How does training effect users’ attitudes and skills needed for highly automated driving?

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Abstract
Highly automated vehicles are expected to increase the safety and quality of road transportation, but because of significant changes in the driver’s role, they introduce new human factors challenges and require learning specific skills. Training has been proposed as a potential tactic to alleviate these challenges and improve driver interaction with automated cars. This study evaluated the effects of Simulator Training and Video Training on procedural and higher-order cognitive skills required for Conditionally Automated Driving (CAD), and users’ attitudes as well. Fifty-four people participated in the experiment, 18 in Simulator Training, 18 in Video Training, and 18 in Control groups. Takeover Time (TOT), speed, speed variance, Standard Deviation of Lateral Position (SDLP), Takeover Decision Accuracy (TODA), trust, and acceptance data were collected before and after training sessions. The results showed that both training methods improved TOT, speed variance, and SDLP. Moreover, the participants in Simulator Training outperformed in deciding whether takeover was necessary or not. The results also indicated that self-reported trust was less erratic in Post-Training Driving Assessment in both Simulator and Video Training. These findings imply that training, especially where interactive learning is provided, helped the participants develop a more developed mental model of CAD and better-calibrated trust. Training programs, however, did not create meaningful changes in the number of crashes, speed, nor automation acceptability. Further research is needed to investigate learning transferability to highly automated driving on the real road.

1. Introduction

Automated driving has been considered as a potential solution for transportation safety enhancement, such as a reduction in traffic conflicts (Morando, Truong, & Vu, 2017), crash rates (Fagnant & Kockelman, 2015), and limiting other risk factors associated with human driver behavior including distraction, fatigue, and drowsiness (van Wee, Annema, & Banister, 2013). Supports provided in automated driving decrease the driver’s controlling roles in certain driving situations, and consequently, reduce risks associated with primary driving tasks. Furthermore, automation in vehicles has shown significant improvement in driver comfort by allowing them to engage in non-driving related secondary tasks (Luo, Liu, Li, & Wang, 2017).
higher levels of automation in cars reduce vigilance and negatively affect SA (Miller, Sun, & Ju, 2014). SA loss impairs the controlling activities to a supervisory role, and provides the least demanding task for one in normal cases; however, it calls for behavioral adaptations (Ma & Kaber, 2005; Saffarian, de Winter, & Happee, 2012).

Concerns, such as erratic workload, loss of Situational Awareness (SA), vigilance decrements, automation complacency, and negative behavioral adaptations (Ma & Kaber, 2005; Saffarian, de Winter, & Happee, 2012). These challenges are associated with the irony of automation, in which the automation allows a driver to shift from controlling activities to a supervisory role, and provides the least demanding task for one in normal cases; however, it calls for behavioral adaptations (Ma & Kaber, 2005; Saffarian, de Winter, & Happee, 2012). Moreover, some of these critical situations require only a few milliseconds to be managed appropriately, but drivers need seconds to handle it. Therefore, automation systems in vehicles enhance safety in most circumstances but degrade it in some critical cases.

Empirical evidence has highlighted the importance of a driver’s mental model of automated functions and features in effective and safe teaming between drivers with automated cars (Jenness, Lerner, Mazor, Osberg, & Tefft, 2008). The knowledge of how a system works is technically described as the mental model of people (Carroll & Olson, 1988). Due to technological, legal, and regulatory issues, different levels of automation have restricted logic and do not perform exactly in a manner that the driver might think (Beggiato & Krems, 2013). Moreover, when the automation authority increases, its functional components also expand. Therefore, humans need to build an extensive mental model of the functionality of each automated feature, and how automation controls the car in different circumstances. This issue is more challenging in CAD where a human supervises the system and periodically leaves the driving loop. Thus, the driver has little chance to update his/her mental model through continuous monitoring of the driving environment.

Zheng and McDonald (2005) discussed that users’ prior beliefs and knowledge establish an extensive internal representation of automation functionality that may not be in line with actual automation capabilities. Because of this inconsistent schema, drivers may overestimate the capabilities of the automation. Moreover, an inaccurate mental model has been regarded as an underlying reason for poorly calibrated trust and negative behavioral adaptation (Rajaonah, Anceau, & Vienne, 2006). A high level of trust shifts the driver from being an alert and active agent to being passive, which leads to a decrease in the sampling rate from the environment. This challenge also may result in negative adapted behavior and a more unsatisfactory performance while the system is not engaged (Choi & Ji, 2015).

A growing body of literature has discussed the effectiveness of training systems in improving driver knowledge and understanding of how automation works (Beggiato, Pereira, Petzoldt, & Krems, 2015; Boelhouwer, van den Beukel, van der Voort, & Martens, 2019; Payre, Cestac, Dang, Vienne, & Delhomme, 2017; Saffarian et al., 2012). A well-developed training program may help drivers build a correct mental model of the system and consequently shape a well-calibrated trust to the automated cars. Studies have shown that participants who experienced automation failures in a simulated environment, outperformed in taking control of the car upon automation failures compared to those without similar practices (Bahner, Hüper, & Manzey, 2008). Similarly, (Beggiato et al., 2015; Payre et al., 2017) explored whether providing basic information about automation capabilities affects the user’s mental model and trust in partially- and highly-automated driving. These empirical results revealed that the learning process improved the mental model by activating knowledge nodes and helped the user have a more accurate mental model and well-calibrated trust over the course of the time.

Despite the notable theoretical supports and discussions about training as a potential tactic to improve driver interaction with automated cars, only a small number of studies have been undertaken to explore the effectiveness of training on improving human factors challenges in CAD. Moreover, basic information provided in the current owner’s manual did not create an accurate mental model of highly automated vehicles’ capabilities (Boelhouwer et al., 2019). This necessitates exploring different training strategies to support drivers in highly automated cars. The current study aims to address this gap by examining which type of training and to what extent may facilitate drivers’ interaction with highly automated vehicles.

1.1. Learning outcomes

To have a deeper understanding of driver training approaches and strategies, we reviewed the available literature on driving training. Although there are a few studies in highly automated driving training (Ebnali, Kian, Ebnali-Heidari, & Mazloumi, 2019; Forster, Hergeth, Naujoks, Beggiato, et al., 2019; Forster, Hergeth, Naujoks, Krems, & Keinath, 2019; Hergeth, Lorenz, &
(1) **Procedural skills**: As one of the primary components of many driver licensing systems, this approach focuses on providing safe driving practices to develop lower-order cognitive skills (Herregods, Nowe, Bekiaris, Baten, & Knoll, 2001). These skills are related to handling and controlling skills such as steering, maneuvering in low- and high-speed conditions, and braking. To boost procedural skills, (Lee & Kahnweiler, 2000; Schendel & Hagman, 1982) suggested using extensive and repetitive practices in vehicle controlling scenarios. This process makes executing a sequence of actions automated and may result in intended learning achievement. Several training formats, including professional instructions, driving schools, and simulator training have been employed to deliver such training outcomes.

(2) **Higher-order cognitive skills**: Procedural skills have been addressed as essential skills for proficient vehicle maneuvering and handling; however, they are not adequate for safe driving. Perceiving hazard, keeping sufficient SA, and balancing attentional allocation are among necessary higher-order cognitive skills that play a crucial role in safe driving on roads. More specifically, improving hazard perception skills through practice and feedback helps drivers to detect potential hazards and enrich their visual scanning strategies (Underwood, Crundall, & Chapman, 2011). Improving SA is another target in higher-order cognitive training. (Walker, Stanton, Kazi, Salmon, & Jenkins, 2009) showed that driving training heightened SA by virtue of improved technical knowledge of driving skills.

(3) **Insight and attitude**: In this approach, the training system aims to improve drivers’ insights and raise awareness of the factors involved in crash and safety-threatening conditions (White, Cunningham, & Titchener, 2011). These factors include, but are not limited to, trust, acceptance, overconfidence, overestimation of personal skills, self-diagnostic, and safe estimation of distance.

### 1.2. Training methods

Regarding these learning outcomes, the use of simulators is suggested as an effective tool for driver training. This training approach, depending on the level of fidelity and technology, offers various practices related to procedural skills and higher-order cognitive skills. Interestingly, simultaneous practice of different skills could happen in interactive contexts provided in simulator training. In regular driving, these advantages enhanced training effectiveness and positively affected post-training performance and driving-related variables, like turning into the correct lane, proper signal use, and reduction of unsafe maneuvers (Fisher, Rizzo, Caird, & Lee, 2011; Roenker, Cissell, Ball, Wadley, & Edwards, 2003). Despite the growing number of simulator-based training being developed for regular driving, very little work has been conducted to explore the effects of such technology in highly automated driving training (Hergeth et al., 2017; Sportillo et al., 2018). Their results highlight the effectiveness of this training approach on takeover performance and drivers’ attitude toward highly automated vehicles. These findings are encouraging to explore such an approach while employing various scenarios targeting procedural skills, higher-order cognitive skills, and attitudinal measures. In the current study, we investigate how a simulator-based training program contributes to improving these learning outcomes in CAD.

Video training also has been employed as a major alternative approach to skill acquisition in regular driving. Several studies have used video training to improve higher-order cognitive skills such as risk perception in manual driving. For example, (Crundall, Andrews, Van Loon, & Chapman, 2010; Horswill & McKenna, 2004) provided relevant traffic scenarios showing or requiring how to respond when drivers detected a hazard. A compelling amount of results suggest that video training helped drivers develop their understanding of risky situations and improve driving performance, e.g., greater speed reductions and larger gaps maintained, when approaching hazards (Crundall et al., 2010; Fisher et al., 2002; Wang, Zhang, & Salvendy, 2010). Compared to simulator training, educating drivers with videos provides far fewer opportunities for interactive learning; however, video training can be implemented easily and less costly without demanding complex equipment or professional instructors. As the other training method, this study also aims to explore how video training influences users’ attitude toward CAD and the skills required for using this technology.

Bearing in mind the learning outcomes mentioned above (procedural skills, higher-order cognitive skills, and attitudes), two types of training programs were developed: non-interactive (Video Training) and interactive (Simulator Training). A variety of scenarios, representing different types of automation failures/limits reached, will be investigated. Details of each training program are presented in Table 1. The participants were split into three groups: Simulator Training, Video Training, and Control (no-training). Compared to the baseline, the participants with training experience are expected to show improved procedural skills, including shorter TOT and smoother manual controlling after takeover (Hypothesis 1). Moreover, regarding higher-order cognitive skills, the participants in training groups are likely to demonstrate higher risk perception in takeover decision scenarios (Hypothesis 2). Training programs also are expected to have a positive impact on automation acceptability and trust (Hypothesis 3). Lastly, with respect to higher transferability resulting from interactive training (Beloufa et al., 2017; Roenker et al., 2003), the participants in Simulator Training are expected to outperform in manual control recovery and higher-order cognitive skills compared to Video Training (Hypothesis 4).
2. Methods

2.1. Participants

54 university students, 26 males, and 28 females with valid driver’s licenses, were recruited to participate in the study. Posters and flyers were distributed in the vicinity of a university with a population of more than 5000 students and staff. Applicants were recruited on a first-come, first-serve basis, and the only inclusion criterion was having a valid driving license for at least one year. During data collection, four participants dropped out of the experiment. In the Simulator Training group, two participants withdrew due to simulator sickness, one after pre-training driving and one after the training session. In Video Training group, as well as in Control group, two participants stopped participation because of time constraints. Finally, 50 individuals (24 male, 26 female) completed the study. Participants were aged between 19 and 37 years old (M = 25.1 years, SD = 4.20 years) and had between 1 and 14 years (M = 6.21 years, SD = 6.13 years) of driving experience.

2.2. Designing training system

Table 1 presents information about the type of training, interaction, feedback, medium, length, repetition regime, and content. The participants in Video Training were assigned to watch the content provided in the video. The participants in Simulator Training, however, practiced the same content in an interactive context. To ensure all participants in training groups received the necessary training content, they were assigned to practice the materials three times. Each of these training sessions happened once a day, and the participant was required to complete the session without significant interruption. They were allowed to take a short break whenever they requested. Moreover, the participants in training groups needed to complete all three training sessions in a week, depending on their availability.

2.3. Apparatus

This research was conducted using a fixed-based simulator with approximately 120 degrees of visual angle provided by two projection screens. A two-channel sound system provided traffic and road noise in addition to engine sounds. The simulator dynamics and virtual driving environments were coordinated with Unity software, Version 5.4.1. The driving environments and scenarios were created using Unity objects and packages. This simulator is operable in two driving modes: normal driving and CAD. The CAD is designed to accommodate lateral and longitudinal controls and did not require drivers’ continuous monitoring. Drivers would only need to take control of the car when the simulator issued a takeover request (TOR). We used an audio message to inform the participants about the driving mode: CAD or regular driving. In the normal driving condition, individuals were entirely responsible for speed control and lane maintenance tasks. The longitudinal controller targets speed limitation posted on the highway, rural, and urban roads.
The driving modes, events, and scenarios were determined by road pad, time, and expression triggers. Moreover, the driver can activate or deactivate the automation features intentionally by pressing a specific button, turning the steering wheel more than fifteen degrees, or pressing the brake pedal by more than five degrees. The road entities and vehicle model were imported from the EasyRoads3D package and include a three-way highway (with speed limit of 110 km/h), rural road (with speed limit of 60 km/h), and urban district (with a speed limit of 40 km/h). All driving parameters, including TOT, speed, SDLP, and the number of collisions were logged by the Unity cells and extracted by the analytics package. Because of technical limitations, the forces applied to the brake and acceleration pedals were not collected.

2.4. Dependent outcome measures

2.4.1. Procedural skills variables

Takeover time (TOT): TOT was measured from the moment the TOR was issued until the participant takes control of the car using the steering wheel, acceleration pedal, or brake pedal. Since no automation is provided in regular driving, TOT did not apply to the manual driving mode.

Speed and speed variance: The average speed and speed variance for each takeover scenario were calculated for two miles of manual driving starting from the moment the driver takes control of the car.

Standard Deviation of Lane Position (SDLP): SDLP for each takeover scenario was calculated based on the standard deviation of the mean lateral position for two miles of manual driving starting from the moment the driver takes control of the car.

Total number of collisions: When a participant fails to control the car and hits another object (car, road object, traffic signs), a crash is recorded.

2.4.2. Higher-order cognitive skills

We used takeover decision accuracy (TODA) to explore whether training programs have an effect on the driver’s risk perception. Generally, two types of situations were employed to evaluate TODA: a) the situation when drivers must take over the control of the car, and b) the situation when takeover is not necessary. When the driver’s risk perception on a case does not match with the system requirement, the decision is considered incorrect. The total score for each participant was calculated based on the percentage of total correct decisions by the total number of overall decisions tendered.

2.4.3. Attitude variables

To assess the effects of training on automation acceptability and trust, the participants were asked to answer a questionnaire after completing the Pre-Training Driving Assessment and Post-Training Driving Assessment blocks. Participants were asked to rate their acceptance and trust of the CAD on a 7-point Likert-scale, ranging from “not at all” (1) to “extremely high” (7). According to this scale, we categorized the results of acceptance and trust in three levels: very low (score: 1–2), moderate (3–5), very high (6–7).

2.5. Driving assessment and scenarios

Driving performance of all participants was assessed before training (Pre-Training Driving Assessment), and after the participants in the treatment groups completed the training sessions (Post-Training Driving Assessment). All driving scenarios were the same in both of these assessments in terms of length, order, and number of events. Generally, two types of scenarios were employed: Takeover Required Scenarios (TRS) and Takeover Decision Scenarios (TDS). TRSs were used to study how training has an impact on procedural skill variables. In these scenarios, the car issued TORs (lead-time: 10 s), and the participants needed to resume control of the car immediately. Each participant was faced with three different types of takeover scenarios shown in Table 2. In TRS, drivers were faced with three situations: very sharp curves on rural roads, heavy traffic in highways, and an emergency vehicle ahead of the car on urban roads. As displayed in Table 2, we also employed some TDSs used by (Boelhouwer et al., 2019) to explore the effects of training on the higher-order cognitive skill takeover risk perception. Three types of necessary takeover scenarios and three types of unnecessary takeover scenarios were developed. In none of these scenarios, the participants received TOR, and they had to decide whether to take back control of the car. Fig. 1 shows all scenarios each participant encountered in Pre- and Post-Training Driving Assessments. Participants in all groups received the same order and number of events in Pre- and Post-Training Driving Assessments. Each event in TRS was repeated three times in different driving sessions. However, as shown in Fig. 1 to make the upcoming event unpredictable, the order of events differed in each replication and scenarios were randomly distributed in different parts of the road. Although speed limits were posted on all highways, rural, and urban roads, the participants were free to drive at their desired speed while manually driving.

2.6. Design and procedure

The study was carried out in a mixed 3 (Training Groups) × 2 (Pre-Training vs. Post-Training) design. 18 participants received Simulator Training, 18 participants received Video Training, and 18 participants served in the Control group and did not receive training. After recruiting and scheduling, each participant was invited to the experiment site and was required to read and sign the consent form approved by the Institutional Review Board. This form provided details of the
experiment process and what the participant was expected to do. Moreover, it was explained that a participant could terminate the experiment at any time without providing a reason, and without any negative consequence. Finally, the participant was informed that participation in the experiment will result in $20 as compensation for time and effort, which will be offered at the end of the experiment. Those participants who chose to withdraw early would be compensated on a pro-rated basis. Fig. 2 displays intervention groups and the experimental procedure.

2.7 Data analysis

All Pre- and Post-Training Driving Assessments data were first investigated to confirm if normality and homogeneity assumptions for the dependent variables are violated. The Kolmogorov–Smirnov test showed that in both the Pre- and Post-Training Driving Assessments, the distributions of the total number of crashes, speed, and acceptance diverged considerably from a normal distribution. Hence, we used the Wilcoxon and Mann-Whitney tests for within-subjects (Pre-Training vs. Post-Training Driving Assessment) and between-subjects comparisons (training groups). For the remainder of the variables, parametric tests (ANOVA and paired t-test) were used. Tukey post hoc tests were performed to determine the training effects, with alpha levels of 0.05 and 0.01.
3. Results

3.1. Impact of training on procedural skills

TOT: Participants in the training groups had shorter TOT (M_Training = 1.84 s, SD_Training = 0.40 s; F (2,47) = 4.09, \( p = 0.02 \)) than those in the Control group (M_Control = 2.29 s, SD_Control = 0.64 s). The post hoc analysis showed that there was no significant difference in TOT between the participants in Simulator and Video training. Both training programs significantly contributed to reducing recovery time. Comparing the results of Pre- and Post-Training Driving Assessments showed that the TOT was also slightly shorter (\( p = 0.063 \)) among Control participants in Post-Training Driving Assessment (M = 2.29 s, SD = 0.64, min = 1.4 s, max = 2.3 s) than Pre-Training Driving Assessment (M = 2.53 s, SD = 0.56 s, min = 1.01 s, max = 4.8 s).

Speed and Speed Variance: Concerning other procedural skills, no significant difference was observed in speed measured in Simulator Training, Video Training, and Control groups. However, a significant effect of training, (F (2, 47) = 3.99, \( p = 0.025 \)), was noted on speed variance of data collected in Post-Training Driving Assessment from Simulator Training (M = 17.1 km/h, SD = 10.26 km/h, min = 8 km/h, max = 45 km/h), Video Training (M = 29.6 km/h, SD = 16.1 km/h, min = 8 km/h, max = 42 km/h), and Control (M = 27.8 km/h, SD = 14.9 km/h, min = 11 km/h, max = 39 km/h).

SDLP: A significant difference between training conditions (F (2, 47) = 3.43, \( p = 0.0 \)) was observed in SDLP of Post-Training Driving Assessment data. The post hoc analysis showed that there was only a significant difference between Simulator Training and Control group (M difference = -8.647). Indeed, participants who followed the Simulator Training exhibited a lower SDLP (M = 19.01, SD = 7.63, min = 12.1, max = 43), than participants following Video Training (M = 26.5, SD = 10.7, min = 9.84, max = 53.), and those participants in the Control group (M = 27.6, SD = 9.98, min = 15, max = 48). Furthermore, a between-subjects Kruskal–Wallis test was conducted to compare the total number of crashes across three groups in Pre- and Post-Training Driving Assessments. This test discovered no significant differences between the groups at either Pre- or Post-Training Driving Assessment (all \( ps > 0.05 \)).
3.2. Impact of training on higher-order cognitive skills

Repeted one-way ANOVA in a between-subject analysis showed that training programs significantly improved the TODA in both training groups (F (2, 47) = 3.17, p = 0.024). The rate of correct takeover decisions was higher in Simulator Training (M = 76%, SD = 21, min = 43%, max = 95%) compared to Video Training (M = 63%, SD = 17, min = 36%, max = 91%) and Control group (M = 56%, SD = 25, min = 32%, max = 75%). According to Tukey analysis, participants in Simulator Training showed significantly higher TODA in Post-Training Driving Assessment compared to people in Video Training.

Moreover, comparing Pre- and Post-Training Driving Assessments data showed a meaningful impact of training on TODA in four out of six takeover decision scenarios in Simulator and Video Trainings (Table 3). In these scenarios, the rate of accurate decisions was significantly higher in Post-Training Driving Assessment. A within-subject analysis also revealed that TODA was higher (p < 0.01) in scenarios where takeover is necessary (M = 63%, SD = 32) than the scenarios where takeover is not necessary (M = 43.1%, SD = 28). As shown in Table 3, the type of risk perception scenarios effects on TODA. The pedestrian scenarios and the traffic controller scenarios resulted in the lowest and highest TODA in all groups in both Pre- and Post-Training Driving Assessment, respectively. In order to avoid learning effects of pre-training and post-training on TODA, we did not consider critical consequences for a wrong take over decision. For example, the participants who did not notice the message of a broken traffic sign did not face any critical circumstance.

3.3. Impact of training on trust and acceptance

In Pre-Training Driving Assessment, 50.3% of participants (N = 27) stated their trust toward highly automated cars as high (scores: 6–7), 31.6% (N = 17) declared moderate trust (scores: 3–5), the rest rated the trust to be low (scores: 1–2). Post-Training Driving Assessment showed that training intervention significantly impacts participants’ trust toward CAD (F(2, 47) = 3.83, p = 0.042). Thirty-two participants (63.1%) indicated to have moderate trust to the highly automated vehicle, while 24.2% (N = 12) declared their trust to be high trust, and 12.6% (N = 6) reported low trust (see Fig. 3). Post hoc analysis did not show a meaningful difference of trust score between participants in Simulator Training and Video Training. Moreover, a paired-samples t-test was conducted to compare the result of trust in Pre- and Post-Training Driving Assessments. The results showed that training shifted trust toward more moderated trust among participants in both training groups.

<table>
<thead>
<tr>
<th>Event</th>
<th>Simulator training</th>
<th>Video training</th>
<th>Control</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Pre-Training</td>
<td>Post-Training</td>
<td>Pre-Training</td>
</tr>
<tr>
<td></td>
<td>M (SD)</td>
<td>M (SD)</td>
<td>M (SD)</td>
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<td>Takeover decision</td>
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<td>42.1(9.4)</td>
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<td>Roadworks no</td>
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<td>74.1(21.1)</td>
<td>35(9.4)</td>
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<tr>
<td>Pedestrians no</td>
<td>25.3(8.5)</td>
<td>29(12.1)</td>
<td>25(15.7)</td>
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<tr>
<td>Dirt roads yes</td>
<td>51(21.2)</td>
<td>69(13.9)</td>
<td>48.8(21.5)</td>
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<tr>
<td>Traffic controllers</td>
<td>83.9(2.3)</td>
<td>94(5.3)</td>
<td>87.9(8.1)</td>
</tr>
<tr>
<td>Broken traffic signs</td>
<td>43.6(20.1)</td>
<td>63(11.5)</td>
<td>39(18.7)</td>
</tr>
</tbody>
</table>

Note. TODA = takeover decision accuracy.

* p < 0.05.

** p < 0.01.

Fig. 3. Self-reported trust in Simulator Training, Video Training, and Control groups, separated based on three levels of low, moderate and high.
(Simulator Training: \( t (15) = 3.4, p < 0.01 \), Video Training: \( t (16) = 4.9, p < 0.05 \)). Regarding automation acceptability, there were no effects of group nor time, nor was there an interaction (\( ps > 0.05 \)), indicating that this measure was insensitive to group differences or training effects. Although comparing the results of Pre- and Post-Training Driving Assessments in the Simulator Training group slightly increased the automation acceptability, this change was not statistically significant.

4. Discussion

The current study is one of a few to examine the effects of training on highly automated driving performance (TOT and takeover quality) and comparing the influence of interactive and non-interactive training programs on users’ attitudes, and procedural and higher-order cognitive skills required for CAD. The main goal of this study was to investigate whether the skills required for CAD can be improved by two different training methods: Simulator Training and Video Training. Moreover, we explored how these training methods influenced users’ trust and acceptance.

Considering the available literature, we hypothesized that both training methods would improve procedural skills including shorter TOT and smoother manual controlling (hypothesis 1). Participants in training groups showed an improvement in procedural skills in recovering control after issuing TOR. Regardless of the type of training, TOT was significantly shorter for participants in both training groups compared to those in the Control group. The improvement in TOT may imply that the trained participants built a more accurate mental model of the automated system, encouraging them to take control sooner. Moreover, compared to Video Training, Simulator Training enhanced safety in posttakeover behavior, e.g., lower speed variance and shorter SDLP. To limit our analysis to the manual controlling skill followed by TORs, posttakeover data including speed, speed variance, and SDLP were calculated for two miles of manual driving starting from the moment that the driver takes control of the car. These findings are in line with (Payre et al., 2016, 2017), where they reported that driving experiences with automated cars helped drivers to better understand how the system works, and consequently improved manual control recovery performance.

Contrary to our hypothesis, Video Training was not effective to advance takeover quality. Lack of interactive and practical learning process in Video Training could potentially explain this finding. Although the content was similar in both training programs, the Simulator Training may outperform in creating more accurate mental models of the system. The importance of extensive and interactive practices in developing procedural skills was also highlighted in earlier studies (Lee & Kahnweiler, 2000; Schendel & Hagman, 1982). Interestingly, TOT and SDLP were also slightly improved in Post-Training Driving Assessment of participants in the Control group, which could be justified considering the effect of learning from Pre-Training Driving Assessment. Neither the type of training nor the time of driving assessment affected the total number of crashes. One potential reason is that most of the takeover scenarios were safe and there were small chances to hit an object. In addition, the drivers were not allowed to engage in secondary tasks; therefore, they might have enough SA to control risky situations.

We also hypothesized that drivers in both training groups are likely to demonstrate higher risk perception in takeover decision scenarios (hypothesis 2). Compared to the control group, our results supported that both types of training led to higher risk perception, where the participants in Simulator Training recorded highest TODA. This finding corresponds to our hypothesis that drivers may take benefits of interactive training in improving higher-order cognitive skills required for highly automated driving. (Boelhouwer et al., 2019) explored how providing structural information effects a driver’s mental model of highly automated cars’ capabilities. According to their findings, educating drivers using the non-interactive training (owner’s manual) did not influence takeover decision accuracy. In lower levels of automation, (Nilsson, 1996) also reported that instructing participants about ACC limitations was not a practical approach to improve their performance and they had still problems in identifying the situations requiring them to take control of the car. Among the most significant reasons for these conflicts, one can point out differences in content and training method. These conflicts may indicate the inefficiency of the conventional education provided in the owner’s manual and the importance of planning and developing more comprehensive and interactive training in this field. Higher learning achievements in Simulator Training confirmed the usefulness of the combination of practical and theoretical training, suggested by (Boelhouwer et al., 2019; Payre et al., 2017).

The results regarding automation acceptability and trust (hypothesis 3) showed that training resulted in relatively well-calibrated trust. Interestingly, less erratic trust was reported by participants who expressed minimal and very high trust before training. This finding suggests that training may help drivers obtain a more transparent view of how highly automated cars operate. This is congruent with (Beggiato et al., 2015) findings of how trust follows the law of learning; the more users learn about a system and its limitations/capabilities, the better-calibrated trust is achieved. Likewise, previous studies have discussed that training plays a useful role in establishing a better mental model of the system and consequently leading to a well-calibrated trust. For example, (Forster, Hergeth, Naujoks, Krems et al., 2019; Hergeth et al., 2017; Payre et al., 2017) reported an indication of greater trust as a result of training and practice in highly automated driving. However, the concept of well-calibrated trust is little understood in human-automation interaction. More trust does not necessarily mean well-calibrated trust. Drivers who reported excessive trust toward assistive technologies tended to overestimate the capabilities of such technologies (Abe & Richardson, 2004; Burns, Knabe, & Tevell, 2000), which may cause critical safety risks in highly automated driving (Nilsson, 1996). Further research is needed to define the concept of balanced trust and how to achieve it in highly automated driving contexts.
Acceptance data did not support a part of hypothesis 3. Neither between-subject nor within-subject analysis showed a meaningful impact of training on automation acceptability. In contrast, by our finding, previous studies reported higher automation acceptability among ACC users who were exposed to a few training sessions (Beggiato et al., 2015). Trust and acceptance are interrelated concepts; however, they do not necessarily follow the same pattern (Koustanaï, Cavallo, Delhomme, & Mas, 2012; Xiong, Boyle, Moeckli, Dow, & Brown, 2012). Besides individual drivers’ features, several design qualities such as level of reliability (Beller, Heesen, & Vollrath, 2013), modality (Stevens, 2016), and timing (Lee, McGehee, Brown, & Reyes, 2002) of assistive systems contribute to developing acceptance. These variabilities make automation acceptability a complex construct which is difficult to be handled solely by training.

We also anticipated that participants would benefit from the interactive and engaging contexts provided in Simulator Training (hypothesis 4). Our findings confirmed that the Simulator Training outperformed in achieving learning outcomes. The interactive nature of the training in Simulator Training was far more extensive than Video Training. This may explain why the former delivered more improvement compared to the latter. However, since the same simulator is used for drive tests, the change in TODA and takeover performance of participants in Simulator Training could have been affected by having more practices with the simulator. To limit this confusing effect, training in future studies needs to be designed and implemented differently from the driving simulator used to collect driving data.

5. Limitation

As a major limitation, we did not explore the long-term effects of these training methods on CAD performance. Further studies need to explore how effectively each of these training tools influences takeover behavior and users’ attitude in longer time. Another significant limitation of this study is that we used the same simulator for driving assessments and training. Some evidence criticizes this approach because of the effects of experience and familiarity with the simulator on learning outcomes (Beanland, Goode, Salmon, & Lenné, 2013; Salas, Rosen, Held, & Weissmuller, 2009). In addition, having interactive scenarios led to longer training session in Simulator Training. Although the content was the same in both training groups, longer exposure to highly automated driving in Simulator Training may influence learning outcomes. This is an open question for future studies to explore how length of training session matters when comparing learning outcomes of two different training programs.

Moreover, we used the same scenarios in Pre- and Post-Training Driving Assessments, which may introduce some extent of learning on the measured outcome (Pradhan, Pollatsek, Knodler, & Fisher, 2009). However, since all drivers participated in both Pre- and Post-Training Driving Assessments, it is less likely that our results were affected by such a drawback. As another limitation of this study, we did not consider all of the major critical conditions, such as severe weather conditions, night-time driving, and engaging in secondary tasks, which are among challenging takeover scenarios. Understanding the best practices in training sessions in automated driving is very important question which futures works might investigate. Lastly, transfer of learning, as a fundamental aspect of every training program, was not explored in real driving conditions. Further research is required to explore whether the results generalize to other settings, tasks (especially where drivers are engaged in non-driving secondary tasks) and populations in real road driving.

6. Conclusion

In summary, these results add further weight to the accumulating research linking contribution of training to highly automated driving, and how training mitigates human factors challenges in driver-automation interaction. The current study proposes that educated drivers may benefit from safer manual recovery, better takeover risk perception, and moderated trust. Highly automated driving training with a focus on procedural skills, higher-order cognitive skills, and driver attitude in the simulator may provide an effective and low-risk alternative to on-road experiences. These results extend available literature regarding the importance of training in developing users’ mental model of highly automated driving, especially where interactive learning is provided. Further research will provide more insight into the question of whether these training approaches could be used in issuing highly automated driving licenses and related regulations.

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Appendix A. Supplementary material

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References


