structures that emerge when the driver does not have authority over activating and deactivating an ADAS (e.g. in Level 4). As automation advances, a more lateral control structure is to be expected, where humans and automation need to collaborate responsively (Chiou & Lee, 2021). Instead of focusing on how AVs affect trust and their drivers, research should focus more on how drivers themselves could affect functions of automated systems. Thus, although automated systems should be trustworthy, users may have different preferences and experiences that need to be considered (Lee & See, 2004). Accordingly, for Level 4 of automation and higher, a different approach is needed on how to utilize trust to increase adoption and safe use of AVs. To investigate how to increase adoption of AVs, this study will focus on Level 4 of automation.

Trust Measures

To calibrate trust, insights are needed into initial levels of trust towards the AV, but also changes in trust when experiencing the AV (see Walker et al., 2018). Overall, trust levels can be measured by using self-report questionnaires. For instance, trust in automated systems can be investigated using the Empirically Derived Trust Scale (Jian et al., 2000). This scale was developed based on trust factors found between people and automated systems. Even though this scale is appropriate for pre- or post-measures of trust, real-time trust cannot be assessed by using questionnaires while driving in an AV. Walker et al. (2019b) propose the use of Electrodermal Activity (EDA) as an indicator of real-time changes in trust. EDA can be measured in form of skin conductance, which indicates changes in the electrical currents of the skin. The higher people’s trust in automation was, the lower was their electrodermal activity, pointing out a reliable and objective measure of trust (Walker et al., 2019b). Similarly, Morris et al. (2017) conducted a study involving automated driving where they concluded that people showed an increase in stress, measured by increased skin conductance, indicating low trust. Akash et al. (2018) put forward the idea that sensors should be able to detect real-time trust in human-computer interactions, such as when using automated systems. Therefore, they tested different methods to measure trust and concluded that skin conductance can be reliably used. These trust measures can be combined, aiming to respond to trust changes in real-time. By using self-reports for pre- and post-measurements and combining it with EDA in real-time, a more complete and conclusive analysis regarding trust can be conducted.

Adaptive Automated Driving

To increase adoption of automated systems, trust is one of the most important factors that needs to be addressed (see e.g. Holthausen et al., 2022; Lee & See, 2004; Qu et al., 2023; Sun et al., 2020; Walker et al., 2018; Wintersberger et al., 2021). Matching the AV's driving style towards the passenger's driving preferences might be one effective way to achieve calibrated trust (Sun et al., 2020). Thereby, driver's preferences should be in line with the AV's performance (Natarajan et al., 2022). Driver's preferences and their driving style in general translate to their driving habits, such as speed, steering habits, and changes in acceleration and deceleration (De Oliveira et al., 2019; Sun et al., 2020). These preferences do not only differ between individuals, but also within individuals (Sajedinia et al., 2022). For instance, preferred driving style may vary for one person depending on emotional state and situation currently experiencing (Sajedinia et al., 2022). As preferred driving style for an AV might not always correspond to people's actual driving habits, a more in-the-moment personalization of driving style is needed (De Oliveira et al., 2019). The more adaptive and predictable an AV behaves, the more it can be expected to be rated as trustworthy (Ekman et al., 2019; Sun et al., 2020). Sun et al. (2020) also explain that personalizing certain aspects of AVs should make it easier for people to understand the automated systems. As a result, AVs that adapt certain aspects of performance towards personal preferences should increase the rate of adoption of those (Sajedinia et al., 2022).

Even though recent research points out the idea of adapting AVs to driver's preferences and characteristics, most studies still focus on calibrating trust by providing information about the system's capabilities in real time (Holthausen et al., 2022). Trust calibration by informing the driver might not be enough for higher levels of automation and a more personalized driving style of AVs might be beneficial to achieve a more positive attitude towards AVs (Sun et al., 2020). Thus, a valuable way to calibrate trust in automated driving would be by adapting variables of a car, such as speed, to real-time trust of people. However, there is little research on how to adapt a system's performance based on driver's characteristics in real time. A study that has focused on Level 2 of driving automation has tried to investigate user's preferred driving styles by letting participants interact with different driving style adaptations and measuring trust in between (Sajedinia et al., 2022). In their study, they interrupted the simulation after critical events to ask the participants about their current trust level. Based on that, it was decided whether the driving style would change. The study showed that driving style adaptations can indeed lead to higher levels of trust and reliability and that this should be considered in future research. Also, Sajedinia et al. (2022)

found that driver preferences vary depending on the context and that trust could be an informative way to study these preferences. However, higher levels of automation are expected to be released in the next years and thus, means on how to increase their adoption should be studied. Also, Sajedinia et al. (2022) do not completely conquer the issue of real-time measurements of trust, considering that they interrupted the simulated driving sessions to use questionnaires in between. Given that trust is a dynamic concept, dependent on context, it should be considered that it changes and shapes through experience (Marsh & Dibben, 2003). Thus, a simple in between measurement of trust might not be representative of real-time trust and might not be a valid basis for adaptive automation. Another study conducted by Hörsting (2022) adapted speed of a simulated AV to the driver's real time trust without interrupting the driving scenario.

Hörsting (2022) tested the relationship between adapting speed to the user's real-time trust levels and general trust in automation. While letting participants experience a 15-minute Level 4 AV driving session, they were continuously asked to indicate their real time trust using a physical slider. In correspondence to their changes in trust, speed was adapted accordingly. Additionally, the researcher utilized a skin conductance measure to measure stress levels as an indicator for trust. Other than expected, Hörsting's (2022) study did not confirm that adapting speed to trust levels leads to an increase of initial trust. However, Hörsting (2022) suggests further research due to technical limitations. Therefore, the current study aims at following Hörsting's (2022) suggestions to test whether adapted automated driving in form of speed adaptation might be a possible solution for the low rates of trust into AVs and therefore the low predicted adoption rates of those.

Current Study

Based on the study conducted by Hörsting (2022), the aim of the current study was to enhance the previously implemented research design to test the effect adapting speed has on initial trust levels in AVs. As research has shown that a low adoption of AVs is partly influenced by low trust levels (see e.g. Holthausen et al., 2022; Lee & See, 2004; Sun et al., 2020; Walker et al., 2018; Wintersberger et al., 2021), the current research aims to investigate whether personalizing speed would lead to an overall increase in trust in low-trusting people. Thus, the research question is: "*When initially indicating low levels of overall trust, does personalized speed in an AV lead to higher levels of trust towards the automated system?*" Based on the literature review, it was expected that adapting speed to real-time trust levels would lead to an overall increase in trust in AVs. For this group of participants, lower levels of EDA were expected during the driving session. To test these expectations, two groups, where higher levels of EDA were expected, were added for comparison. One group experienced no changes in speed at all, another group encountered random changes in speed.

Method

Participants

Ethical approval was given by the Ethics Committee of the Faculty of Behavioural Sciences (Request number 221408). Participants were recruited using convenience sampling. First, students could register for the study via Sona Systems, the University of Twente's test subject pool (SONA). For their participation, they were credited 2 SONA credits. In addition, the researcher's acquaintances were asked to participate, making use of snowball sampling. In total, 60 participants registered for the study and completed the first questionnaire. However, only 45 were eligible, defined by low trust through the questionnaire, and ended up completing the study. The final sample consisted of 26 females and 19 males. Participants were aged between 18 and 46 years old (M = 23, SD = 5.68). Nationalities included in the study were German (n = 36), Dutch (n = 6), Indonesian (n = 1), Bulgarian (n = 1), and Romanian (n = 1). Driving experience of participants ranged between 0.08 and 20 years (*M* = 4.72, *SD* = 4.03) and they reported to be driving every day (n = 18), twice per week (n = 11), once per week (n = 3), once per month (n = 9), and never (n = 4).

Inclusion criteria specified to have proficient English skills, have a valid driver's license, normal or corrected to normal vision and no colour-blindness, no previously experienced motion sickness, no previous experience as a passenger or driver of an AV. Only people with low initial trust, as measured by a pre-questionnaire, were invited to complete the study. For that purpose, participants were assigned randomly to one of three experimental groups. Each group consisted of 15 participants.

Apparatus & Materials

Pre- and Post-Questionnaire

A pre- and post-questionnaire was utilized to measure initial trust and trust after experiencing the AV. For both tests, a modified version of the Empirically Derived Trust Scale was used (Jian et al., 2000). As in the study of Walker et al. (2018), the scale included seven questions which could be answered on a 7-point Likert scale. Item 1 (“I am cautious about self-driving cars”) and Item 5 (“Self-driving cars can have harmful consequences”) were phrased opposite to the other items of the scale and needed to be reverse coded before analysing the data. The pre-questionnaire started with additional questions referring to demographics (Appendix A). Participants were asked about their age, gender, nationality, driving experience, regularity of driving and their handedness. The post-questionnaire did not include demographic questions but was phrased in the past tense to refer to the experience of the driving session in the AV (Appendix B). Additionally, participants were asked whether any speed changes were experienced in their driving session.

Simulator Set-Up

To conduct the study, an automated vehicle simulator in form of a fixed base simulator was used, which included a seat, pedals, and a steering wheel (Figure 2 & 3). Participants wore the VARJO XR-3 virtual reality headset (Figure 4) to experience the simulation as immersive as possible. The simulation was programmed in Unity (https://unity.com/), a development platform. In the simulation, the participant was sitting in a 5-seater car, driving on a highway without any traffic or obstacles (Figure 5 & 6). The simulation included mountains on the side and streetlamps. Thus, the route did not include any unexpected take-over requests.

Figure 2

Fixed Based Simulator (Frontview)

Figure 3

Fixed Based Simulator (Backview)

Figure 4

VARJO XR-3 Virtual Reality Headset

Figure 5

Track Used in the Simulation

Figure 6

Driver s View of the Simulation

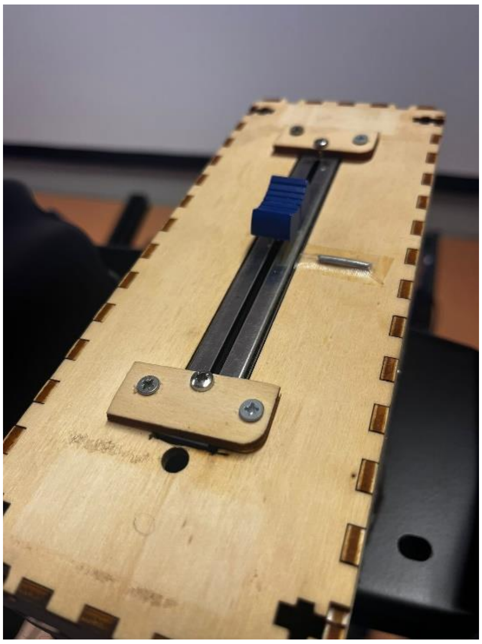
From a computer, the simulation could be run while recording time, trust values, speed of the car, the location of the car on the track and whether a significant change in trust was detected. Speed of the car could be adapted by the researcher in real-time. The researcher could decide the minimum target speed, which was set to 30km/h in this experiment, the maximum target speed, set to 70km/h, and target speed mode, which was set to 40km/h. This was also set as the speed for the control condition (*fixed speed* condition). In Unity, a threshold could be defined for detecting a significant change in trust, which was 10 in this case. Additionally, it was determined how much km/h the car would increase or decrease if a change in trust was detected. In this study, the km/h change per significant change in trust was 5km/h.

Trust Slider

The trust slider (Figure 7) used in this study to measure in-the-moment trust was initially developed by Walker et al. (2019a). In their study, the trust slider was used to measure levels of feelings of safety of pedestrians when crossing a road in a simulated environment. In the current study, the slider was incorporated to measure in-the-moment trust on a continuum, ranging from 0 (no trust) to 100 (full trust) in the simulated AV. The slider has already been used in two further studies in the context of trust towards AVs (Hörsting, 2022; Kowalski, 2023). Since then, revisions to the slider have been made. First, a rod was added in the middle of the continuum to provide a form of haptic feedback for participants using the slider in a VR environment. Second, Kowalski (2023) developed a more accurate algorithm to process data (FiFo). As the FiFo algorithm was not recommended to be used due to flaws in data processing, the current study applied an even more revised version of that algorithm. That way, issues from the first study and from the second study were aimed at to be resolved. The functioning of the revised algorithm will be explained in a later section. The trust slider is connected to a computer and provides trust values continuously.

Figure 7

Trust Slider Used in the Study Set-up



Empatica E4

The Empatica E4 wristband was used to measure skin conductance to draw conclusions about participants’ trust levels based on their stress responses recorded. The wristband was worn on the non-dominant hand during the experiment and EDA was recorded at a sampling rate of 4 Hz.

Data Processing and Algorithm Functioning

Based on limitations and corresponding recommendations reported by Hörsting (2022), the current study implemented some changes regarding data processing and the algorithm used to detect changes in speed. In addition, a new algorithm was defined to ensure a more accurate response to changes in real-time trust.

The algorithm used in this study for the adaptive speed experimental group followed the rule: *For every significant trust change, increase/decrease speed by 5km/h. A* ***significant trust change is defined*** *as a change of* ***at least 10% from 100% from the previous value*** *within a time frame of two seconds.* If the algorithm identifies a significant trust change, thus a change of 10 from the previous value, then speed should be changed accordingly by 5km/h. To avoid rapid jumps in speed, the change in trust must be constant. Thus, if a significant change in trust is detected, a 2 second delay is introduced, where several cases are checked and based on that, it is determined whether a speed increase, decrease or nothing will be initiated (See Table 1 for the cases).

Table 1

Cases to be Checked for Identifying a Significant Change in Trust as Implemented in the Algorithm

	Condition	**Result**
Case 1	If a significant increase is detected AND the significant increase is cancelled	No speed change
Case 2	If a significant decrease is detected AND the significant decrease is cancelled	No speed change
Case 3	If a significant increase is detected AND is followed by a significant decrease	Decrease in speed

Case 4	If a significant decrease is detected AND is followed by a significant increase	Increase in speed
Case 5	If several significant trust increases are detected within two seconds	Increase in speed only once
Case 6	If several significant trust decreases are detected within two seconds	Decrease in speed only once

Note. The conditions in the table describe the cases that were checked within two seconds after a significant trust change was detected. If one of the cases were identified, the corresponding result were initiated regarding changes in speed. A cancelled increase or decrease describes the situation where the user slides back and forth, without staying on one point for a significant amount of time.

Another function of the algorithm addresses the problem with the two extremes of the slider. When reaching the extremes of the slider, the participant's trust may continue to decrease or increase, even if the slider's position remains unchanged. In these situations, the algorithm was designed to detect a sustained increase or decrease in trust, suggesting that a speed adaptation might be needed to achieve personalized speed. This addressed the limitations of the slider, about matching driver's preferences, and expectations even when the slider is at minimum or maximum position already. Therefore, the current study implemented a function, where an increase/decrease of trust was detected after staying at the extremes of the slider for a significant amount of time. In this case, the time was defined as 30 seconds. Accordingly, changes in speed of the experimental group could be induced after 30 seconds of staying at the extremes. This was to ensure a more accurate representation of the participant's trust levels to allow for a higher level of personalization.

Design

The study utilized a between-subjects design. Three experimental groups served as the independent variables. Dependent variables were in-the-moment trust as measured by the trust slider, differences in trust between pre- and post-measures and skin conductance as measured by the EDA wristband.

Task

The main part of the study consisted of a 15-minute driving session in the simulator. Participants were instructed to indicate their real-time trust levels continuously using the trust slider throughout the whole driving session. The study included three participant groups which differed in their speed condition. The experimental group performed in the *adaptive speed condition*, during which speed of the simulated vehicle was adapted in accordance with participant's real-time trust. Whenever a significant trust change, as indicated by the trust slider and the cases of the algorithm, was detected, speed increased or decreased by 5 km/h accordingly.

The other two groups performed in two control conditions. Speed was not affected by real-time trust measures, even though both speed and trust were still recorded in both conditions. In the *fixed speed condition*, speed was set at 40km/h and did not change throughout the whole driving session. In the third condition, the *semi-random speed condition*, speed changes were randomly initiated by the researcher in one-minute time intervals. These speed changes followed a protocol of semi-random speed changes, where speed changed every minute according to this pre-defined protocol (Appendix C). In total, speed changed 15 times in the s*emi-random speed condition*. In all conditions speed was not displayed. Thus, they were not aware of how fast the AV was driving. Additionally, it should be noted that speed in a simulator might be perceived as faster than in a physical car as it was not calibrated properly. Therefore, speed variables should not be compared to real-life speed in this case.

Procedure

Participants started the study on Qualtrics (https://www.qualtrics.com), which is a web-based software enabling creating surveys and corresponding reports. First, informed consent was asked (Appendix D). This included ensuring that the participants did not have any neurologic, psychiatric, or psychological condition and no colour vision deficits, ensuring immersiveness of colour-coded information. Furthermore, they were asked to confirm that they were sober during the study. Participants were informed that they could withdraw from the study at any time and that participation was voluntary. Then, they continued with demographic questions and the pre-questionnaire. If initial trust in AVs was high on average (>4), participants were immediately thanked for their participation and data was deleted. In that case, they were also not rewarded with any credits. If initial trust was low on average (=<4), participants were directly invited to continue with the study and schedule a time slot at the simulator room of the BMS lab. However, they were not informed about their overall initial trust level.

At the driving simulator of the University of Twente, participants were informed about the procedure of the study (Appendix E), while the technical set up was adjusted. Thereby, attention was paid to whether participants understood how to use the trust slider during the study. It was explained that the participant would have to take part in a 15-minute AV driving session, which would not require any form of take-over request. Meanwhile, participants would need to continuously indicate their in-the-moment trust levels. They were also told that they could withdraw at any time. While briefing the participant, they were seated in the simulator and the seating position was adjusted to resemble their preferred position as in a real car. The Empatica wristband was attached, and the VR headset was also adjusted and calibrated. Then, the 15-minute driving session started.

Directly after the simulator driving session, participants were asked to fill in the post-questionnaire on a laptop. Then, they were debriefed about the aim of the study and the participant group they were assigned to. In the end, additional questions were asked on whether they have experienced any symptoms of nausea, what parts of the track felt most trustful and most distrustful, and if they had any further remarks regarding the study. As a last step, participants were thanked for their contribution and students were granted 2 credits via Sona. Overall, the study took 45 minutes.

Results

Changes in Trust-Score

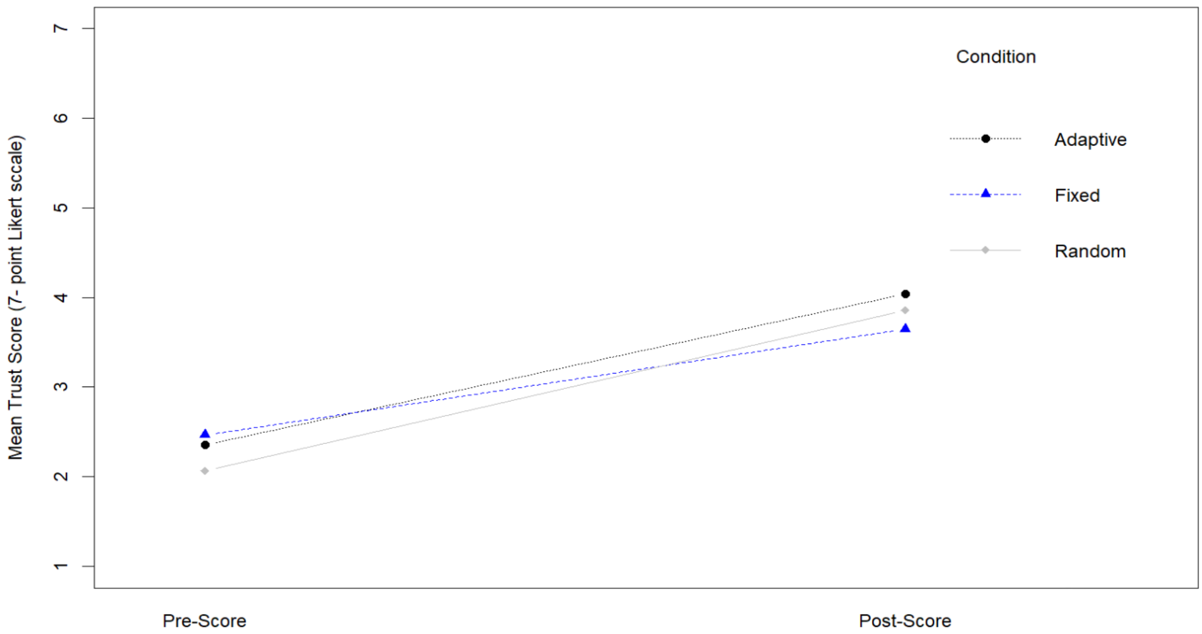
For the planned analysis, the trust scores of the pre- and post-questionnaire were transformed first. Therefore, scores of the seven items indicating trust were averaged. This was the basis for the analyses including the change in trust between the two measurements.

To examine the impact of driving conditions on trust score changes and to investigate trust score changes within each of the conditions, a 3 (conditions) x 2 (pre- and post-trust scores) mixed factors ANOVA was performed. Before conducting the analysis, assumptions were tested. One outlier, but no extreme outliers were found, as tested using the rstatix package in RStudio (https://cran.r-project.org/). In this case, the analysis included the outlier. Next, normality of the data was checked using the Shapiro-Wilk Test of Normality. The scores did not significantly differ from a normal distribution ($p > .05$). Homogeneity of variance was checked using the Levene’s test, which confirmed the assumption of equal variance for the pre-score (p = .51) and for the post-score (p = .22). As tested using the Mauchly's Test, sphericity could be assumed for all conditions (p > .05).

The two-way ANOVA shows a significant effect of measurement (pre- and post-), $F(1, 42) = 66.01$, $p < .001$. However, this effect was not dependent on condition, $F(2, 42) = 0.97$, p = .39. Therefore, no significant interaction effect was found. Bonferroni adjusted p-values show significant effects for both pre- and post-measurements ($p < .001$), but no main effects for conditions. Figure 8 visualizes the average trust scores for pre- and post-measurement per condition. Although the adaptive speed condition has the highest average trust score for the post-measurement, the difference in the score is not significantly different from the scores in the other conditions. Against the expectations, post-scores remain low in all conditions.

Figure 8

Average Trust Score Plotted per Condition for Pre- and Post-Trust Scores and the Corresponding Differences.



Trust Slider Value

The mean trust slider score for each participant was calculated over a 15-minute time frame. Before performing a one-way ANOVA, assumptions were tested. There were no outliers in the data. The Shapiro-Wilk Test (p > .05) showed that normality of the data could be assumed for each condition. Lastly, the Levene's test indicated that homogeneity of variance could also be assumed (p = .35).

To evaluate how driving conditions influenced the overall trust slider values, a one-way ANOVA was performed. Participants in all three conditions showed similar mean scores of trust (Table 2). Indeed, the analysis showed that there were no significant differences between the mean scores of the three conditions, $F(2, 42) = .01$, $p = .99$. Figure 9 depicts the distribution of the mean trust slider scores per condition.

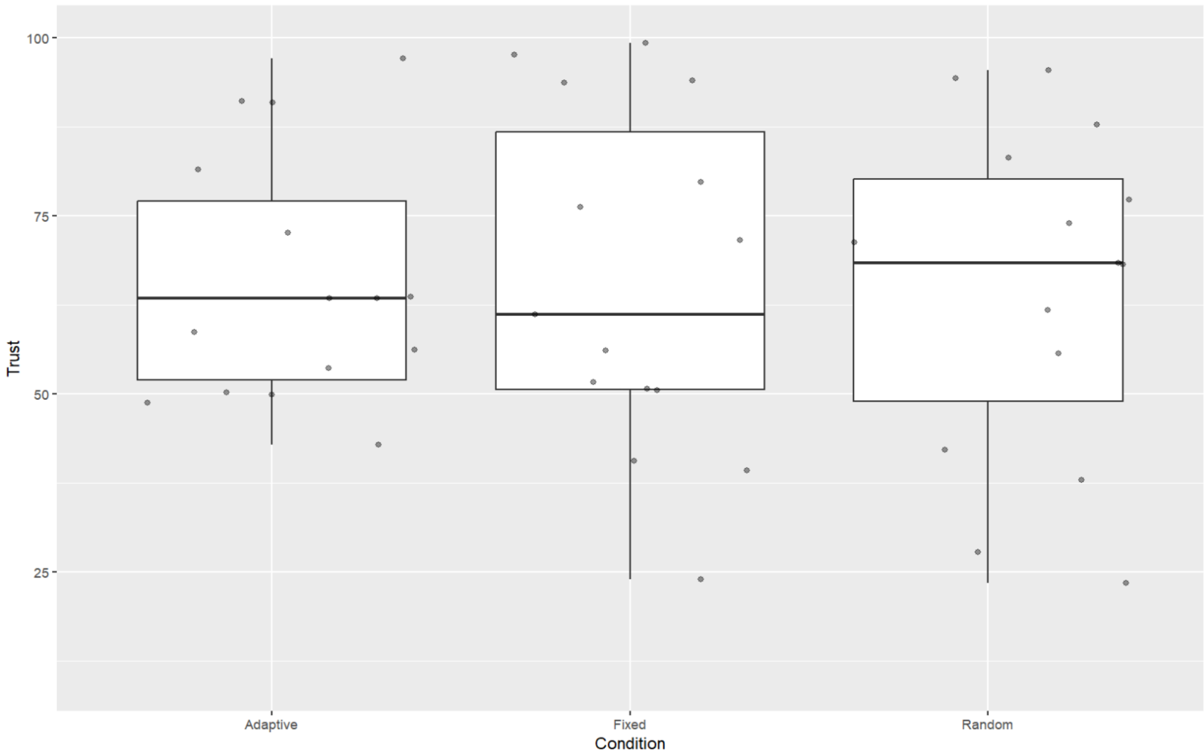
Table 2

Average Trust Ratings per Condition with SD

Condition	Trust Slider *Mean*	Trust Slider *SD*
1 – *Adaptive Speed Condition*	65.63	17.23
2 – *Semirandom Speed Condition*	64.60	22.96
3 – *Fixed Speed Condition*	65.76	23.78

Figure 9

Boxplot and Jitterplot Depicting the Mean Trust Slider Values per Condition and per Participant.



Electrodermal Activity

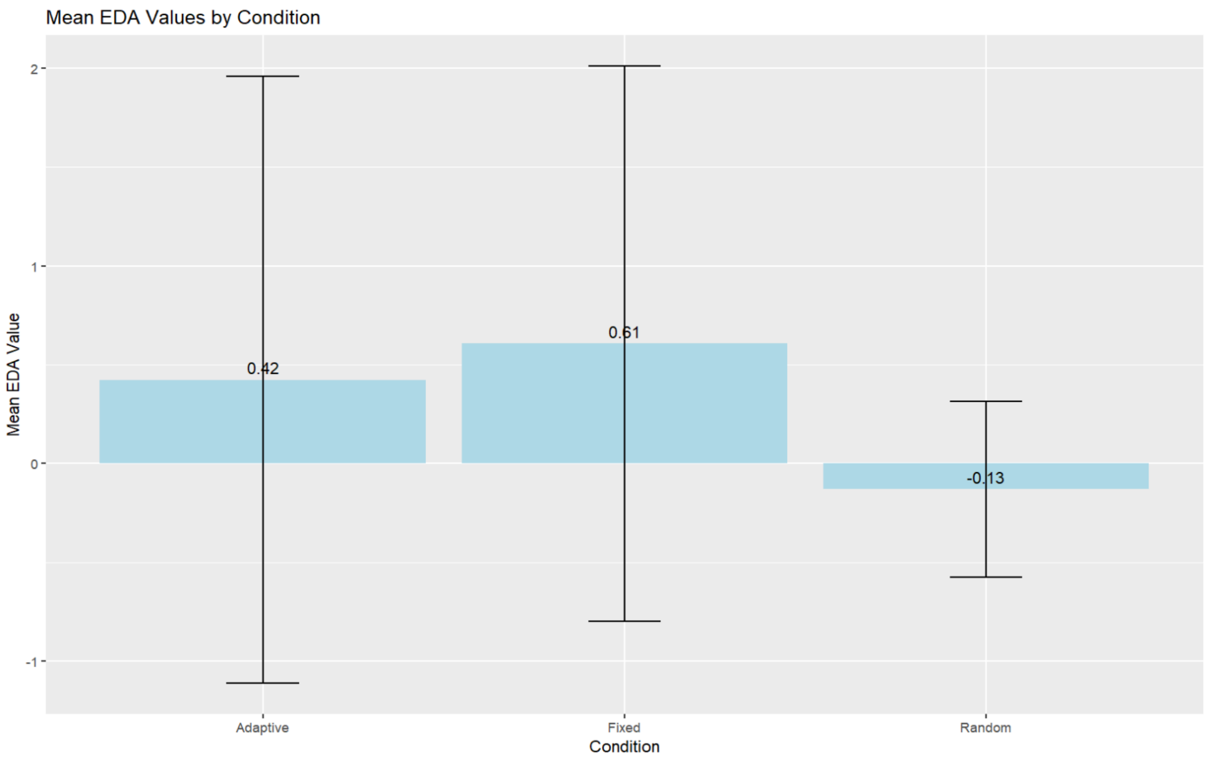
First, an average EDA score was determined per participant. This was done by calculating a baseline by averaging, per participant, EDA values collected during the first minute of the recording. Then, that baseline was subtracted from every other measurement in the recording. Lastly, these new, subtracted scores were averaged to achieve the average, adapted EDA score.

For the one-way ANOVA, assumptions of normality and homogeneity needed to be checked. The Shapiro-Wilk test showed that normality was violated ($p < .05$). However, ANOVA is known to be robust against violations of normality, especially for equal group sizes (Lix et al., 1996; Skidmore & Thompson, 2012). Therefore, the analysis was still conducted and interpreted. The Levene’s test shows that homogeneity can be assumed for each condition ($p = .61$).

A one-way ANOVA was performed to evaluate the relationship between condition and EDA value. Results show that there was no significant difference between the conditions in regard to EDA values, $F(2, 42) = 1.46$, $p = .24$. Figure 10 shows the average EDA values, per group. It depicts the different mean scores per condition.

Figure 10

Mean EDA values plotted by Group. The length of the bar represents the magnitude of the mean. The error bars represent the variance around the mean.



Discussion

While it is shown that trust is one of the main factors limiting acceptance of automated driving, research on how to calibrate trust practically and properly in real-time is limited. This study aimed to examine the effect of adapting speed on initial trust levels in AVs among low-trusting individuals. Therefore, a driving simulator study was conducted. Participants, identified as low trusting through an initial trust level assessment were randomly assigned to one of the three groups: i) *adaptive speed condition*, ii) *fixed speed condition*, iii) *semi-random speed condition*. In a 15-minute driving session, where speed was only personalized in the *adaptive speed condition*, participants indicated their real-time trust levels using a slider while EDA was measured concurrently using a wristband. Afterwards, the initial trust assessment was repeated to assess overall changes in trust. It was expected that adapting speed to real-time trust levels would lead to an overall increase in trust in AVs. This was expected to be supported by corresponding lower EDA values. For the two control groups, the *fixed* and *semi-random speed* condition, no significant change in trust between the two trust measurements was anticipated. This was also expected to be reflected by higher levels of EDA during the autonomous driving sessions than for the *adaptive speed condition*.

A trust change after having experienced the simulator was not only found in the *adaptive speed group*, but also in the two control groups. Thus, results indicate that simply experiencing an AV might already increase overall trust towards them. This is reflected in previous research, which shows that the experience of an AV alone already increases levels of trust (Xu et al., 2018). Clement et al. (2022) conducted a driving simulator study and found that trust increase was highest for initially low-trusting people after experiencing a simulated automated vehicle. Sun et al. (2020) explain that the first-time experience of AVs might increase trust through a demonstration of their benefits in comparison to the demanding task of driving manually. Furthermore, experience with an AV leads to a better understanding of the system (Clement et al., 2022). Thus, experience and exposure with a simulated AV might be a valuable method to increase public acceptance of AVs as a first step, before addressing long-term determinants. This is also in line with the argumentation Walker et al. (2023) put forward, where trust is explained as a dynamic concept, developing continuously with more experience. Also, even though the AV did not perform as preferred by participants in real-life driving scenarios in all three conditions, there were no incidents in the simulation. This might be the reason for an overall increase in trust in all three conditions.

There was also no difference in the real-time trust between the three groups as measured by the trust slider. If personalizing speed would increase overall trust, this should be also reflected in the real-time trust. Furthermore, results of the EDA measurement during the driving sessions were not as expected either. There was no difference in EDA between the three conditions. A possible explanation for this finding could be the awareness of driving in a simulated car. Even though the high resolution of the VARJO headset, participants were aware that nothing consequential could happen as the car was not driving on a real-life road. A simulation where something is happening on the road could require more attention and EDA levels could differ under the three different conditions. In this study however, physiological arousal did not differ between the three different conditions. As outlined by Walker et al. (2023), to calibrate trust appropriately, experience under various conditions is needed. Therefore, the conditions might not have been variable enough.

Personalization might be important not only to be responding in real-time, but also to anticipate certain changes in trust. Sun et al. (2020) attempted to personalize automated driving by monitoring driving style characteristics of people and adapting the AV's behaviour accordingly. In their study, this approach of personalization demonstrated positive outcomes regarding increasing trust. Brück et al. (2021) also concluded from their study, testing personalized AVs by including a priori knowledge of the driver, that prior knowledge of driving styles, driver characteristics and demographic data could enhance personalization of AVs. Thus, in addition to adapting characteristics of the vehicle to real-time changes in trust, a priori knowledge or machine learning could also improve personalization overall. That way, the behaviour of the car would not only rely on real-time trust, but also on more personal aspects of the driver.

The idea of adapting speed towards real-time trust was based on the problem that preferred driving style does not always translate to actual driving style (De Oliveira et al., 2019) and that driving styles often differ within people depending on several factors and circumstances (Sajedinia et al., 2022). Thus, even though it can be assumed that the experience with an AV itself already increases trust, long-term solutions need to be explored on how to adapt performance of the car to further calibrate trust when driving in an AV (Ayoub et al., 2023).

Limitations and Future Research

Based on recommendations for future research provided by Hörsting (2022), some improvement regarding the functionalities of the simulation and the slider were already made prior to the study. However, due to limited resources in development, some limitations of technical nature remain and should be improved in future research. For instance, the slider has been improved in terms of algorithm, but it still displays flaws regarding sensitivity. During the pilots, it was discovered that the slider only recognizes changes in trust if sliding not too abruptly. Thus, some significant changes in trust might have not been discovered and speed may not have changed accordingly. This was attempted to be solved by providing clearer instructions on how to use the slider, but this again might have created a bias in the usage of the slider. Therefore, future studies should plan enough resources for the technical testing and unexpected improvements of the equipment.

Another limitation caused by a lack of developmental resources regards immersiveness of the simulation environment. The track was rural, without any incidents or other participants in traffic. A lot of participants mentioned that traffic would have been a valuable addition to evaluate the trustworthiness of the vehicle. As there was nothing happening in the 15-minute ride, they might have habituated to that, no matter in what condition they were in. This is often a concern regarding attention when driving in AVs (Balters et al., 2017). When driving autonomously in an environment with consistent stimuli over some time, neuronal activation decreases which leads to the phenomenon of habituation (Balters et al., 2017). Additionally, immersiveness could be increased by using a motion-based simulation. Thus, if the AV would drive in a curve, the simulator should move accordingly. Even though the simulator used in the current study can adjust movements according to events in the simulation, this function was not incorporated into the current study. Simulator studies are of great value in research. However, results need to be validated in real-life scenarios when having access to a safe track. This could happen after several rounds of research and testing, when safety of participants can be guaranteed.

Considering that EDA responds to skin conductance which is influenced by sweating (Hossain et al., 2022), the setting of the simulator must be considered. The simulator is in a small room without any windows. Thus, it gets warm quickly which might have had an influence on the physiological response. To account for such factors, a second behavioural observation could be added. For instance, Walker et al. (2019b) suggests that gaze behaviour can be added to a physiological measure to arrive at more valid conclusions regarding stress levels. As the current simulator entails a VR headset with built-in eye-tracking, this could be incorporated in future studies.

A general recommendation for future research addresses the study design and analyses. First, it could make sense to include a repeated measure of the post-questionnaire to test whether the trust measure after experiencing the vehicle is stable. To understand how individual’s mental models develop over time with increasing experience with the AV, repeated measures is advised (Walker et al., 2023). That could also aid in comparing the three conditions more in detail. Furthermore, a time-series analysis might be helpful to analyse the data in a more meaningful way. Instead of only looking into averages, data could be related to certain points on the track. That way, in combination with traffic on the streets, a more complete picture of certain measurements can be created.

Lastly, a recommendation for future research is to incorporate machine learning into the algorithm. By learning in what situations the participant indicates a decrease in trust, the system could anticipate similar situations and react accordingly in advance. A mixed approach to adaptive automation could be valid where real-time trust measures are incorporated into a machine learning model, where a priori knowledge is combined with real-time measures and previous responses. That way, trust-decreasing situations could be minimized. Ayoub et al. (2023) tested a similar idea and found a model utilizing machine learning to predict real-time trust. This allows for trust calibration in real-time to adjust the car’s behaviour. For instance, a pre-questionnaire could be used to categorize participants based on their preferences. Then, they would start with the fitting vehicle default, which would continuously be adapted to the participant’s real-time trust. As adaptive driving has been suggested to have potential for accurate trust calibration and acceptance of AVs (Ekman et al., 2019; Sajedinia et al., 2022; Sun et al., 2020), research should allocate resources to examine which form of adaptation could be effective and efficient. This study may have showed that a revised study design combined with further functions in personalization could yield different results, even though adapting speed to trust is not working through this specific algorithm.

Conclusion

With ever increasing developments in automated driving, the challenge of lacking acceptance and trust towards AVs needs to be addressed in research. This study examined a way to adapt automated driving to real-time trust of passengers. By conducting a driving simulator study, it was shown that personalizing speed by reacting ad hoc to changes in trust did not influence trust as expected. Rather, results indicate that the experience with an AV alone already increases trust towards them in the short term. This research clearly shows that trust calibration can be addressed successfully in low-trusting people, but it also raises the question which form of adaptation could foster the process to overall increase acceptance of AVs in the general population. Further research is needed to study the different ways of adaptive automation in anticipation of changes in trust of the passengers. Overall, this study addressed the research gap of real-time personalization as a means towards trust calibration and poses recommendations for future studies.

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Appendix A. Pre-Questionnaire

Figure A1

The Pre-Questionnaire on Qualtrics, Depicting Part 1.

Please type in the participant number you have been assigned to. If you have signed up via Sona, use the code provided there. If you do not enter the correct code, credits cannot be granted in the end. Also, make sure to keep that code in mind for later.

Figure A2

The Pre-Questionnaire on Qualtrics, Depicting Part 2, Demographic Questionnaire.

Before starting with the questionnaire, please provide some demographic information.

How old are you?

What is you gender?

- Male
- Female
- Non-binary / third gender
- Prefer not to say

What is your nationality?

- German
- Dutch
- Other

If your nationality is other, please indicate:

Years of driving experience (e.i. years passed since when you have got your driver's license):

On average, how often do you drive on European roads (including Dutch roads)?

- Never
- Once per month
- Once per week
- Twice per week
- Every day

Figure A3

The Pre-Questionnaire on Qualtrics, Depicting Part 3, Questionnaire.

Through this brief questionnaire, we would like to measure your attitudes toward self-driving cars. In self-driving cars, the vehicle operates independently. So, there is no need or possibility for you as the driver to take over control. We understand that your knowledge of self-driving cars might be limited, so please answer based on your ideas and expectations. Please respond as truthfully as possible, and keep in mind that there is no “correct” answer. Please indicate your answer.

1 = not at all
7 = extremely

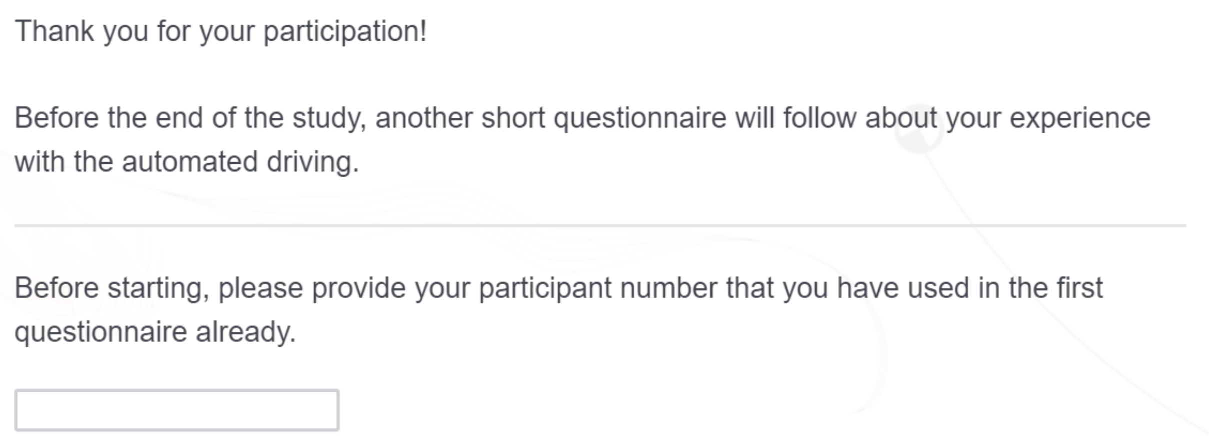
Click to write the question text

	1 (not at all)	2	3	4	5	6	7 (extremely)
I am cautious about self-driving cars.	○	○	○	○	○	○	○
Self-driving cars are reliable.	○	○	○	○	○	○	○
I would entrust my car to self-driving functions for lane keeping, lane changing, alerts following object recognition, etc.	○	○	○	○	○	○	○
I can count on self-driving cars.	○	○	○	○	○	○	○
Self-driving cars can have harmful consequences.	○	○	○	○	○	○	○
I trust self-driving cars.	○	○	○	○	○	○	○
I assume that self-driving cars will work properly.	○	○	○	○	○	○	○

Appendix B. Post-Questionnaire

Figure B1

The Post-Questionnaire on Qualtrics, Depicting Part 1.

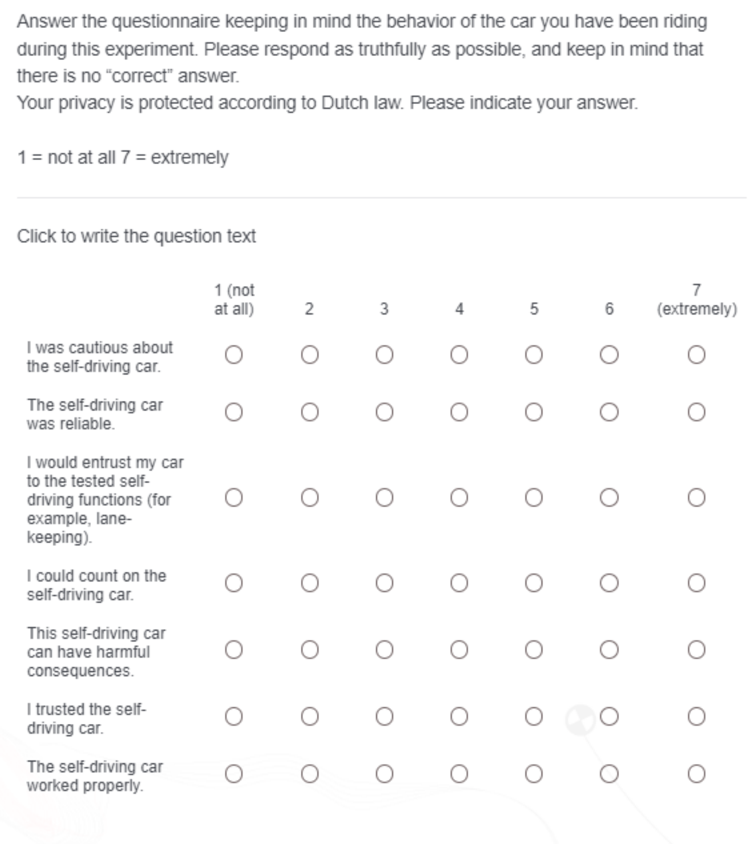

Thank you for your participation!

Before the end of the study, another short questionnaire will follow about your experience with the automated driving.

Before starting, please provide your participant number that you have used in the first questionnaire already.

Figure B2

The Post-Questionnaire on Qualtrics, Depicting Part 2, Questionnaire.


Answer the questionnaire keeping in mind the behavior of the car you have been riding during this experiment. Please respond as truthfully as possible, and keep in mind that there is no “correct” answer.
Your privacy is protected according to Dutch law. Please indicate your answer.

1 = not at all 7 = extremely

Click to write the question text

	1 (not at all)	2	3	4	5	6	7 (extremely)
I was cautious about the self-driving car.	○	○	○	○	○	○	○
The self-driving car was reliable.	○	○	○	○	○	○	○
I would entrust my car to the tested self-driving functions (for example, lane-keeping).	○	○	○	○	○	○	○
I could count on the self-driving car.	○	○	○	○	○	○	○
This self-driving car can have harmful consequences.	○	○	○	○	○	○	○
I trusted the self-driving car.	○	○	○	○	○	○	○
The self-driving car worked properly.	○	○	○	○	○	○	○

Figure B3

The Post-Questionnaire on Qualtrics, Depicting Part 3, Final Question.

You are almost finished with the study. We have one more question left.

Did you experience any speed changes while driving in the simulator?

- ○ No
- ○ Yes

Appendix C. Speed Change Protocol

Table C1

Speed Changes per Minute as Used in the Semi-Random Speed-Change Condition.

MINUTE	SPEED
1	**40**
2	**50**
3	**40**
4	**50**
5	**60**
6	**70**
7	**60**
8	**50**
9	**40**
10	**30**
11	**50**
12	**60**
13	**40**
14	**50**
15	**40**

Appendix D. Informed Consent

Figure D1

Informed Consent on Qualtrics, Taken from the Pre-Questionnaire.

Welcome to my study on automated driving!

Thank you for participating in my study. In line with my Master's project, I am aiming to analyze your experiences with automated driving. In this study, I will first ask you to conduct a short questionnaire and provide some demographic information. If you will be selected for the further steps of the study, you will be asked to schedule a timeslot at the driving simulator in the BMS lab of the University of Twente. This will take approximately 30 minutes. Afterwards, another short questionnaire will follow.

In case of any questions, you can contact me, Anna Boyko via a.boyko@student.utwente.nl. I will be happy to help you.

To participate in the study, you need to agree with the following terms. Additionally, I want to stress that you can withdraw from the study at any point without any need of explanation.

By consenting, you confirm that:

- you do not suffer from any neurologic, psychiatric or psychological condition.
- you do not have any colour deficits and that you do not wear glasses (does not include contact lenses).
- you do not suffer from motion sickness.
- you have never driven or been a passenger in an automated vehicle before (for example, Tesla with Autopilot).
- you have a driver's license.
- you understand that you can terminate my participation immediately if I feel uncomfortable or unwell.
- you participate in a sober state and of my own free will.

Do you consent and confirm with the latter terms of participation?

○ Yes, I do.

○ No, I don't.

Appendix E. Introduction and Instructions to the Study Procedure

Okay, so we are currently testing a new, real system on automated driving in collaboration with a car manufacturer. Although it is not perfect yet, it will never ask you to take over control, it will simply drive by itself. To test it, you will be sitting in the simulator for a 15-minute ride. I will give you the VR headset and I will also adjust an EDA wristband (on the hand not with the slider). You do not need to use any of the simulator equipment, as this is a self-driving car. While driving in the vehicle, please use the slider next to you to indicate your current level of trust in the self-driving car. Please try to avoid abrupt movements when using the slider. You may use it throughout the whole drive, just slide up for increased trust and up for decreased trust.

I want to repeat that you can withdraw from the study at any given time with no explanation. If motion sickness might come up, just let me know and I will stop the recording.

In the end, I will ask you to fill out another questionnaire on my computer and then the study will be over.