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Evaluating advanced driver-assistance system trainings using driver performance, attention allocation, and neural efficiency measures

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ABSTRACT

There are about 44 million licensed older drivers in the U.S. Older adults have higher crash rates and fatalities as compared to middle-aged and young drivers, which might be associated with degradations in sensory, cognitive, and physical capabilities. Advanced driver-assistance systems (ADAS) have the potential to substantially improve safety by removing some of driver vehicle control responsibilities. However, a critical aspect of providing ADAS is educating drivers on their operational characteristics and continued use. Twenty older adults participated in a driving simulation study assessing the effectiveness of video-based and demonstration-based training protocols in learning ADAS considering gender differences. The findings revealed video-based training to be more effective than demonstration-based training in improving driver performance and reducing off-road visual attention allocation and mental workload. In addition, female drivers required lower investment of mental effort (higher neural efficiency) to maintain the performance relative to males and they were less distracted by ADAS. However, male drivers were faster in activating ADAS as compared to females since they were monitoring the status of ADAS features more frequently while driving. The findings of this study provided an empirical support for using video-based approach for learning ADAS in older adults to improve driver safety and supported previous findings on older adults' learning that as age increases there is a tendency to prefer more passive and observational learning methods.

1. Introduction

According to the National Highway Traffic Safety Administration (NHTSA), in 2016, there were an estimated 7,277,000 motor vehicle crashes in which 37,461 people were killed and an estimated 3,144,000 people were injured. Among these, 6764 people 65 years and older were killed which made up 18% of all traffic fatalities (NHTSA, 2018b). In the past decade, the number of crash related fatalities has increased 14% among older adults (NHTSA, 2018b). There are about 44 million licensed older drivers in the U.S which is an increase of approximately 35% over the past decade (NHTSA, 2019). In an early study and considering the number of kilometers driven, Ryan et al. (1998) found that older adults have relatively high crash rates similar to young population. Another investigation on the changes in motor vehicle crashes, injuries, and deaths per mile driven in relation to driver age from 1995 through 2010 revealed that mileage-based crash rates were highest for the youngest drivers, ages 16 to17, and decreased with increasing age until ages 60 to 69 and increased afterwards (Tefft, 2012). Older adults (above 70 yrs older) had similar crash rates to younger adults. In a more recent report from AAA foundation for traffic safety (Tefft, 2017) on injuries and death per mile driven in relation to driver age from 2014 to 2015, drivers age 80 and older have been found to have the highest rates of deaths. In addition, drivers between 70 and 79 years of age had high fatal crash rates (per 100M miles driven) similar to middle age drivers. These trends might be associated with degradations in sensory, cognitive, and physical capabilities (Dickerson et al., 2017). Research has shown elderly drivers to have poorer driving performance and reaction time to hazards as compared to other age groups (Karali et al., 2017; Zahabi et al., 2017a,b). In addition, approximately 94% of the serious crashes were attributable to human error, including errors related to

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distraction, impairment, or drowsiness (NHTSA, 2018a). Advanced driver-assistance systems (ADAS) that help to control vehicle acceleration, deceleration, and lane position have the potential to substantially improve safety by removing some of driver vehicle control responsibilities. However, a critical aspect of providing ADAS is educating the public on their operational characteristics and continued use. A survey by AAA foundation for traffic safety (AAAFTS, 2008) found that older adults learn to use advanced in-vehicle technologies through instructions from the dealership, vehicle owner manual, and trial-and-error. However, up to 20% of drivers reported that they were not familiar with these technologies in their vehicles. Without proper training older drivers will be unaware of system strengths and weaknesses which may result in unanticipated or unintended responses that may negatively impact crash rates (Parasuraman, 2000). Therefore, it is critical to understand and establish methods to train drivers on the use of ADAS. Within the context of this work, we refer to training as a continuous and systematic process that teaches individuals a new skill or behavior to accomplish a specific task (Salas et al., 2006). Ideally, training should promote permanent behavioral changes that support an optimal relationship between humans and the systems they operate. A successful training program is expected to promote the necessary knowledge, skills, and attitudes related to ADAS and ultimately, safe driving.

1.1. Advanced driver-assistance systems (ADAS)

The society of Automotive Engineers (SAE) defines vehicle automation framework into six levels from a completely manual system (level 0) to fully autonomous vehicles (level 5) in which the automation controls all aspects of the driving task (SAE, 2016). Based on this taxonomy, level 1 automation refers to a situation where automation controls either the steering or acceleration/braking of the vehicle while the human controls all other elements of the driving task and monitors the driving environment. Examples of these features include lane keeping assist system (LKAS) or adaptive cruise control (ACC). In level 2, automation controls both the steering and acceleration/braking of the vehicle while the human monitors the driving task and is ready to take control with little notice. Examples of driver support features in this level include using the LKAS and ACC at the same time. Studies have found level 1 automation to be beneficial in general (Cicchino, 2017), while the safety benefits of higher levels of automation are still unclear (Endsley, 2017) mainly due to the interaction issues between the human driver and vehicle automation features (McDonald et al., 2019). One way to resolve these interaction issues is through proper training on ADAS. Training and prior experience with automated driving functions have been found to impact human performance and mental model of automation system (Krampell et al., 2020). For example, training drivers on ACC or providing explanation on takeover process improved driver performance (Hergeth et al., 2017). However, there has been no study on the effectiveness of different training approaches and how they might affect driver performance, visual attention allocation, and mental workload in using ADAS. Prior studies have found ADAS usage rate to be lower for elderly drivers as compared to other age groups mainly due to the lack of knowledge and experience (Trübswetter and Bengler, 2013). Proper training is critical for removing this barrier and reducing the risk of motor vehicle crashes due to misunderstanding or misuse of ADAS. Therefore, the current study focused on assessing the effect of two training protocols on older drivers' use of and interaction with ADAS.

1.2. ADAS training programs

The development and evaluation of ADAS training programs can be informed by both practical and theoretical considerations. Practically, an effective training protocol should be compatible with the training objectives, suitable to the anticipated training environment and available resources, and consider the intended audience. The selection of training programs may also be associated with driver-related factors. For example, some individuals might prefer self-led technology-based methods such as online videos or game-based training, while other drivers prefer more traditional instructor-led demonstration methods. In terms of ADAS, information can be taught through online videos (e.g., My Car Does What, YouTube, dealer provided videos), face-to-face instructions with professionals (here after called demonstration-based training) such as those in the American Driver Traffic Safety Education Association (ADTSEA), Driving School Association of the Americas (DSAA), or dealerships, vehicle owner manuals, and driving simulation-based training.

A number of theoretical frameworks have been developed to guide the science of design, delivery, and evaluation of training systems (Bell and Kozlowski, 2008; Burke and Hutchins, 2008). These frameworks do not rate the relative effectiveness of specific training methods so it is difficult to select one that might be applied to various training approaches for ADAS. However, elements of these theories can be applied to the understanding of the video and demonstration-based approaches. Video-based training is supported by the "interactivity principle" that says the information presented in any animation is better comprehended if the learner has control (e.g., by starting, stopping, and reviewing part or all of a video) over the pace of information (Betrancourt, 2005). This process allows for information to be chunked into a more efficient mental model, which facilitates learning. A second element that can be applied to video-based learning relates to the cognitive load theory of multimedia learning which posits that multi-media instructional formats lead to better acquisition of information and foster deeper learning than a purely visual or verbal instructional format (Mayer, 2003).

In contrast, demonstration-based training is instructor-led and occurs in the working environment (i.e., in the vehicle in the case of training on ADAS). Demonstration provides an opportunity to observe and practice the behaviors needed to perform a task; practicing the behaviors facilitates the establishment and reinforcement of the neural pathways employed with those actions, ultimately reducing the mental effort needed to perform the practiced actions (Torriero et al., 2007). Related to driving, the development of the neural pathways results in learning the skills necessary for the effective and safe operation of vehicles. It is important to note that training effectiveness also depends on cognitive abilities of trainees. Young and older adults are different in terms of their attentional demand, working memory capacity, etc. (Czaja, 1996) For example, Morrell et al. (1990) found that older adults had more difficulty learning the material that was presented with a combination of pictures and words (similar to video-based training) as compared to verbal instructions (similar to demonstration-based training). Beyond this, one of the fundamental elements in older adult education and training is motivation (Wlodkowski and Ginsberg, 2017). Instructors have a critical role in learning process of older adults especially to maintain and increase their motivation (Martínez-Alcalá et al., 2018). Demonstration-based training provides an opportunity for drivers to observe and practice the tasks, and receive real-time feedback, which could enhance their engagement and motivation. Related to this, Taylor and Rose (2005) study with adults over 45 yrs of age identified teachers/trainers as one of the main strategies for successful engagement and retention of older adult learners.

Other ADAS training approaches such as driver owner manuals and driving simulation-based training have been found to be ineffective due to drivers not reading detailed written instructions (Leonard, 2001), cost, and/or accessibility issues. Portouli et al. (2008) was the only study that compared different ADAS training protocols (i.e., written manual, video-based training, and video-based training with driving simulation) and found no difference in terms of driver accuracy in responding to knowledge surveys. However, this study had several limitations, which limits its generalizability to driver population. For example, the study was focused on young and educated drivers, participants were not native English speakers (the training was provided in English), the authors did not consider learning style differences between males and females, and the study did not consider driving performance data.

1.3. Training and mental workload

Previous studies have assessed the effect of ADAS on driver mental workload using performance measures, subjective ratings, and physiological responses (Biondi et al., 2017; Davidse et al., 2009; De Winter et al., 2014). For example, using secondary task performance (i.e., reaction time and accuracy), Davidse et al. (2009) did not detect any reduction in driver workload when using ADAS, while a meta-analysis study by De Winter et al. (2014) revealed that using ACC led to small reduction in driver workload as measured by self-reported (i.e., NASA Task Load Index, Rating Scale Mental Effort) and physiological responses (i.e., heart rate, blink rate).

Expertise development due to training has the potential to reduce mental workload, i.e., reduces the requirements of attentional resources (Schneider and Shiffrin, 1977; Shiffrin and Schneider, 1977). It is reasonable to expect that an effective ADAS training system would reduce drivers' mental workload as they utilize ADAS features. While most training assessments have targeted improvements in performance outcomes (such as driver accuracy in responding to knowledge surveys as examined by Portouli et al., 2008), it is important to assess driver neurocognitive load (i.e., a measure of how hard the brain is working to meet driving demands) as workload can be disassociated with performance outcomes owing to changes in motivation and strategies (Matthews et al., 2000; Sperandio, 1978). Of the various objective mental workload assessment techniques, changes in brain function using functional near infrared spectroscopy (fNIRS) has gained wide attention in determining operator workload and expertise development, particularly in the transportation domain (Khan and Hong, 2015; Zhu et al., 2019a). In particular, it is important to understand whether driving performance is associated with additional neural "cost" that may be imposed on drivers to safely perform driving tasks. Neural efficiency metrics, obtained from fNIRS, can emphasize different strategies used by drivers (Curtin and Ayaz, 2019) to maintain task performance and can provide novel insights into the impact of different training programs on driving performance.

1.4. Gender learning style differences

Literature in learning and education identifies several differences between the learning styles of males and females; however, these is no consensus regarding gender differences. Some studies have found that females are more field-dependent (Witkin, 1979), prefer more concrete learning style (Kolb, 1984), but have less experience in hands-on applications (Milgram, 2007) as compared to males. Related to this, a survey by Philbin et al. (1995) reported that females learn better in practical settings (i.e., watch and do) as compared to males who learn best by thinking and watching. While Slater et al. (2007) reported no gender-specific preference of learning style, Wehrwein et al. (2007) reported that males preferred multi-modal instruction (using visual, auditory, read-write, and kinesthetic modes), whereas females preferred single-mode instruction with a preference toward kinesthetic mode. In another study focused on learning style differences among older adults (above 55 yrs of age), there was no significant difference between the learning styles of males vs. females (Truluck et al., 1999). The contrasting results of gender learning style differences suggest that either there may not be an observable effect of gender on learning style or the methods used to observe possible effects were not optimal.

1.5. Problem statement

The older driver population is increasing and it is at high risk of crash related injuries and deaths that might be associated with degradations in physical and/or cognitive abilities. ADAS have the potential to improve older adult driving safety if drivers are well-trained in using such systems. Although prior studies identified advantages of both video-based and demonstration-based training in general, there has been no investigation on the effectiveness of such protocols in training ADAS. In addition, there has been no investigation on how different training protocols might affect the performance of different genders in using ADAS. Therefore, the objective of this study was to determine the effectiveness of video-based and demonstration-based training protocols on older drivers' use of and interaction with ADAS considering gender differences. In addition, we went beyond the traditional measures of mental workload into an "efficiency metric" to understand why such differences occur. The comparison provides a mechanism to establish the effectiveness of the two theoretically-based training approaches that have immediate practical implications for those who develop training materials and for the students who must learn and use ADAS.

2. Method

2.1. Participants

Twenty drivers (10 males), mean (SD) age of 63.1 (5.1) years, participated in this study (See Table 1). Equal number of males and females were prospectively assigned to either the video-based or the demonstration-based group. To reduce biases that may influence study results, participants did not own or operate a vehicle with ADAS driving technologies, were not taking medications that would impair driving performance or decision making, and possessed normal or corrected to normal vision via corrective lenses. Each participant read and affirmed their written consent using the approved Texas A&M University Institutional Review Board (IRB) human subjects consent form prior to participation in the study.

2.2. Experiment setup and equipment

The study was conducted in the Texas A&M Transportation Institute's driving environment simulator which was manufactured by Realtime Technologies, Incorporated (Fig. 1). The driving environment simulator consists of a single vehicle seat placed in front of three screens that subtended a 165 and 35° horizontal and vertical fields of view, respectively. Drivers controlled their virtual vehicle through a force feedback steering wheel, accelerator pedal, and brake pedal. The simulator collected data at a rate up to 60 Hz. The level two automation was provided to drivers through an adaptive cruise control (ACC) and a lane keeping assist system (LKAS). Eye glance metrics were collected using a Seeing Machines Incorporated single camera Fovio system.

A functional near-infrared spectroscopy (fNIRS) system (Techen CW6 system, Techen Inc. MA, USA) was used to record neural hemodynamic responses of the prefrontal cortex (PFC). The intensity of the light signal in the 690 and 830 nm wavelengths, emitted from 6 sources and absorbed while traveling through neural tissue, were recorded at 8 detectors to obtain hemodynamic responses at a total of 12 channels (C1-12; Fig. 2). The Atlasview (Aasted et al., 2015) was employed to determine the regions of interest where the brain activation was monitored based on 10/20 international EEG system. The logarithm of the input signal converted the acquired light intensities into optical density that was low pass filtered at 3 Hz to reduce high-frequency noise. Motion artifacts were visually marked and corrected using spline interpolation algorithm (Scholkmann et al., 2010) and smoothed using wavelet

Table 1
Participant demographics.

Gender	Video-based		Demonstration-based	
(No. of Participants)	Male n = 5	Female n = 5	Male n = 5	Female n = 5
Age (Stan. Dev.)	64.75 (5.37)	62.20 (6.30)	63.00 (5.79)	61.80 (4.66)

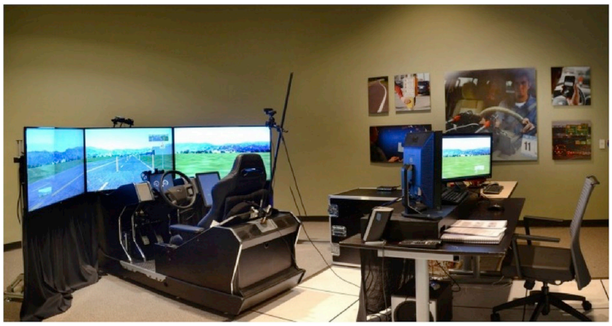


Fig. 1. Driving simulator setup.

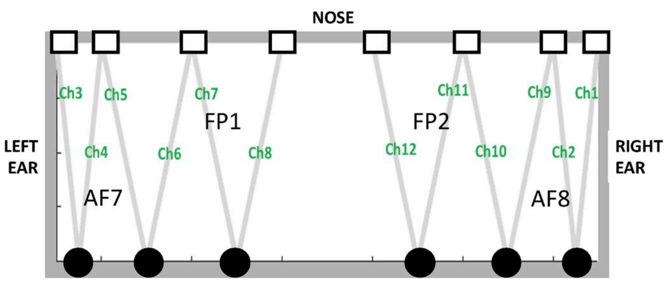


Fig. 2. fNIRS probe design. Solid circles represent sources, and squares represent detectors. Gray lines represent channels created between optodes, from C1-C12. Regions of interests consist of AF7 (lateral) and FP1(medial) in the left and FP2 (medial) and AF8 (lateral) in the right hemispheres.

algorithm (Chiarelli et al., 2015). To reduce the effect of physiological noise and slow wave drifts, the corrected signal was bandpass filtered at 0.5–0.016 Hz. Finally, oxygenated (ΔHbO) and deoxygenated (ΔHbR) hemoglobin at the 12 channels were calculated using modified Beer-Lambert law (Delpy et al., 1988), and the present investigation focused on ΔHbO as it has shown greater task-related changes than ΔHbR (Rhee and Mehta, 2018). We obtained task-related neural action within each trial by averaging 2 s around maximum HbO activation, from which mean HbO were computed across the trials, based on procedures recommended by (Zhu et al., 2019b). Four regions of interests (ROIs) in the PFC were identified corresponding to AF7 (C3,4,5) and FP1 (C6,7,8) in the left hemisphere and AF8 (C1,2,9) and FP2 (C10,11,12) in the right hemisphere to increase sensitivity to smaller effects (Powell et al., 2018). Mean HbO values from the channels in each ROI were averaged to obtain overall mean HbO per ROI per condition.

2.3. ADAS design

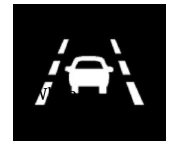
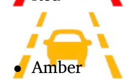
2.3.1. Lane keeping assist system (LKAS)

The LKAS function supported drivers' ability in keeping the vehicle within the current lane. The LKAS recognized the position of the vehicle within the lane and when required, helped to maintain lateral movement of the vehicle. LKAS did not perform automatic driving nor prevent possible lane departures. The responsibility for safe operation of vehicle always remained with the driver. Table 2 shows the icons and audio associated with LKAS activity. Fig. 3 shows the flowchart of LKAS operations in this study.

2.3.2. Adaptive cruise control

Cruise control (CC) allows a driver to set a vehicle speed, which is maintained by the CC system. Adaptive cruise control (ACC) is an enhancement to conventional cruise control systems that allows a driver's vehicle to follow a forward vehicle at a pre-selected time gap by controlling vehicle acceleration and/or the brake, up to a maximum speed set by the driver. The vehicle automatically accelerates, decelerates and stops to match the speed changes of the preceding vehicle even if the accelerator pedal is not depressed. ACC operates as normal cruise control if no vehicle is detected ahead. Fig. 4 shows how the flowchart of ACC operations in this study.

Table 2
System activity, icons, and audio for lane keeping assist system.

LKAS System Activity	Icon and Color	Audio
Turn system on		None
Standby		None
System active (all requirements met)		None
System Interruption		8 quick beeps
Steering wheel is released		3 quick beeps

2.4. Visual interface

Participants interacted with touchscreen buttons (Fig. 5a) which were used instead of buttons on the steering wheel. The central touchscreen was divided into two sections. The top section displayed the buttons used for CC and ACC. The bottom section displayed the button used for LKAS. Fig. 5b shows the location of the icons in the driver information center (DIC). CC and ACC icons were displayed on the top half, while the LKAS was displayed on the bottom. Icon color change was reflected in both the central touchscreen and the DIC. For example, if LKAS is on and active, the button on the central touchscreen will be green and the LKAS icon in the DIC will also be green.

2.5. Experiment design and variables

The experiment followed a 2 × 2 × 2 mixed within- and between-subject design with training condition (video-based or demonstration-based training) and gender (female, male) as between subject factors and driving condition (manual or automated) as a within subject variable. Although not a focus of our study, driving condition manipulation was added to compare the visual attention allocation and mental workload of drivers during automated driving segments as compared to manual driving and to understand to what extent the training could reduce the gap between these two conditions. The dependent variables were grouped into three main categories including driving performance, visual attention allocation, and mental workload. Driving performance measures included the time to activate level 2 automation (i.e., both ACC and LKAS), standard deviation of steering position angle (SD-SPA), and the standard deviation of time headway (SD-THW). Participants who have been trained on the automated vehicle systems are more likely to recognize when the conditions (e.g., minimum travel speed, presence of both lane lines, presence of a lead vehicle) are appropriate to activate ADAS features and to know how to activate ACC and LKAS. The LKAS system, when activated, should maintain lane position more consistently than a human driver in manual steering mode. In addition, the ACC system, when activated, should maintain time headway more consistently than a human driver in manual driving mode. Both ACC and LKAS were activated in a two-step process. The ACC system required participants to first activate the system (to go to the stand-by mode) and then press "Set-" to turn on the system (Fig. 4). Therefore, we only considered

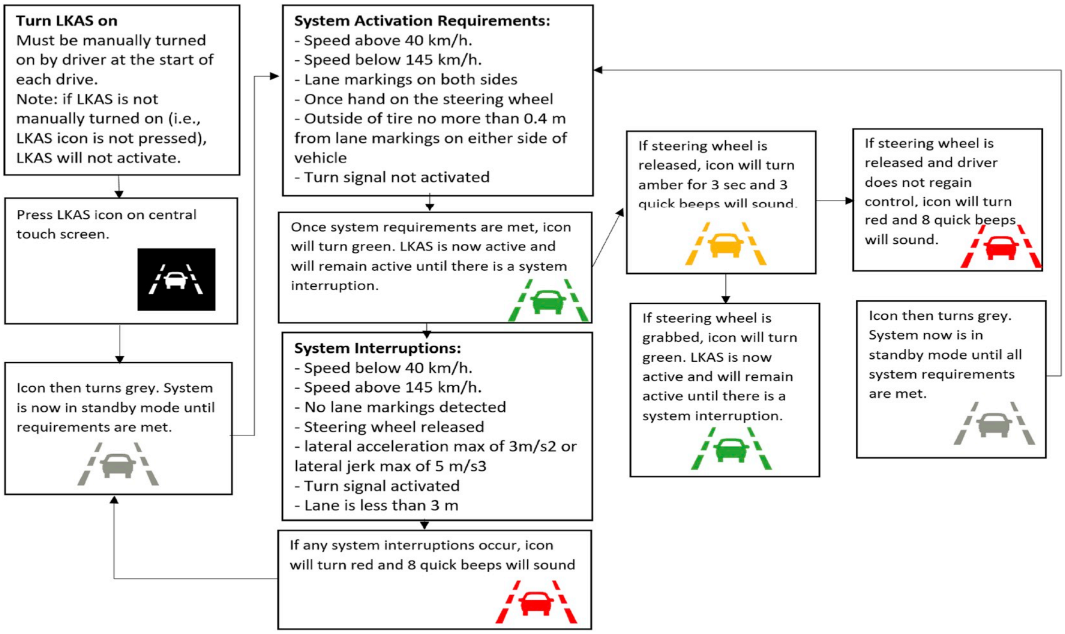


Fig. 3. Lane keeping assist system operational flowchart.

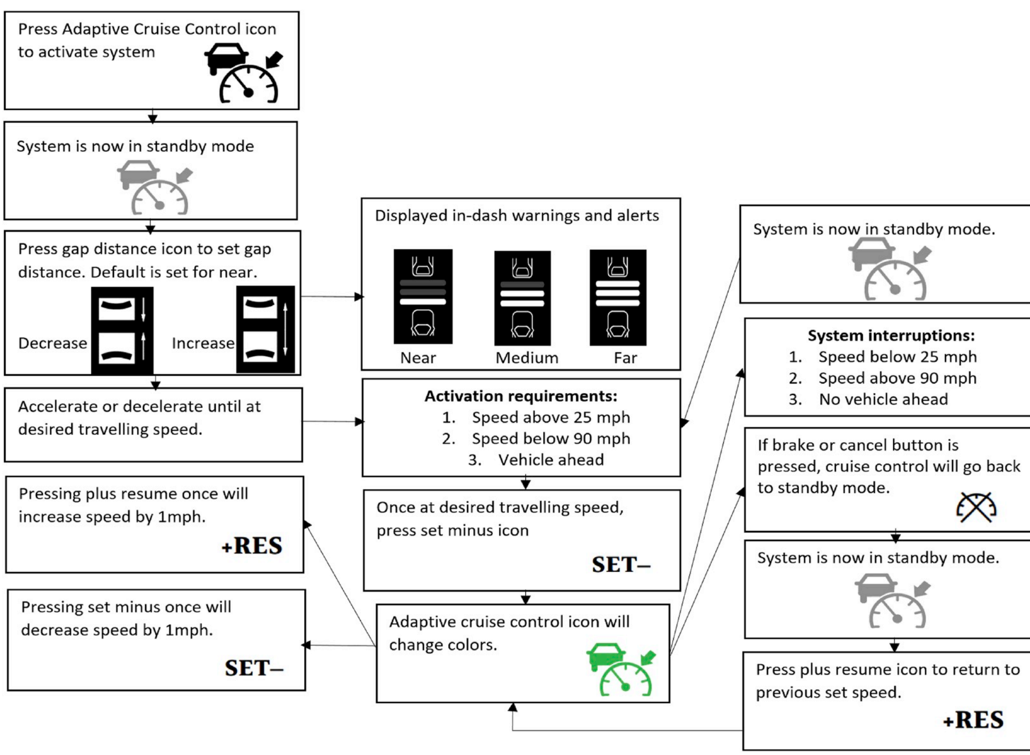
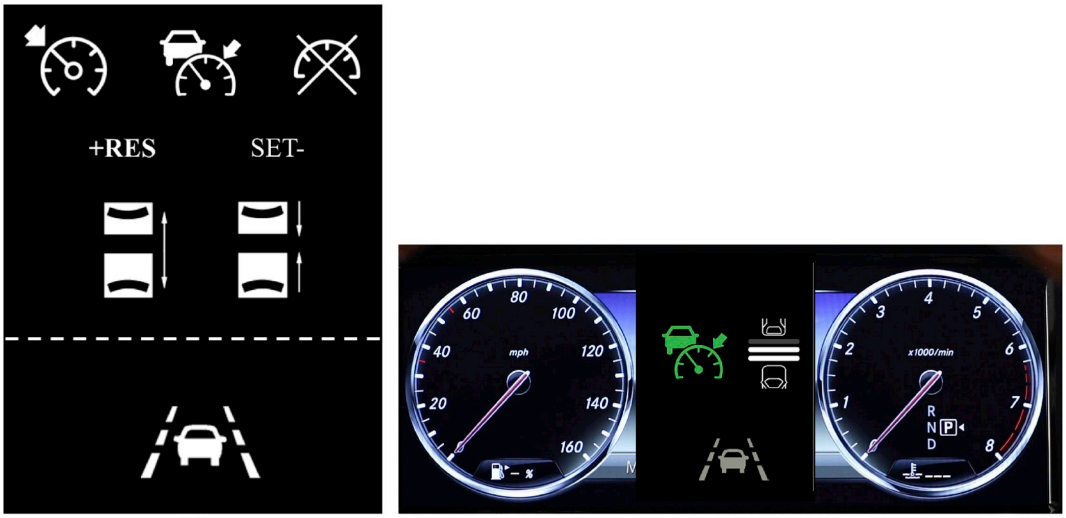


Fig. 4. Adaptive cruise control system operations flowchart.

the system in use after participants selected "Set-". LKAS was also a two-step process. Participants must first turn on the LKAS system. Then, the LKAS became activated when the following three conditions were met: (1) speed is in a proper range, (2) lane markings are present, and (3) vehicle is no more than 0.4 m from the marking. The ACC system was considered activated only after the second button has been pressed. The LKAS was considered activated only after the three conditions were met. We calculated time to activate when both systems were activated to represent level 2 automation. Therefore, faster activation of level 2 automation and lower SD-SPA and SD-THW are indicators of better performance. Attention allocation measures were calculated as the percentage of time participant glances occurred in each of the two areas of interest that included the DIC (contained icons with ADAS system status) and side touch screen (where the ADAS controls were located), also called glance location proportion (GLP). Mental workload was measured using the amount of oxygenated hemoglobin (Oxy-Hb) present in prefrontal cortex, which was captured using the fNIRS system. The amount of oxygenated hemoglobin present in prefrontal cortex increases with increased mental workload. Therefore, lower levels of HbO indicate the most efficient use of neural resources (Curtin and Ayaz,



(a) (b)

Fig. 5. (a) Central touchscreen buttons and locations; (b) Driver Information Center icons and locations.

2019). However, to further elucidate the relationship between mental effort and performance, we employed an efficiency metric, grounded in the neural efficiency hypothesis (Haier et al., 1988) to quantify changes in neural resource requirements with expertise. Neural efficiency was calculated as Equation (1), in which $z(P)$ and $z(CE)$ are normalized (z-score) of behavioral performance (P) and neural or cognitive effort (CE) respectively (Curtin and Ayaz, 2019).

$$NE = \frac{z(P) - z(CE)}{\sqrt{2}} \tag{1}$$

2.6. Procedure

Upon arrival to the lab, each participant completed a background survey to collect information on driving history, caffeine and nicotine consumption, video game experience, and a knowledge assessment of ADAS vehicle technologies. Responses revealed that participants were regular drivers, consumed less than two cups of caffeine drinks per day, did not use any nicotine products, did not have any video game experience, and did not own or operate a vehicle with ADAS driving technologies. This information was used to verify homogeneous participant characteristics across experimental conditions. Participants then completed a 5-min practice drive to become familiar with the driving simulator and controls (McGehee et al., 2004).

Subsequently, each participant was randomly assigned to one of the ADAS training protocols (i.e., video-based or demonstration-based training). Both training protocols followed the knowledge and skill taxonomy of training drivers for ADAS equipped vehicles as shown in Fig. 6. Participants in the video-based training protocol condition watched instructional videos describing the operation and characteristics of the ACC and LKAS systems and how they operated together to create a Level 2 automation. This protocol was analogous to online training. Participants in the demonstration-based training protocol condition received identical instructions that were delivered by a trainer/instructor and were provided with a demonstration, a method that is analogous to typical driver training approaches. Each training protocol was administered in a personal session and took approximately 30 min to complete. Participants in demonstration-based training could practice ADAS activation during the training. Participants in video-based training did not practice ADAS during training but they were seated in the simulator and could see the display and icons they would use on the side touchscreen. Participants in both training conditions could ask questions at the end of the training (to reduce any bias that

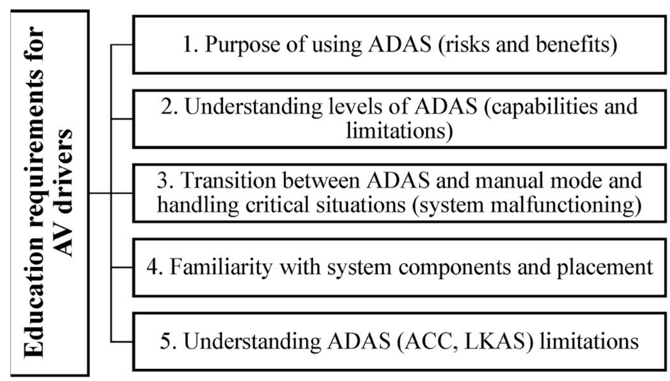


Fig. 6. Knowledge and skill taxonomy of training drivers for ADAS equipped vehicles.

might have occurred from asking questions at different times).

Upon completion of the training, the eye tracking system was calibrated and fNIRS sensors were placed on participant's forehead. Each participant completed three trials, each composed of eight driving segments that alternated between roadway conditions requiring manual control (i.e., driver responsible for all driving actions) and conditions suitable for ADAS control (i.e., when participants could use the combined ACC and LKAS). Participants were asked to activate ADAS as soon as system activation requirements are met (see Figs. 3 and 4). Throughout each trial participants performed a car following task in which they were instructed to follow a lead vehicle, that randomly changed speed, at a close and consistent distance at all times. Each trial took approximately 16 min to complete. Participants were provided 5 min rest period in between each trial. No simulator sickness was observed among participants.

2.7. Data analysis approach

Before conducting any inferential tests, data screening was performed to identify any outliers due to participants' not following the instructions (e.g., did not activate the ADAS) or any equipment issues (e.g., eye tracking calibration problems). The data from all systems (driving simulator, fNIRs, eye-tracking) were synched to a common time stamp (GMT). Subsequently, univariate analysis of variance (ANOVA) was conducted on all response measures to assess residual normality and variance homogeneity assumptions using Shapiro-Wilk's test and Bartlett's test, respectively. In case of parametric assumption violations, data transformation was conducted using log, square root, and exponential transformations to the power of lambda (identified by the Box-Cox method). If transformations were not effective, the data were ranked and nonparametric approaches were used. As mentioned by Montgomery (2017), if the results of nonparametric tests were similar to the results on untransformed measures, analyses on the untransformed responses were considered valid and were reported. It is important to note that driving performance measures were only collected during the segments in which the driving condition was suitable for activation of ADAS control (i.e., automated segments). Therefore, the driving condition factor (i.e., automated or manual driving) was not included in the statistical model for driving performance measures. Trial number was included in the models as covariate and was removed if found to be insignificant. This effect was only significant in driving performance and attention allocation models and therefore was discussed in the results section. Trial number did not show any significant effect on other responses and therefore was removed from the models. A significance level of $p \leq 0.05$ was set as a criterion for the study. All error bars in Figs. 7-12 represent one standard deviation from the mean. Separate ANOVAs were conducted on mean HbO from the AF7, FP1, FP2, and AF8 regions of interest. To compute neural efficiency, behavioral performance (P) was measured in terms of time to activate ACC and/or LKAS features and brain-derived measures of cognitive effort (CE) was measured using the summative HbO activation from the four regions of interest, as described in Nuamah et al. (2019).

2.8. Hypotheses

We formulated three research hypotheses (H1-H3) based on the existing literature regarding the effect of different training protocols on driver performance, visual attention allocation, and oxygenated hemoglobin and NE. The hypotheses were formulated based on Torriero et al. (2007), Morrell et al. (1990), Wlodkowski and Ginsberg (2017), Martínez-Alcalá et al. (2018), and Taylor and Rose (2005) studies. We also explored gender differences (i.e., interaction effects between the training protocol and gender).

2.8.1. Driving performance

H1. We expect the demonstration-based training to improve driving performance (i.e., faster time to activate level 2 automation, lower SD-SPA, and lower SD-THW) as compared to video-based training.

2.8.2. Off-road visual attention allocation

H2. We expect the demonstration-based training to reduce off-road visual attention allocation (i.e., fewer off-road glances to DIC and side-screen) as compared to video-based training.

2.8.3. Oxygenated hemoglobin and NE

H3. We expect drivers who receive demonstration-based training to exhibit lower levels of oxygenated hemoglobin, as measured by fNIRS, and have higher NE than drivers who receive video-based training.

3. Results

3.1. Driving performance

An ANOVA on SD-THW revealed a significant effect of trial number ($F(1,124) = 5.97$, $p = 0.0159$, $\eta_p^2 = 0.046$), with the response significantly increasing as the trial number increased. However, there was no effect of gender ($F(1,124) = 2.74$, $p = 0.10$, $\eta_p^2 = 0.02$) or training condition ($F(1,124) = 0.125$, $p = 0.72$, $\eta_p^2 = 0.00$) on the response.

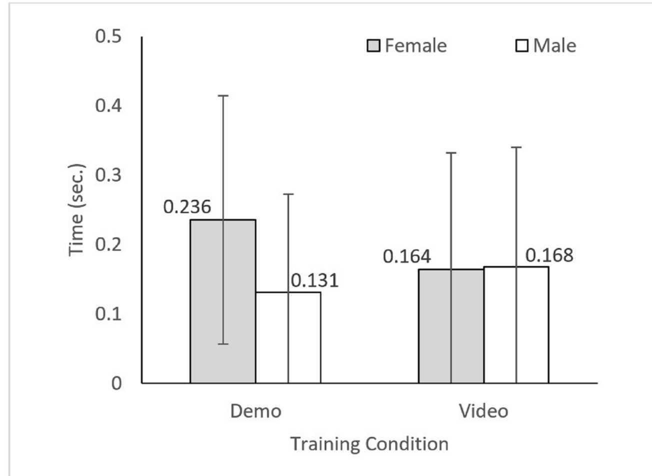


Fig. 7. Interaction effect of gender and training condition on time to activate level 2 automation.

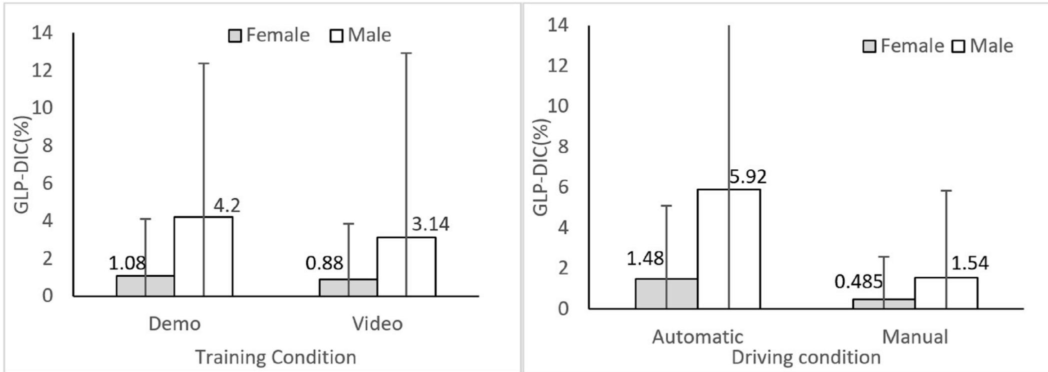
Regarding the SD-SPA, there was a significant effect of training condition ($F(1,200) = 4.13$, $p = 0.0434$, $\eta_p^2 = 0.02$), with drivers who received demonstration-based training exhibiting higher deviations in the steering position angle ($M = 0.19$, $SD = 0.43$) as compared to those who went through video-based training ($M = 0.18$, $SD = 0.32$). However, there was no effect of gender on SD-SPA ($F(1,200) = 0.40, p = 0.53, \eta_p^2 = 0.002$).

An ANOVA on time to activate level 2 automation revealed a significant effect of gender ($F(1,200) = 5.47, p = 0.02, \eta_p^2 = 0.027$) and a significant interaction between the gender and training condition ($F(1,200) = 6.48, p = 0.017, \eta_p^2 = 0.031$). It was found that male drivers were faster in activating level 2 automation as compared to females and this effect was significant under demonstration-based training (Fig. 7). However, video-based training was effective for females and could improve their performance as compared to male drivers. There was no effect of training condition on the response ($F(1,200) = 0.67, p = 0.42, \eta_p^2 = 0.003$).

3.2. Attention allocation

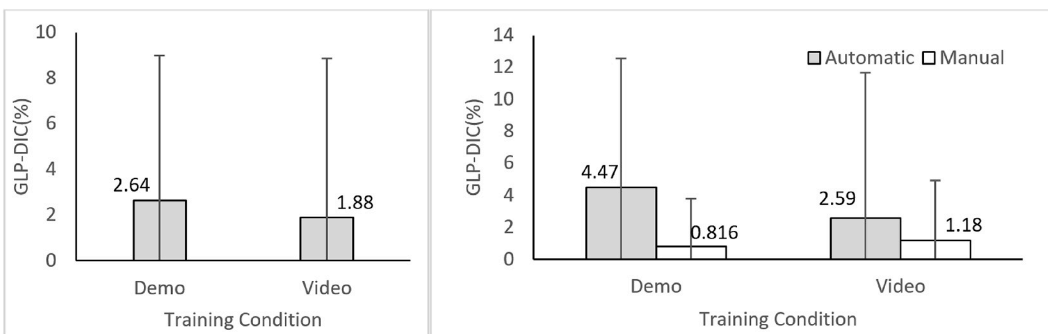
Regarding the percentages of off-road glances to the DIC, there was a significant effect of gender ($F(1,433) = 10.70, p = 0.0012, \eta_p^2 = 0.024$), training ($F(1,433) = 110.95, p < .0001, \eta_p^2 = .20$), and driving condition ($F(1,433) = 45.03, p < .0001, \eta_p^2 = 0.094$). In addition, there was a significant two-way interaction between gender and training condition ($F(1,433) = 5.06, p = 0.025, \eta_p^2 = 0.011$), gender and driving condition ($F(1,433) = 4.02$, $p = 0.046$, $\eta_p^2 = 0.01$), and training and driving condition ($F(1,433) = 25.33, p < .0001, \eta_p^2 = 0.055$). Male drivers had significantly higher GLP to the DIC as compared to females especially those who received demonstration-based training and during automated driving segments (Fig. 8). In addition, video-based training resulted in significant reduction in GLP to the DIC during automated driving as compared to the demonstration-based training (Fig. 9). Drivers had higher GLP to the DIC during the automated driving segments ($M = 3.58\%, SD = 8.61\%$) as compared to manual segments ($M = 0.99\%, SD = 3.36\%$).

Results on the percentages of off-road glances to the side touchscreen display revealed a significant effect of trial number ($F(1,432) = 4.828$, $p = 0.0285, \eta_p^2 = 0.018$) and a two-way interaction between the training and driving conditions ($F(1,432) = 18.79$, $p < .0001$, $\eta_p^2 = 0.068$).



(a) **(b)**

Fig. 8. (a) Interaction effect of gender and training condition; (b) Interaction effect of gender and driving condition.



(a) **(b)**

Fig. 9. (a) Effect of training condition on off-road glance proportion to the DIC; (b) Interaction effect of training and driving condition.

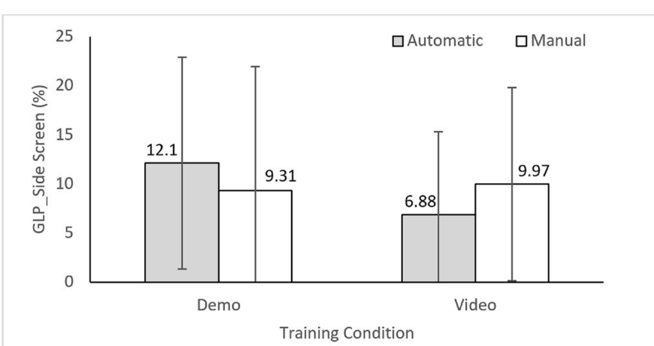


Fig. 10. Interaction effect of training and driving condition.

There was no effect of gender ($F(1,432) = 1.09, p = 0.30, \eta_p^2 = 0.004$), training condition ($F(1,432) = 1.78, p = 0.18, \eta_p^2 = 0.007$), or driving condition ($F(1,432) = 0.19, p = 0.66, \eta_p^2 = 0.000$) on the response. Drivers' glances to the side screen decreased as the trial number increased. As shown in Fig. 10, the video-based training resulted in significant reduction in visual attention to the side screen during the automated driving segments.

3.3. Oxygenated hemoglobin and neural efficiency

ANOVA on mean HbO revealed significant increase in brain activation in the left lateral AF7 ($F(1,87) = 14.11, p = 0.0003, \eta_p^2 = 0.14$) but a decrease in the right lateral AF8 ($F(1,87) = 8.42, p = 0.0047, \eta_p^2 = 0.09$) during the demonstration training condition when compared to the video-based training condition. Additionally, compared to females, males exhibited significantly greater activation in the right medial FP2 ($F(1,87) = 12.76, p = 0.0006, \eta_p^2 = 0.13$) and lower activation in the right lateral AF8 ($F(1,87) = 8.54, p = 0.004, \eta_p^2 = 0.09$). Significant two-way interactions between gender and training conditions were observed in both the AF7 ($F(1,87) = 17.75, p < 0.0001, \eta_p^2 = 0.17$) and FP2 ($F(1,87) = 5.68, p = 0.0193, \eta_p^2 = 0.061$). While males and females exhibited comparable activation in AF7 during the video condition, females exhibited greater activation than males in the demonstration condition. However, greater activation in the FP2 were seen for males than females in the video condition (Fig. 11).

Regarding the NE, results revealed a significant effect of gender on time to activate level 2 automation efficiency ($F(1,51) = 5.82, p = 0.0195, \eta_p^2 = 0.1023$). However, this effect was only significant in FP2 channel. As shown in Fig. 12, female drivers required lower investment of mental effort to maintain performance (higher efficiency) relative to males. There was no significant effect of training condition on time to activate efficiency in any of channels (AF7: $F(1,51) = 2.33, p = 0.14, \eta_p^2 = 0.079$; FP1: $F(1,51) = 6.50, p = 0.016, \eta_p^2 = 0.183$; FP2:

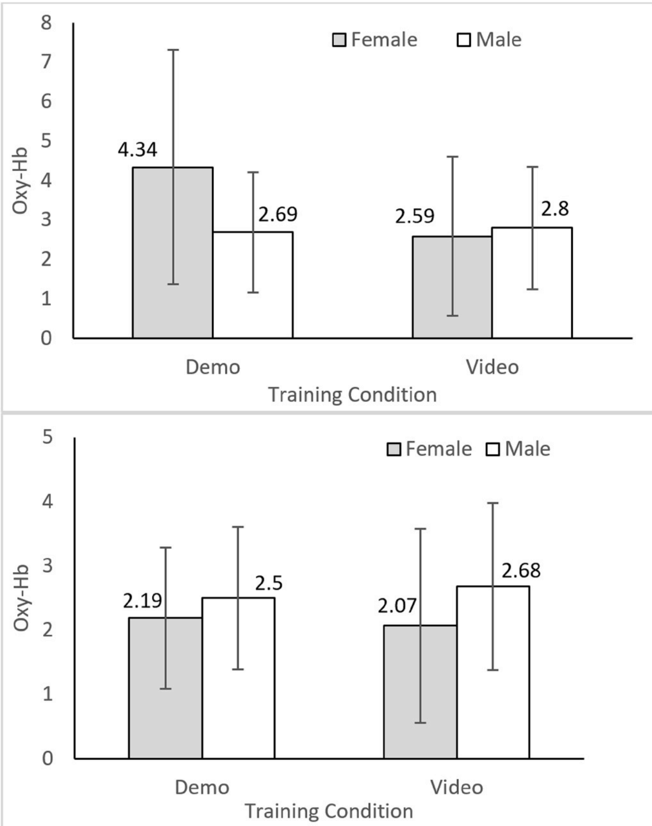


Fig. 11. Interaction effect of training condition and gender on Oxy-Hb in channel AF7 (top) and FP2 (bottom).

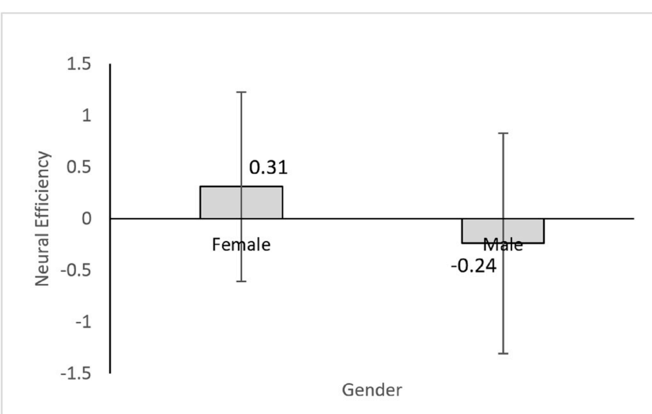


Fig. 12. Effect of gender on neural efficiency.

$F(1,51) = 1.93, p = 0.17, \eta_p^2 = 0.036$; AF8: $F(1,51) = 0.84, p = 0.37, \eta_p^2 = 0.029$).

4. Discussion

4.1. Driving performance

Hypothesis 1 (H1) posited that the demonstration-based training should improve driving performance (i.e., faster time to activate level 2 automation, lower SD-SPA, and lower SD-THW) as compared to video-based training. This hypothesis was not supported by the data. While there was no significant effect of training condition on time to activate level 2 automation and SD-THW, the findings of the SD-SPA revealed the video-based training to be more effective than demonstration-based training. A majority of drivers who received video-based training could successfully use the LKAS feature. The LKAS system, when activated, results in lower SD-SPA than a human driver in manual steering mode. Therefore, our findings indicated that older adults who went through the video-based training better understood the LKAS feature and its activation requirements.

Regarding the interaction between training condition and gender, it was found that the video-based training was effective for females and resulted in reduction in time to activate level 2 automation (Fig. 7). Male drivers, on the other hand, performed better under demonstration-based training. Our results were not in line with the findings of prior studies on learning style differences between males and females that found females to learn better in practical settings (i.e., watch and do) as compared to males who learn best by thinking and watching (Philbin et al., 1995; Wehrwein et al., 2007). However, previous studies were not in driving training context and were limited to mostly young individuals (i.e., college students). Our study was the first investigation considering gender differences in learning ADAS, particularly with older drivers. One other explanation for better performance of females under video-based training compared to demonstration-based training might be that they had more control on the pace of information through starting, stopping, and repeating the videos. The findings also suggested that, on average, male drivers were faster in activating ADAS features as compared to females. This might be due to females having less willingness to use automated features as compared to males. Results are in line with previous studies which found males to be more willing to use automated vehicles (Payre et al., 2014) and have more positive emotions toward them as compared to females (Hohenberger et al., 2016). Furthermore, considering the effect of gender on visual attention to the DIC (discussed below), faster reaction time in activating ADAS features might have been due to the fact that male drivers were monitoring the status of ADAS features more frequently as compared to females while driving.

4.2. Off-road visual attention allocation

Hypothesis 2 (H2) stated that demonstration-based training would reduce off-road visual attention allocation (i.e., fewer off-road glances to the DIC and side-screen) as compared to the video-based training. This hypothesis was not supported by the data. Video-based training significantly reduced glance proportion to the DIC and side screen as compared to demonstration-based training during automated segments. As a reminder, the ADAS features were controlled on the side touchscreen and system status (i.e. enabled or disabled) could be confirmed in the DIC or on the side touchscreen. These results strongly suggest that participants who received demonstration-based training allocated more attention to check the status of the ADAS features, but it is recognized that attending to system status, while informative, may be counterproductive to safety due to the increased proportion of time that these drivers did not look at the forward scene. Therefore, similar to the driving performance results, our findings indicated that video-based training should be used for training ADAS to reduce off-road visual attention.

Regarding the interaction between training condition and gender, it was found the video-based training was more effective than demonstration-based training in reducing off-road visual attention to the DIC and this effect was more pronounced for male drivers as compared to females. In addition, on average, male drivers had significant higher proportion of off-road glances to the DIC as compared to females especially during automated driving segments. Results suggest that males checked/confirmed the status of ADAS features (such as icons and color changes which were located on the DIC) more often as compared to females. Video-based training of ADAS might be effective in reducing the off-road visual attention for male drivers.

Beyond the above findings, during automated driving segments, drivers had higher percentage of off-road glances to the DIC. This might be due to the fact that drivers had to monitor the dash to check the status of ADAS icons (e.g., whether the LKAS and/or ACC icons are activated) in order to take appropriate actions in case of any system interruptions. It is also possible that drivers' off-road visual attention increased due to decrease in workload in automated driving condition which is in line with the findings of previous studies (De Winter et al., 2014; Llaneras et al., 2013). In addition, Drivers' glances to the side screen decreased as the trial number increased. This might be due to the short duration of the training sessions and therefore, some learning might have occurred as drivers went through more driving trials and experienced ADAS control features more.

4.3. Oxygenated hemoglobin and NE

Hypothesis 3 (H3) posited that drivers who received demonstration-based training would exhibit lower levels of oxygenated hemoglobin and have higher NE than drivers who received video-based training. This hypothesis was not supported by the data. While there was no significant effect of training condition on NE, it was found that drivers who received demonstration-based training exhibited greater activation of the left PFC and lower activation of the right PFC compared to those who received video-based training. Previous studies found higher mental workload to signify an increase in oxygenation, especially in the left PFC (Herff et al., 2014). Our findings suggested the video-based training to reduce driver mental workload when using ADAS as compared to the demonstration-based training. These findings also explain the differences in performance and visual attention allocation of drivers trained by video-based vs. demonstration-based training. It is possible that drivers under the demonstration-based training did not understand the ADAS features well and therefore had higher mental workload in using/understanding the system while driving which led to more off-road glances to the DIC for status check and/or confirmation. In addition, due to the less effective nature of demonstration-based training and higher driver workload, a majority of drivers that received this training did not activate the LKAS and therefore they had higher SD-SPA as compared to the drivers who received the video-based training.

Another explanation for greater activation of the left PFC and lower activation of the right PFC under demonstration-based training is that this type of learning requires individuals to engage their visuomotor resources during the training process (i.e., learning by action), whereas the video-based learning requires individuals to adopt observational based learning strategies. While both types of learning approaches have shown to engage the PFC during memory encoding (Monfardini et al., 2013), functional neuroimaging studies have reported increased engagement of the left PFC during visuomotor learning (Jueptner et al., 1997) as compared to observational learning (Monfardini et al., 2013) processes. It is thus likely that similar neural regions were engaged when drivers utilized and interacted (i.e., during memory retrieval) with the different ADAS features during the various driving trials.

Male drivers exhibited increased right PFC activation compared to their female counterparts, across both training groups. Female drivers also exhibited greater NE than male drivers across both training groups and this was largely observed in the right PFC. Our results suggested that female drivers required lower investment of mental effort to maintain the performance relative to males. Prior studies have reported gender differences in cortical activation of the right hemisphere across different working memory, emotion, and learning tasks (Bracco et al., 2011; Marumo et al., 2009). In particular, greater right PFC lateralization is reported to occur with spatial memory tasks in men compared to women (Bracco et al., 2011). Our study also observed a similar trend in gender-specific activation of the right PFC as a result of both the video- and demonstration-based trainings.

Collectively, the findings of this study provide support for video-based training of ADAS for older adults to improve their driving performance and reduce off-road visual attention and mental workload. Although the results were not in line with Torriero et al. (2007) and Morrell et al. (1990) that found advantages of demonstration-based training in other domains, our findings provided further support for the findings of Truluck et al. (1999) that found not all older adults are active, hands-on learners as adult education literature suggests, but as age increases there is a tendency to prefer more passive and observational learning methods.

5. Conclusion

The objective of this study was to assess the effectiveness of video-based and demonstration-based training protocols on the older drivers' use of ADAS considering gender. The findings revealed the video-based training to be more effective than the demonstration-based training in improving driver performance and reducing off-road visual attention allocation and mental workload. Video-based training is supported by the interactivity principle in which a trainee can control the pace of information by starting, stopping, and reviewing part or all of a video. This process allows for information to be chunked into a more efficient mental model, which facilitates learning. Video-based training is also supported by the cognitive load theory of multimedia learning which states that multi-media instructional formats (i.e., combination of spoken or printed text and static or dynamic graphics) lead to better acquisition of information and foster deeper learning. This study provided an empirical support for use of the video-based training approach which is a less costly and more efficient training solution as compared to the demonstration-based training. Our results also indicated that overall, female drivers required lower investment of mental effort (i.e., higher neural efficiency) to maintain the performance relative to males and they were less distracted by the DIC. However, male drivers were faster in activating level 2 automation mainly due to the fact that they were monitoring the status of ADAS features more frequently as compared to females while driving.

The main limitation of this study was its small sample size (i.e., 20 drivers) which led to insignificant findings in some responses (e.g., no effect of training condition on time to activate level 2 automation or NE). Second, due to the focus of this study on older adults, we did not include other age groups. Some of the observed effects might also be present in younger age categories. Third, all roadway scenarios presented daylight condition with moderate traffic level. Driving at night or under higher level of traffic density might change driver visual attention allocation, performance, and/or workload. Finally, the effect of ADAS training protocols was assessed immediately after the training. Based on Ebbinghaus forgetting curve, individuals usually forget about 75% of knowledge they have learned after one week (depending on the strength of memory). Therefore, the comparison between demonstration and video-based training approaches should also be made at least one week after the training to understand how much information was retained. Furthermore, to improve the generalizability of findings, future studies should validate the results of this investigation with larger sample size, considering wider age range, and under various roadway and environmental conditions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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