Summer 2024

Young Driver Training and Socioeconomic Status: A Human-in-the-Loop Driving Simulator Evaluation

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YOUNG DRIVER TRAINING AND SOCIOECONOMIC STATUS: A HUMAN-IN-THE-LOOP DRIVING SIMULATOR EVALUATION

by

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B.A. May 2021, University of Connecticut

A Thesis Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

PSYCHOLOGY

OLD DOMINION UNIVERSITY
August 2024

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ABSTRACT

YOUNG DRIVER TRAINING AND SOCIOECONOMIC STATUS: A HUMAN-IN-THE-LOOP DRIVING SIMULATOR EVALUATION

Jeffrey Edward Glassman
Old Dominion University, 2024
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Previous research consistently shows that young drivers are poor at anticipating latent hazards on the roadway compared to more experienced drivers. The Road Awareness and Perception Training (RAPT) program is a driver training program that aims to accelerate young drivers' learning of hazard anticipation (HA) skills. More recent research has started showing evidence that RAPT may be even more effective at reducing accidents for young drivers with a lower socioeconomic status (SES), though the direct impact of RAPT on HA skills in the driver population is yet unclear. The current experiment thus directly evaluated the effectiveness of RAPT on the HA performance of drivers differing in SES using a high-fidelity driving simulator. Fifty-two participants were randomly assigned to the active or passive RAPT training group. Participants in the active RAPT group completed the original RAPT-3 that provides them the opportunity to make and mitigate errors and master the skill (3M method) to anticipate HA via error-feedback mechanism. Participants in the passive RAPT group received the knowledge about latent HA identical to that of the active RAPT group without the 3M method. Participants drove a series of eight simulated HA scenarios in the virtual environment immediately before and after completing the respective training program. The results showed credible improvement of HA performance in the active but not in the passive RAPT group, indicating the error-feedback mechanism was crucial for their learning. Additionally, contrary to our expectation, regardless of their assigned training program, high-SES drivers demonstrated greater HA skills

after completing either training program than before, while low-SES drivers did not. The results imply that high-SES drivers may employ a different learning mechanism than low-SES drivers to anticipate latent hazards better on the second encounter to the scenarios. The present work suggests that the error-feedback mechanism is essential for accelerating young drivers' learning for road safety and that low-SES drivers may not benefit equally well even from the RAPT program. More research is urgent in better understanding and characterizing how SES and other related variables influence their learning from the available driver training programs.

For my parents who always supported me and encouraged me to pursue my interests and passions. James, who has been a mentor to me. My friends Bakey, Eric, and Ryan who are always there to support me and provide me with honest advice.

ACKNOWLEDGEMENTS

The pursuit of scientific knowledge is not a solitary endeavor. I would like to thank the members of my committee, Dr. Jeremiah Still and Dr. Xiao Yang for taking the time and effort to make this thesis possible.

I would like to thank the members of the ACPL lab who have listened to and provided feedback on my presentations and introduced me to new ways of thinking and problem solving. James Unverricht, Sarah Yahoodik, Tetsuya Sato, Mike Politowicz, Austin Jackson, and Samuel Petkac, thank you for your help and support.

Most of all I would like to thank Yusuke Yamani, who has provided me with patient and thoughtful guidance over the last two years. You have helped me to develop my research skills and grow more competent. I have become more confident in my writing, more clear in my thinking, and more skillful in my communication. Your dedication to your students, skill as a researcher, and devotion to science was apparent from the beginning. I could not have asked for a better advisor.

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CHAPTER I

INTRODUCTION

Statistics indicate a steady decrease in the number of fatal passenger vehicle crashes in the United States involving young drivers aged between 16 and 19 years old over the past twenty years (Foss et al., 2014; IIHS, 2022). Unfortunately, though, young drivers still face a disproportionately higher rate of involvement in fatal vehicular crashes compared to any other age group of drivers. For example, based on 100 million miles traveled, passenger vehicle crash rates per mile are roughly five times higher than drivers aged between 30 and 60 years, contributing to a loss of 2,738 teenagers in 2020 in the United States alone (IIHS, 2022). Despite the commonly accepted view that young drivers are “careless”, literature on driver’ behaviors and performance instead suggest the opposite view that young drivers are in fact “clueless” and that their driving-related cognitive abilities are amenable to training. McKnight and McKnight (2003), for example, explored factors that predict young driver accidents by analyzing narrative descriptions of over 2,000 accidents that involved 16-19-year-old drivers in the United States. The results demonstrate, strikingly, that cognitive factors such as inattention and inadequate visual search accounted for 23% and 42.7% of the accidents while deliberate risky behaviors accounted for only 5% (see also Braitman et al., 2008; Curry et al., 2011). This opened the door to explore, develop and evaluate driver training programs focusing on psychological processes that are critical for road safety and amenable to training such as attention and visual search.

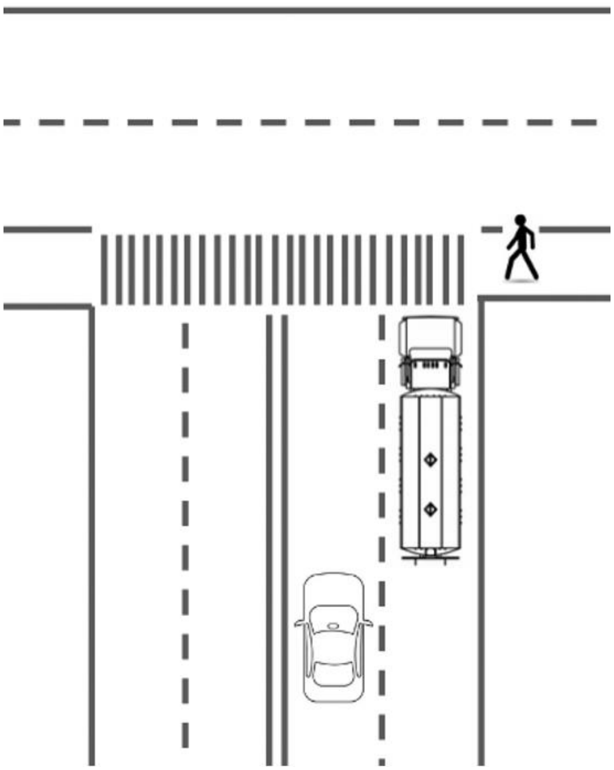
Experienced drivers display demonstrably different glance behavior when compared to those of young drivers (Mourant & Rockwell, 1972; Underwood et al., 2003). Specifically, young drivers constrict breadth of their eye gaze to the road ahead and closer to the vehicle’s hood compared to more experienced drivers who more broadly scan the road environment. Underwood et al. (2002) argued that these differences in eye glance behaviors were in large part driven by young drivers' lack of cognitive skills necessary to spot information that can indicate the presence of a road hazard and not driven by the demand of controlling the vehicle.

Latent hazard anticipation.

One of the higher cognitive skills that is critical for young drivers' road safety is latent hazard anticipation (HA; Yamani et al., 2016; Crundall & Underwood, 1998; Horswill & McKenna, 2004; Pradhan et al., 2005). Specifically, latent HA refers to a cognitive skill that allows drivers to recognize the risk of a dynamic traffic scene and anticipate an imminent latent hazard that has not yet materialized (Fisher et al., 2007; Unverricht et al., 2018). That is, successful latent HA requires perception, comprehension, and integration of environmental and situational data into a coherent mental model of the immediate, surrounding driving environment. Notably, these driving-critical psychological processes allow the driver to predict how the driving situation unfolds over time and anticipate latent threats (e.g., situation awareness; Endsley, 1995). Consider a four-lane road with two lanes for each direction of traffic with a parked truck on the side obscuring the crosswalk entrance (Figure 1). Using this and similar risky scenarios, Pradhan and colleagues (2006), showed that young drivers successfully glanced toward the location of latent hazards in only 35.1% of the scenarios compared to older drivers in 66.2%, highlighting that young drivers show poorer HA compared to older drivers.

Figure 1

Truck obscures crosswalk HA scenario.



Note. The parked truck obscures the crosswalk entrance from the view of the driver approaching in the left lane.

Failure of latent HA in young drivers

One hypothesis that may explain why young drivers fail to anticipate latent hazards on the forward roadway is that young drivers are particularly poor at selectively perceiving and identifying precursors (e.g., parked truck) that signal the location of a latent hazard (e.g., pedestrian). Previous research suggests that such precursors can be classified into two categories -- behavioral and environmental precursors (Crundall et al., 2012; also see Pradhan & Crundall, 2016; Yamani et al., 2022). An *environmental* precursor is an environmental element of a driving scene that predicts a hazard (e.g., a truck obscuring the right extremity of a crosswalk) while a *behavioral* precursor is the same stimulus as the hazard which has not yet materialized as a hazard (e.g., pedestrian walking towards a crosswalk but has not stepped onto the road yet). To dissociate these two types of precursors, Crundall and colleagues (2012) examined young and experienced drivers' eye fixations on environmental and behavioral precursors in a driving simulator. The results showed that young drivers anticipated environmental hazards more poorly than experienced drivers although their fixation patterns on the environmental precursors are similar between young and experienced drivers. More recently, Crundall (2016) found that environmental precursors are better than behavioral precursors at discriminating between young and experienced drivers. These studies not only expose different effects of environmental and behavioral precursors on eye movement behaviors but also suggest that young driver recognition of hazards on the roadway may be enhanced through driver training programs (see also Krishnan et al., 2019). Thus, in this study, I focus on environmental/latent hazards.

Hazard perception and hazard anticipation

Previous research found differences in hazard perception (HP) skills between young drivers with an accident history and those with accident-free drivers. HP is a cognitive process in which the driver has an accurate and actionable assessment of their current driving environment (Horswill & Mckenna, 2004), generally encompassing a broader concept than latent HA. HP contrasts with the HA process in which, to anticipate a latent hazard, drivers must perceive the current driving situation picking up on cues and predict hazards that may appear in the near future. A classic study by Spicer (1964) showed that a driver's likelihood of being in an accident was related to their HP skills. In the study, eleven 34-minute segment films of traffic situations were shown to two groups: a group of young drivers with an accident history and a group of accident-free drivers. At the end of each segment, drivers were given a checklist for which they marked each element within the film that appeared important to them. The young accident-involved drivers were shown less able to perceive the critical features of the traffic scenes than the accident-free drivers (Spicer, 1964; Pelz & Krupat, 1974). Later, researchers developed HP tests that could identify the drivers most at risk of accidents and developed training interventions to improve HP skills.

Researchers have developed a variety of HP training programs since Spicer (1964) that were shown to enhance HP performance among young novice drivers (e.g., Mckenna & Crick 1992; Mckenna & Crick 1997; Grayson & Sexton 2002). One of the most successful HP training programs was developed for the United Kingdom’s Theory Test which all new drivers must pass before full licensure in the UK (Grayson and Sexton, 2002). The Driving Standard Agency (DSA) (currently the Driver & Vehicle Standards Agency; DVSA) developed three 60-minute training modules, one for basic training and two for advanced training. The training modules included a combination of video, video-freeze techniques, animations to illustrate points, and work cards. When the video freezes, the trainees identify situations and indicate if the driving situation is hazardous. The advanced training modules include more “dynamic situations” than the basic training module. An analysis compared the HP skills of three groups of learner drivers: Group A was the control group and did not receive HP training, Group B received the basic training module, and Group C received all three basic and advanced training modules. Trainees then completed a HP test in which they analyzed and watched a set of scenarios that contained hazards. Participants indicated the presence of a hazard by pressing a key on the keyboard within a predesignated scoring window. The scoring window was determined by an expert, beginning as soon as the event became hazardous and ending when the hazard passed. In addition, the scoring window was evenly divided into five sub-time-windows, with the fastest hazard detection (that occurred within the first sub-time window) being scored a 5, and participants that did not indicate the presence of a hazard within the time window given a score of 0. An analysis of trainees HP skills following training indicated that training was highly effective. Group B showed modest gains from basic training, while Group C showed gains that put them on par with the HP performance of experienced drivers (Grayson and Sexton 2002). Although this HP training program was successful, it takes a significant amount of time to administer the program to trainees, and the presence of instructors is integral to the training procedure. Researchers recognized that hazard prediction and feedback were a crucial component to detecting and avoiding hazards (Mckenna and Crick, 1997). Therefore, researchers developed a new training program known as the Risk Awareness and Perception Test (RAPT) that takes less time and resources and focuses on training drivers to recognize hazard precursors and predict hazards that have not yet materialized.

Several iterations of RAPT have been developed to accelerate driver's learning of HA skills (Unverricht et al., 2018). The RAPT training program has been extensively evaluated using both driving simulator and field tests. The first version of RAPT (RAPT 1) utilized top-down (exocentric) views of each driving scenario, and the training was shown to improve HA performance in a driving simulator (Pollatsek et al., 2006). RAPT 2 incorporated the birds-eye view employed by RAPT 1 and added an egocentric (driver's point of view) as well as three new scenarios. Improvements in HA skills learned from the RAPT 2 training program were retained after a period of 4 days on average (Pradhan et al., 2006). Finally, RAPT 3 included perspective views using a progressively advancing series of snapshots. RAPT-3 has been shown to improve

HA performance in field tests (Fisher et al., 2006) for up to 6-8 months after training (Taylor et al., 2011).

The training technique used in RAPT is based on empirical evidence in the field of memory and learning (Unverricht et al., 2018). Specifically, RAPT uses an error-based feedback mechanism that provides trainees with opportunities to make a *m*istake, teaches how to *m*itigate the mistake, and then *m*aster the target skill, also known as the *3M method* (Fisher et al., 2004). Briefly, typical RAPT programs consist of pre-training, training, and post-training parts. In pre-training, RAPT first asks trainees to view a short video clip of the target scenario and to click locations of potential hazards in a risky scenario. Then, RAPT evaluates whether the identified locations contain the target hazard, which serves as a baseline for each trainee. Then, during the training part, trainees are provided with a top-down view of each risky scenario with descriptions and detailed explanations on the risky aspects of each scenario. For each scenario, trainees are again asked to view the video clips and identify areas of potential hazard. Trainees are allowed to move to the next scenario if they detect the potential hazard correctly, and if not, then the program asks the trainees to repeat the task up to four times to correctly identify the risky areas in the video. Finally, the post-training segment of RAPT is identical to the pre-training.

Individual differences in trainees of RAPT

More recent research indicates that effectiveness of RAPT training may not be equal across the population of young drivers but varies markedly on various individual differences measures. A recent large-scale evaluation study employing over 5,000 young drivers randomly assigned to either the RAPT or a control condition showed an interaction between the training manipulation and gender on crashes (Thomas et al., 2016). The results indicate that RAPT is partially effective in reducing crashes involving young drivers, particularly among male drivers but not females. Zhang and colleagues (2018) showed in a driving simulator that a driver training program that involves HA training like RAPT is only effective on careful drivers but not careless drivers. In the study, the driver classifications were based on several individual difference measures such as sensation-seeking (Arnett, 1994), aggression (Buss & Perry, 1992), aggressive driving (Snow, 2000) and violations and errors. More generally, the literature on young driver training has started recognizing that the young driver population is not homogenous but heterogeneous. That is, young drivers vary in different trajectories including personalities, driving behaviors, demographics, and backgrounds. Thus, it is urgent to characterize relationships between the effectiveness of RAPT and driver profiles to systematically approach their learning and development of latent HA skills.

Socioeconomic status as a predictor of the effectiveness of RAPT

A recent work by Roberts and colleagues (2021) examined relationships between trainees' socioeconomic status (SES) and the effectiveness of RAPT on crashes. The researchers reanalyzed the original crash data from Thomas et al. (2016) that gauged the effectiveness of RAPT on reducing crashes in young, newly-licensed drivers aged between 16 and 17 years to explore whether two SES metrics relate to the number of crashes within the first 12 months after licensure. The two measures were poverty rate estimated by a participant's zip code provided to California Department of Motor Vehicle (DMV) and SES level determined by whether a participant resided in a zip code with a poverty level exceeding 20% (Roberts et al., 2021).

Results indicate poverty rate and the interaction term between poverty rate and training significantly predicted crash rates in the young drivers. Most importantly, crash rates increased as poverty rate increased in the drivers who received the Placebo training program but decreased more significantly for RAPT trained drivers with zip codes displaying increasingly higher poverty rates. Additionally, when the binary SES measure was used in the model, none of the independent variables were predictive of crashes. Overall, the results are consistent with previous findings that low-SES driver populations are four times more likely to be involved in motor vehicle accidents than high-SES populations (Harper et al., 2015; Males, 2009).

Although Roberts et al. (2021) provide novel insights into potential impacts of SES on the drivers' learning and driving behaviors, several limitations exist in the study. First, the SES measure was based on neighborhood level characteristics and was not a granular measure of SES based on income and education information. Second, accident rate is an indirect measure of HA skills because accidents can be caused by other drivers other than by HA failures (e.g., driving in high-crash locations). Third, an accident in which no injuries occur and that do not result in property damage exceeding $750 are not required to be reported to the state. Thus, some accidents may not have been included in the analysis. Despite these limitations, low-SES drivers exposed to RAPT training reported a significantly greater reduction in accident rates, and the current study seeks to address several of the limitations in a driving simulator experiment.

One factor that may underlie the different effects of RAPT on accident rates between low-SES and high SES drivers is relative differences in their exposure to driver training education. Individuals with low-SES have limited access to driver training programs compared to individuals with high-SES (Curry et al., 2012). Further, when driver training is required (such as through graduated driver licensing), low-SES populations are more likely to delay obtaining a license (Tefft et al., 2014) at the expense of not completing driver training. With less driver training, low-SES drivers may possess worse HA skills than high-SES drivers at the outset of RAPT training. These characteristics of low-SES drivers may bring an opportunity for transportation human factors researchers to develop driver training program tailored to the low-SES drivers and improve their cognitive skills critical for their road safety.

Cognitive load theory as a framework of the current research

One framework that may explain the influence of SES on the effectiveness of RAPT is cognitive load theory (CLT). According to CLT, learning is an effortful process, and the design of training programs should be informed based on the current skill level of the trainee and the number of resources demanded by the target task (Sweller 2010; Wickens et al., 2013). Training programs can present three sources of cognitive load on a trainees' working memory, intrinsic cognitive load, extraneous cognitive load, and germane cognitive load. *Intrinsic cognitive load* is determined by the trainees' current skill level and the difficulty of the task. The amount of intrinsic load of a task can be influenced in two ways. The first way is to change the nature of the task to be learned such that it is more complex (increases cognitive load) or less complex (decreases cognitive load). The second way is to increase the learner's experience such that the learner is more familiar with material which decreases the intrinsic load of the task (Sweller, 2010). *Extraneous cognitive load* is nuisance load that is imposed by the training program itself (such as a poor user interface). *Germane cognitive load* is determined by the number of resources required to *learn* the task itself. If extraneous cognitive load is low and intrinsic cognitive load is high, then germane cognitive load will be high (Wickens et al., 2013). Because the experience of the learner influences the intrinsic cognitive load of the material (Sweller et al., 2010), a training program may require a greater germane load for individuals with less experience than more experienced individuals. Thus, the germane load of RAPT may be greater for low-SES individuals because they have less experience with driving training (Curry et al., 2012; Tefft et al., 2014).

Current study

The current study directly examines whether the effectiveness of RAPT training on HA varies across different levels of SES of participants receiving different versions of RAPT. Family income and parental education level were employed as a measure of SES (Sackett et al., 2009; 2012). Participants were assigned to either the active or passive RAPT group and completed the assigned training program. Immediately before and after completion of the training program, participants navigated in various driving scenarios in a high-fidelity driving simulator with their eyes tracked via a head-mounted eye tracker for pre- and post-training evaluation. I hypothesized:

1. Participants that received active RAPT training would detect latent hazards correctly in more scenarios than participants that receive passive RAPT training (Slamecka & Graf, 1978).
2. High-SES drivers would detect latent hazards correctly in more scenarios than low-SES drivers (Roberts et al., 2021).
3. The completion of RAPT would offset SES-related declines in HA performance (Roberts et al., 2021).

CHAPTER II

METHODS

Participants

Fifty-two participants were recruited from the community of Old Dominion University (ODU). All participants were screened for holding a valid U.S. driver's license and for normal or corrected-to-normal visual acuity using the standard Snellen chart and color perception using the Ishihara Color Blindness test (2014). Each participant received either 2 SONA credits or $20 for their participation in the study.

Apparatus

Driving simulator

A Realtime Inc. (RTI) high-fidelity driving simulator at ODU was used for the study (Figure 2). The driving simulator provides three degrees of freedom of realistic motion along lateral, longitudinal, and vertical axes on a hydraulic platform (Real-Time Technology, 2020). The simulator consisted of a single seat with three 65' screens providing a 205-degree horizontal view and a 35-degree vertical view. An audio system produced realistic wind, rain, ambient traffic noise, direction, and doppler shift that matches with the simulated driving scenes.

Figure 2

The Realtime Technologies RDS 1000 driving simulator

Note. The driving simulator (back left) and researcher' control center (front center).

Eye tracker

A head-mounted eye tracker (Pupil Labs, 2021) was used to collect eye glance data. The eye tracker consisted of an eye camera that enabled eye movement data captured at 200 Hz, while the world camera captured the forward scene at 120 Hz. Pupil Core software superimposed glance location onto the forward scene represented by a crosshair (Pupil Core V3.5, 2021).

Training Programs

RAPT-3

The latest version of RAPT, known as RAPT-3 (Unverricht et al., 2018), was used for the active-training group. RAPT-3 has three sections. First, trainees are asked to complete a pretest where they are shown a progressively advancing series of snapshots from nine driving scenes. Trainees are then instructed to click on the areas in each scene to indicate where a latent hazard may be located. Then, a training section involved a module in which trainees are shown a bird's eye view of each of the scenarios identical to those used in the pretest with specific areas containing latent hazards along with a written description of the reason why each scenario is risky. Finally, trainees are asked to repeat the task in the pretest. However, when the trainee failed to identify the hazard correctly, they are instructed to review the training section for the scenario until they were able to identify the hazard or failed four times. It takes approximately 30 minutes to complete a RAPT training session.

Control training program

For the control, or passive training program, participants read a series of Microsoft PowerPoint slides containing the same written instructions and illustration examples of HA identical to that offered in the original RAPT program. Note that the material in the control training program did not include any modules that involve error-based feedback such as opportunities to select areas containing latent hazards on the progressive series of snapshots. Participants were asked to answer multiple-choice questions at the end of the training to gauge their understanding of the training material.

Measure of SES

Participants' SES was measured via an unweighted composition of three items, father's education, mother's education, and family income (Sackett et al., 2009; 2012). Specifically, each score was transformed to a z-score, and the sum of the three z-scores was computed for each participant. The criterion validity of older adolescent's (14 – 19 years old) self-report of their mother's education level indicated good reliability (Cohen's $\kappa = .70$) (Ensminger et al., 2000).

No data related to the validity and reliability of adolescent self-reported measures of father's education, or family income is available in the literature.

Driving scenarios.

Table 1

Latent hazard anticipation scenario names and descriptions.

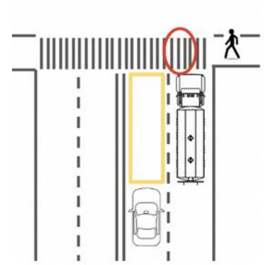
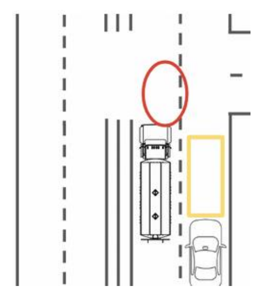
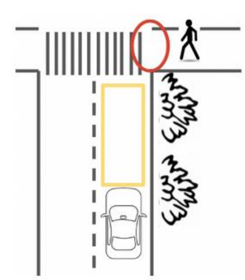
Scenario Name	Description	Top-Down View
S1: Truck Obstructs Crosswalk	The driver is in the left lane of a divided street approaching a crosswalk at a T intersection. A truck parked in the right lane obstructs the right crosswalk entrance and any pedestrian that may be attempting to cross. The driver must scan the front-left corner of the truck.	
S2: Free-Way Truck Obstruction	The driver is in the right lane of a two-lane divided free-way approaching an intersection with a truck parked in the left lane obstructing the view of potential cross traffic. The driver must scan the front right corner of the truck for any traffic that may be attempting to cross in front of the driver.	
S3: Hedge Obstructs Crosswalk	The driver is on a two-lane road approaching a crosswalk in front of a T intersection with a hedge obstructing the right crosswalk entrance. The driver needs to scan the right crosswalk entrance beyond the far-left corner of the hedge where a pedestrian may emerge.	

Table 1 (Continued)

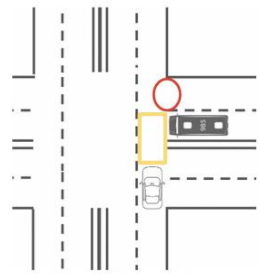
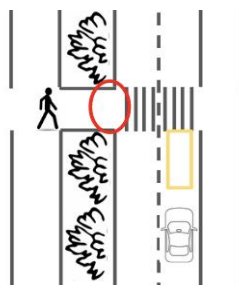
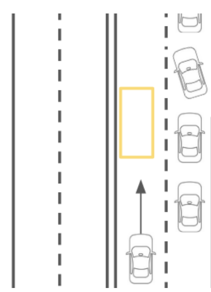
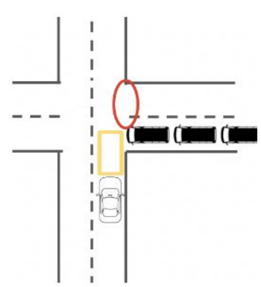
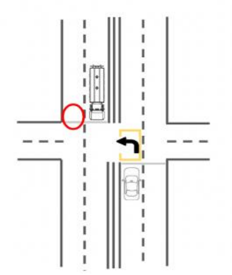
Scenario Name	Description	Top-Down View
S4: Bus Obstruction	The driver has a green light as they pass through a four-way intersection in the right lane with a bus parked in the left lane on the right side of the intersecting cross traffic. The bus blocks the driver’s view of vehicles that might be to the right of the bus. The driver must glance toward the right lane of the intersecting cross traffic where a car may be attempting a right-on-red turn.	
S5: Midblock Crosswalk	The driver is in the right lane of a straight two-lane road with a crosswalk intersecting it. A hedge obstructs the crosswalk entrance on the left side along with any pedestrian that may be attempting to cross. The driver must scan the gap just after the near hedge and just before the far hedge.	
S6: Car Merge	The driver is in the left lane of a four lane road with a line of cars parked in the right lane. One of the parked cars signals their left blinker and is angled toward the left lane. The driver must watch the signaling vehicle to ensure it does not intend to merge in front of their vehicle.	
S7: Obscured Cross-traffic	The driver approaches an intersection controlled by a stop sign with three vans obscuring the cross traffic approaching in the right lane. The driver must look to the area just beyond the front side of the front van for any sign of emerging cross-traffic.	

Table 1 (Continued)

Scenario Name	Description	Top-Down View
S8: Opposite Lane Truck Obstruction	The driver attempts a left hand turn from the left lane of a four-way intersection controlled by a stop sign. A truck parked in the left lane of the opposing street obstructs the driver's view of traffic approaching in the right opposing lane. The driver must look toward the area to the left side of the truck in the right lane as they engage in the left-hand turn.	

Note. Launch zones indicated by yellow rectangles, and target zones indicated by red ovals.

Procedure

Each participant was assigned to either the active- or passive-training group. Participants were asked to read an informed consent document and provide written consent if they agreed to participate in the study. First, participants were screened for normal near and far visual acuity using the Snellen chart and color perception using the Ishihara color blindness test (Ishihara, 2014). Next, the participants completed a 5-minute practice session in which they learned basic skills to operate a vehicle in the driving simulator by weaving in between traffic cones, changing lanes, and turning at intersections. Then, participants completed a pretest in which they navigated through eight driving scenarios with their eye movements tracked in an order randomized across participants. The passive group reviewed a 30-minute PowerPoint about HA behavior in the RAPT training module. Then, participants completed the same eight driving scenarios in a different order from that of the pretest with their eye movements tracked. Finally, participants completed an SES demographics form and a driving history questionnaire and were remunerated and dismissed.

Experimental Design

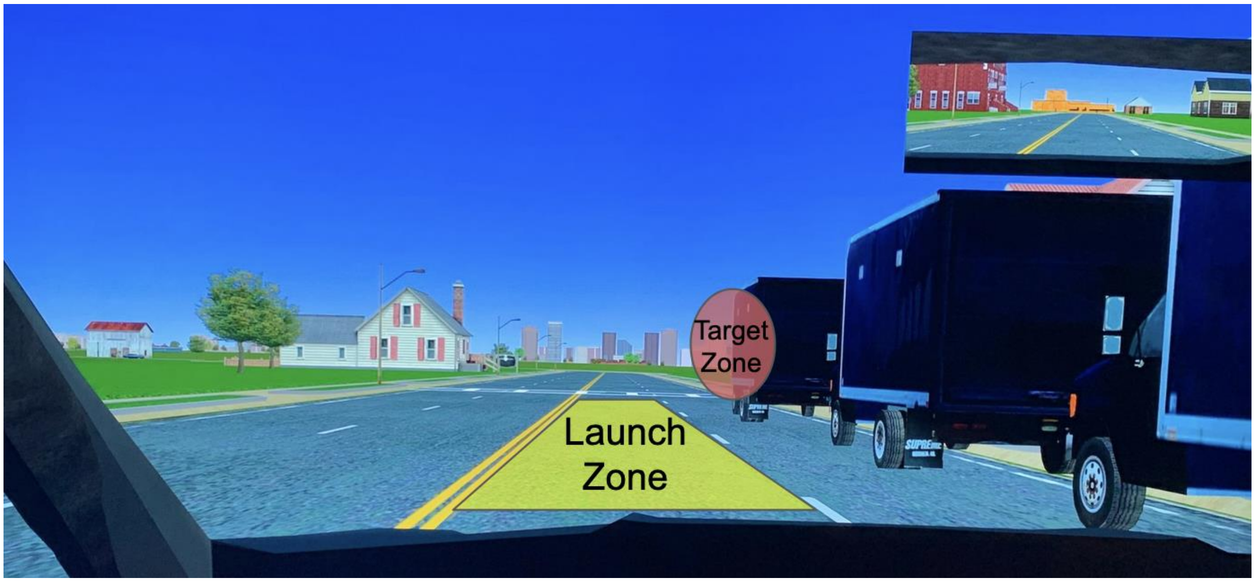
The present study employed a mixed design with Training (Active vs Passive) and SES (High vs Low) as between-subjects factors and Time (Time 1 vs Time 2) as a within-subject factor.

Dependent Variables

Participants' eye movement data were manually coded into latent HA scores by two experienced researchers. Successful HA is operationally defined as the proportion of the participants' glances located at the predefined target zone while within a predefined launch zone (see Figure 3). The target zone is the area of the visual field that contains a latent hazard while the launch zone is the area of the roadway immediately preceding the hazard where the driver must glance toward the target zone. If the participant glanced on the target zone while their vehicle is within the launch zone, they received a 1 indicating that they anticipated the latent hazard or 0 otherwise. Any disagreements were discussed by the original two independent coders until a consensus was reached.

Figure 3

Perspective view of HA Scenario 2.



Note. The launch zone is indicated by the yellow rectangle and the target zone by the red oval.

Vehicle data captured between 100 feet before and 50 feet after the latent hazard were analyzed including the average velocity, the standard deviation of velocity, and the average absolute acceleration (Agrawal et al., 2018; Yamani et al., 2024). The average absolute acceleration is defined as the average of the absolute value of the acceleration at each point that was measured 100 feet before the latent hazard and 50 feet after the latent hazard.

Statistical Analysis

Default Bayesian Hypothesis testing (Rouder & Morey., 2012) instead of conventional null-hypothesis significance tests (NHST) was used for analyzing HA scores and vehicle measures in the current study. Default Bayesian tests offer at least two advantages compared to NHSTs. First, Bayesian tests can provide evidence for alternative hypotheses or null hypotheses, whereas NHSTs can only provide evidence for the alternative hypothesis. Second, unlike

NHSTs, Bayesian analysis does not force dichotomous decision-making (reject or fail to reject the null hypothesis) but enables more graded decision-making. That is, Bayesian analysis can provide relative support for the alternative hypothesis or the null, permitting relative statistical decision-making. One measure of evidence in default Bayesian analysis is the Bayes factor (BF). The BF indicates the relative support for the alternative hypothesis compared to the null hypothesis, given the obtained data. The BF is calculated with the following formula.

$$BF = \frac{p(H1 \mid data)}{p\,(H0 \mid data)} = \frac{p(data \mid H1)}{p(data \mid H0)}\ X\ \frac{p(H1\,)}{p\,(H0)}$$

In this equation, The BF value represents a ratio of the evidence in support of a statistical model including the effect of interest, p(H1|data), compared to that excluding the effect, p(H0|data). Therefore, the BF greater than 1 represents statistical evidence for the effect while below 1 represents against the effect. For example, a value of the Bayes factor of 10 indicates that obtained data are 10 times more likely to have resulted from a statistical model that assumes the effect of interest than a model that does not. Similarly, a BF value of 1/10 indicates evidence that data are 10 times more likely to have been produced from a statistical model that assumes the absence of the effect of interest than the presence. A magnitude of the BF is interpreted using the nomenclature provided by Jeffreys (1961) (refer to Table 2).

The proportion of correct anticipatory glances were analyzed with a three-way mixed Bayesian analysis of variance (ANOVA) with Training (Active vs Passive) and SES (High vs Low) as between-subjects factors and Time (Time 1 vs Time 2) as a within-subject factor. All credible interactions were followed up with relevant Bayesian t-tests. All the analyses were conducted using the *BayesFactor* package in R.

Table 2

Interpretation of Bayes Factor Values.

B_{10}	Interpretation
<100	Decisive evidence for H1
30-100	Very strong evidence for H1
10-30	Strong evidence for H1
3-10	Substantial evidence for H1
1-3	Not worth more than a bare mention
1/3-1	Not worth more than a bare mention
1/10-1/3	Substantial evidence for H0
1/30-1/10	Strong evidence for H0
1/100-1/30	Very strong evidence for H0
<1/100	Decisive evidence for H0

Note. Descriptive labels for each range of Bayes factors (Jeffrey, 1961).

CHAPTER III

RESULTS

Data Preparation

Eye tracking failures and data noise caused the loss of data for a total of 30 scenarios (15 for drivers in the Active-Training group and 15 in the Passive-Training group) resulting in 3.6% of data excluded.

Missing data for the father's education subcomponent of the SES composite measure occurred for five participants and was replaced with the mean father education level of 13.98 years (two for the High-SES group and three for the Low-SES group). For the measure of family income, 11 participants were missing data that were replaced with the mean value of family income, which was $88,244 (four in the High-SES group and seven in the Low-SES group). There was no missing data for mother's education. To create the SES composite measure the Z-score was calculated independently for each of the three subcomponents (mothers' education, fathers' education, and family income). The three subcomponent Z-scores were then summed and a final composite Z-score formed a continuous measure. The median SES score of the composite measure was calculated and participants with a Z-score that fell above the median of the composite Z-score were placed in the High-SES group, and participants with SES scores that fell below the median were placed in the Low-SES group. A Levene's test of homogeneity of variance was not significant between High- and Low-SES groups for latent hazard anticipation scores, $F(1, 102) = 0.49$, $p = .487$, supporting equality of variance.

Figure 4

Distribution of fathers' years of education.

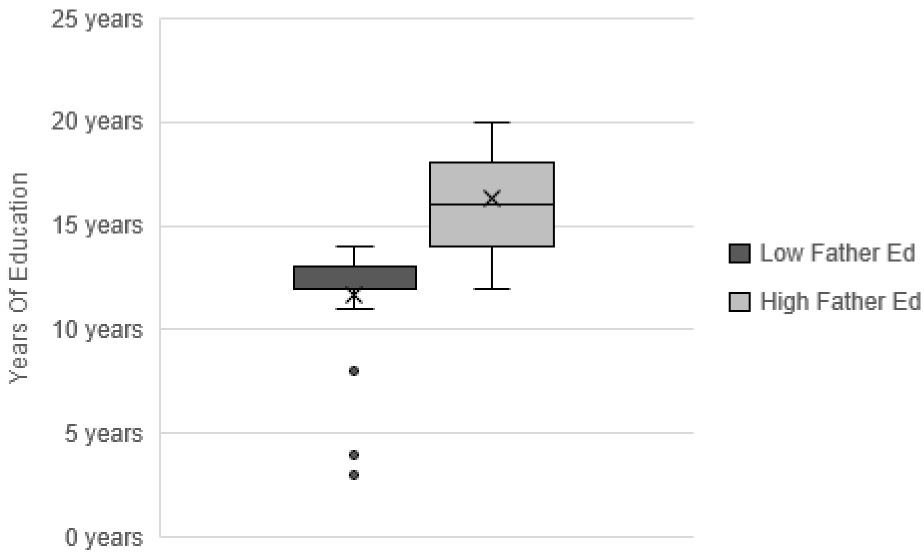


Figure 5

Distribution of mothers' years of education.

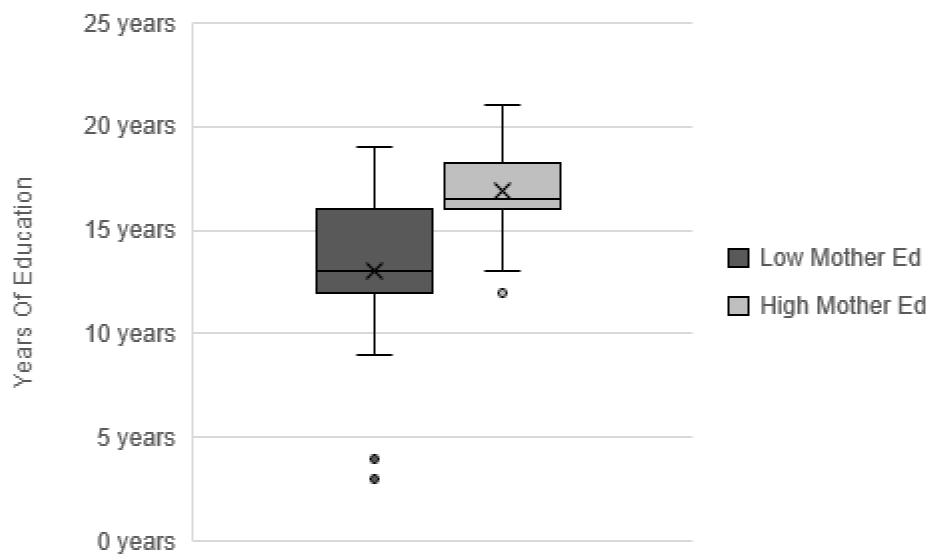
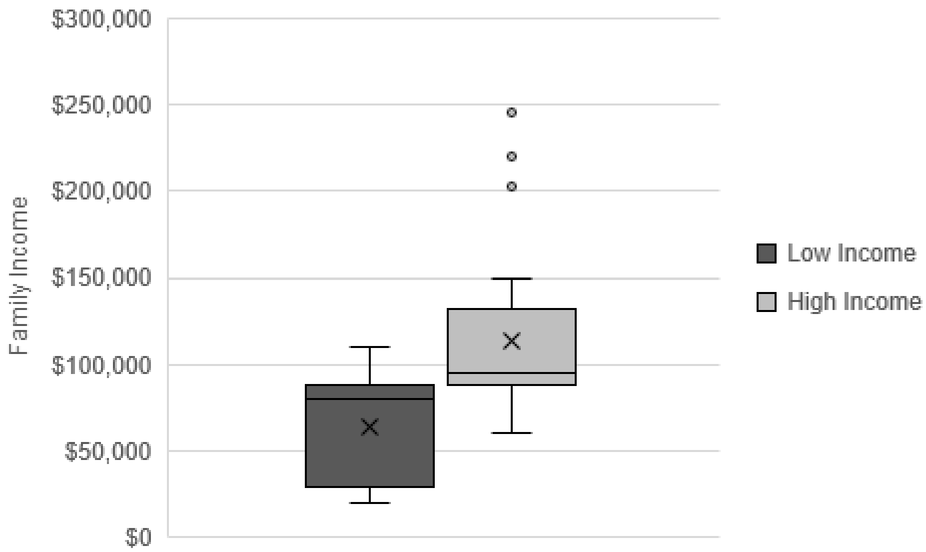


Figure 6

Distribution of family income per year.



To explore the effects of the independent variables on driving performance, a series of 2 (Training) × 2 (SES) × 2 (Time) mixed Bayesian ANOVAs were performed for each of the three exploratory measures – average velocity, average absolute acceleration, and standard deviation of velocity. Credible interactions were followed up with Bayesian t-tests.

Hazard Anticipation

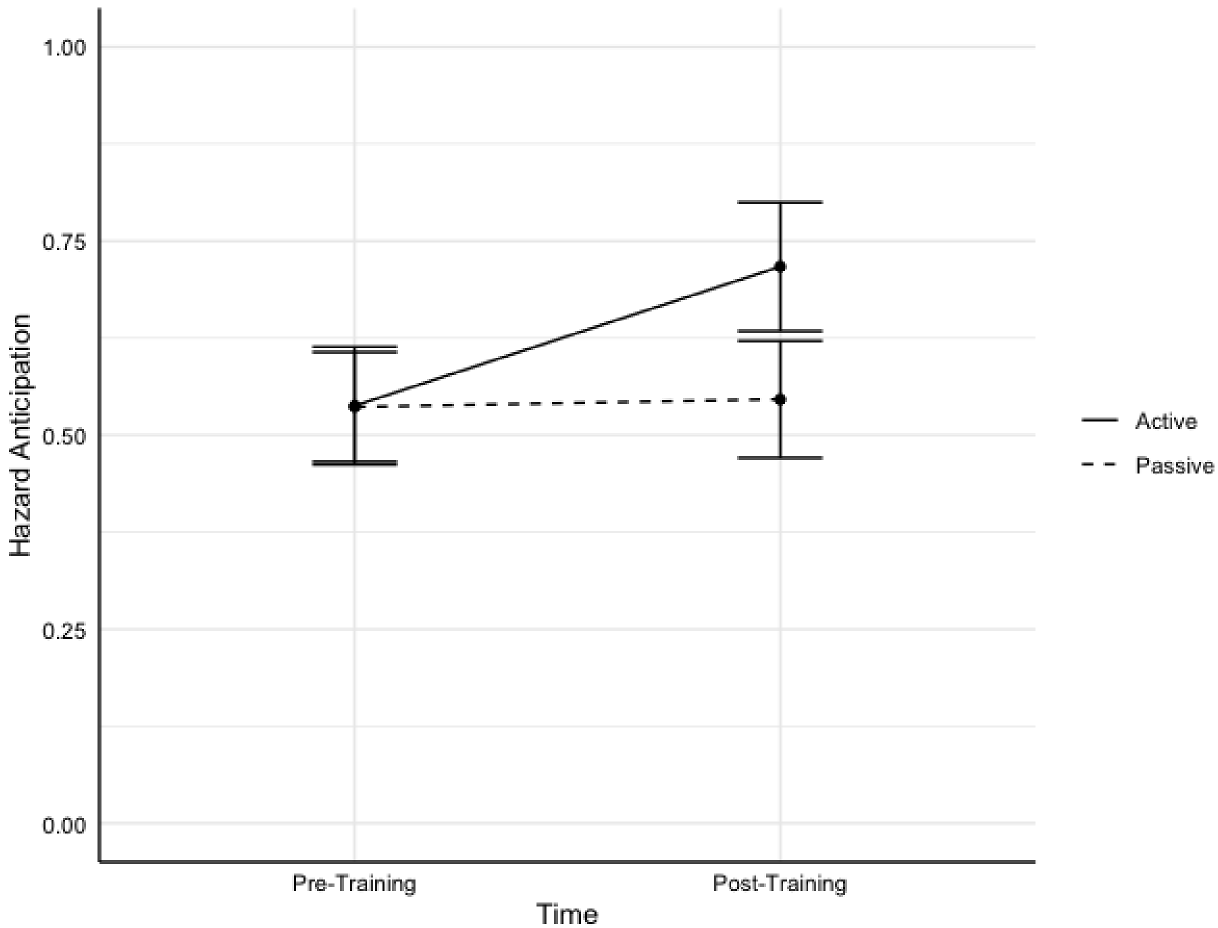
Consistent with the previous data, the results indicated substantial evidence for the presence of the Training by Time interaction, $F(1, 48) = 8.83$, $B_{10} = 4.50$, $\eta^2_G = .064$, showing the effectiveness of the active training program on improving latent hazard anticipation (Figure 7). Follow-up Bayesian t-tests showed strong evidence that drivers improved latent hazard anticipation after the completion of the active training program, M = 53.8% vs. 71.7%, $t(25) = -3.47$, $B_{10} = 19.40$, but not after the passive training program, M = 53.6% vs. 54.6%, $t(25) = -$

0.217, B_{10} = 1/4.72. The main effect of Time remained substantial, F(1, 48) = 9.23, B_{10} = 4.29, η^2_G = .067. However, interestingly, collapsing across Time, evidence for the main effect of Training was only anecdotal, F(1, 48) = 4.77, B_{10} = 2.96, η^2_G = .059.

On the effect of SES on latent hazard anticipation, data gave substantial evidence for the presence of the SES by Time interaction (Figure 8), F(1, 48) = 10.61, B_{10} = 7.56, η^2_G = .076. Follow-up Bayesian t-tests indicated that drivers in the high SES group anticipated hazards correctly in decisively more scenarios after completing either active or passive training than before, M = 69% vs. 50.1%, t(25) = -4.37, B_{10} = 150.64, but this pattern was absent among drivers in the low SES group, M = 57.3% vs. 57.3% t(25) = - 0.00, B_{10} = 1/4.83. The remaining effects were not substantial, 1/3.84 < B_{10} < 1/2.91.

Figure 7

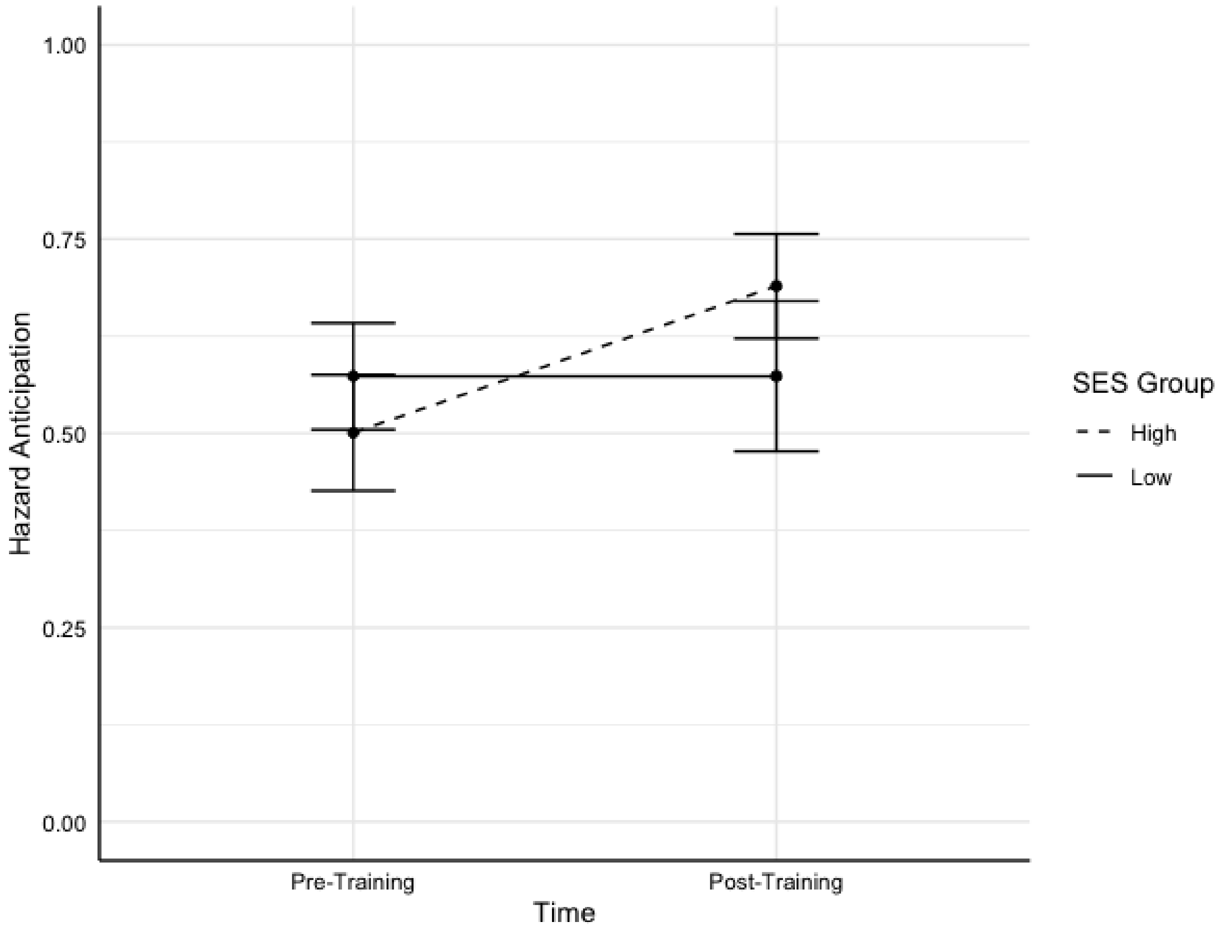
Mean proportion of successful HA by training condition and time.



Note. Error bars represent within 95% confidence intervals of the means.

Figure 8

Mean proportion of successful HA by SES condition and time.



Vehicle Measures

Below, only analyses with credible results are reported. For full analyses, refer to Table 3 - 10.

Average velocity

No comparisons were substantial 1/6.12 < all B_{10} < 2.06.

Standard deviation of velocity

No comparisons were substantial, 1/4.20 < all B_{10} < 2.47.

Average absolute acceleration

Drivers substantially changed their speed more precipitously after the completion of either training program than before in Scenario 3, M = 1.46 vs. 1.27 m/s^2, $F(1, 45) = 12.58$, B_{10} = 3.03, η^2_G = .061, and strongly in Scenario 7, M = 1.75 vs. 1.43, $F(1, 44) = 32.56$, B_{10} = 46.96, η^2_G = .113. In Scenario 5, drivers in the passive training group adjusted their speed substantially more quickly than those in the active training group, M = 0.54 vs. 0.34 m/s^2, $F(1, 42) = 4.58$, B_{10} = 3.04, η^2_G = .063. The rest of the effects were not substantial, 1/4.90 < all B_{10} < 1.79.

Table 3

Results of the statistical analyses on the vehicle control measures for Scenario 1.

	Scenario 1		
	Average Velocity	SD Velocity	Average Absolute Acceleration
Training	B_{10} = 1/4.37, Active (*M* = 34.20) vs. Passive (*M* = 34.77)	B_{10} = 1/1.93, Active (*M* = 0.67) vs. Passive (*M* = 0.97)	B_{10} = 1/3.13, Active (*M* = 0.30) vs. Passive (*M* = 0.39)
Time	B_{10} = 1/3.88, Time 1 (*M* = 35.16) vs. Time 2 (*M* = 33.81)	B_{10} = 1.4378, Time 1 (*M* = 0.57) vs. Time 2 (*M* = 1.08)	B_{10} = 1/1.22, Time 1 (*M* = 0.26) vs. Time 2 (*M* = 0.42)
SES	B_{10} = 1/1.08, High (*M* = 35.95) vs. Low (*M* = 33.02)	B_{10} = 1/1.55, High (*M* = 0.65) vs. Low (*M* = 0.99)	B_{10} = 1/2.88, High (*M* = 0.29) vs. Low (*M* = 0.39)
Time:Training	B_{10} = 1/1.11, Active-Time 1 (*M* = 33.55) vs. Passive-Time 1 (*M* = 36.77), Active-Time 2 (*M* = 34.85) vs. Passive-Time 2 (*M* = 32.78)	B_{10} = 1.2917, Active-Time 1 (*M* = 0.64) vs. Passive-Time 1 (*M* = 0.49), Active-Time 2 (*M* = 0.71) vs. Passive-Time 2 (*M* = 1.44)	B_{10} = 1.47, Active-Time 1 (*M* = 0.31) vs. Passive-Time 1 (*M* = 0.21), Active-Time 2 (*M* = 0.28) vs. Passive-Time 2 (*M* = 0.56)
SES:Training	B_{10} = 1/3.75, High-Active (*M* = 35.55) vs. Low-Active (*M* = 32.84), High-Passive (*M* = 36.36) vs. Low-Passive (*M* = 33.19)	B_{10} = 1/1.60, High-Active (*M* = 0.35) vs. Low-Active (*M* = 0.99), High-Passive (*M* = 0.94) vs. Low-Passive (*M* = 1.00)	B_{10} = 1/2.49, High-Active (*M* = 0.19) vs. Low-Active (*M* = 0.41), High-Passive (*M* = 0.39) vs. Low-Passive (*M* = 0.38)
SES:Time	B_{10} = 1/3.12, High-Time 1 (*M* = 36.20) vs. Low-Time 1 (*M* = 34.12), High-Time 2 (*M* = 35.71) vs. Low-Time 2 (*M* = 31.92)	B_{10} = 1/2.47, High-Time 1 (*M* = 0.45) vs. Low-Time 1 (*M* = 0.68), High-Time 2 (*M* = 0.84) vs. Low-Time 2 (*M* = 1.31)	B_{10} = 1/3.12, High-Time 1 (*M* = 0.23) vs. Low-Time 1 (*M* = 0.30), High-Time 2 (*M* = 0.35) vs. Low-Time 2 (*M* = 0.49)

Table 3 (Continued)

	Scenario 1		
	Average Velocity	SD Velocity	Average Absolute Acceleration
Training:Time:SES	B_{10} = 1/2.52, Active-Time 1-High (*M* = 34.97) vs. Active-Time 1-Low (*M* = 32.13), Passive-Time 1-High (*M* = 37.43), Passive-Time 1-Low (*M* = 36.10), Active-Time 2-High (*M* = 36.14) vs. Active-Time 2-Low (*M* = 33.56), Passive-Time 2-High (*M* = 35.28) vs Passive-Time 2-Low (*M* = 30.28)	B_{10} = 1/2.64, Active-Time 1-High (*M* = 0.354) vs. Active-Time 1-Low (*M* = 0.924), Passive-Time 1-High (*M* = 0.55), Passive-Time 1-Low (*M* = 0.43), Active-Time 2-High (*M* = 0.36) vs. Active-Time 2-Low (*M* = 1.06), Passive-Time 2-High (*M* = 1.33) vs Passive-Time 2-Low (*M* = 1.56)	B_{10} = 1/2.44 , Active-Time 1-High (*M* = 0.224) vs. Active-Time 1-Low (*M* = 0.401), Passive-Time 1-High (*M* = 0.23), Passive-Time 1-Low (*M* = 0.19), Active-Time 2-High (*M* = 0.15) vs. Active-Time 2-Low (*M* = 0.41), Passive-Time 2-High (*M* = 0.56) vs Passive-Time 2-Low (*M* = 0.57)

Table 4

Results of the statistical analyses on the vehicle control measures for Scenario 2.

	Scenario 2		
	Average Velocity	SD Velocity	Average Absolute Acceleration
Training	B_{10} = 1/4.65, Active (M = 34.16) vs. Passive (M = 34.59)	B_{10} = 1/2.74, Active (M = 0.99) vs. Passive (M = 0.74)	B_{10} = 1/5.09, Active (M = 0.40) vs. Passive (M = 0.35)
Time	B_{10} = 1/1.35, Time 1 (M = 35.61) vs. Time 2 (M = 33.14)	B_{10} = 1/1.20, Time 1 (M = 0.65) vs. Time 2 (M = 1.08)	B_{10} = 1.12, Time 1 (M = 0.28) vs. Time 2 (M = 0.47)
SES	B_{10} = 1/5.18, High (M = 34.24) vs. Low (M = 34.51)	B_{10} = 1/4.61, High (M = 0.83) vs. Low (M = 0.91)	B_{10} = 1/4.58, High (M = 0.35) vs. Low (M = 0.41)
Time:Training	B_{10} = 1/1.95, Active-Time 1 (M = 34.50) vs. Passive-Time 1 (M = 36.72), Active-Time 2 (M = 33.81) vs. Passive-Time 2 (M = 32.47)	B_{10} = 1/2.15, Active-Time 1 (M = 0.92) vs. Passive-Time 1 (M = 0.38), Active-Time 2 (M = 1.07) vs. Passive-Time 2 (M = 1.10)	B_{10} = 1/2.24, Active-Time 1 (M = 0.36) vs. Passive-Time 1 (M = 0.21), Active-Time 2 (M = 0.43) vs. Passive-Time 2 (M = 0.50)
SES:Training	B_{10} = 1/1.21, High-Active (M = 32.83) vs. Low-Active (M = 35.48), High-Passive (M = 35.64) vs. Low-Passive (M = 33.53)	B_{10} = 1/2.54, High-Active (M = 1.07) vs. Low-Active (M = 0.91), High-Passive (M = 0.58) vs. Low-Passive (M = 0.90)	B_{10} = 1/2.81, High-Active (M = 0.41) vs. Low-Active (M = 0.39), High-Passive (M = 0.28) vs. Low-Passive (M = 0.43)
SES:Time	B_{10} = 1/3.10, High-Time 1 (M = 34.94) vs. Low-Time 1 (M = 36.28), High-Time 2 (M = 33.54) vs. Low-Time 2 (M = 32.74)	B_{10} = 1/3.13, High-Time 1 (M = 0.66) vs. Low-Time 1 (M = 0.64), High-Time 2 (M = 1.00) vs. Low-Time 2 (M = 1.17)	B_{10} = 1/4.26, High-Time 1 (M = 0.27) vs. Low-Time 1 (M = 0.30), High-Time 2 (M = 0.42) vs. Low-Time 2 (M = 0.51)

Table 4 (Continued)

Scenario 2			
	Average Velocity	SD Velocity	Average Absolute Acceleration
Training:Time:SES	B_{10} = 1.35, Active-Time 1-High (*M* = 7.27) vs. Active-Time 1-Low (*M* = 8.01), Passive-Time 1-High (*M* = 7.93), Passive-Time 1-Low (*M* = 8.98), Active-Time 2-High (*M* = 9.06) vs. Active-Time 2-Low (*M* = 9.26), Passive-Time 2-High (*M* = 7.74) vs Passive-Time 2-Low (*M* = 9.23)	B_{10} = 1/2.02, Active-Time 1-High (*M* = 5.33) vs. Active-Time 1-Low (*M* = 5.61), Passive-Time 1-High (*M* = 5.54), Passive-Time 1-Low (*M* = 5.64), Active-Time 2-High (*M* = 6.74) vs. Active-Time 2-Low (*M* = 5.29), Passive-Time 2-High (*M* = 5.67) vs Passive-Time 2-Low (*M* = 5.27)	B_{10} = 1.35, Active-Time 1-High (*M* = 1.17) vs. Active-Time 1-Low (*M* = 1.30), Passive-Time 1-High (*M* = 1.23), Passive-Time 1-Low (*M* = 1.36), Active-Time 2-High (*M* = 1.69) vs. Active-Time 2-Low (*M* = 1.34), Passive-Time 2-High (*M* = 1.29) vs Passive-Time 2-Low (*M* = 1.51)

Table 5

Results of the statistical analyses on the vehicle control measures for Scenario 3.

	Scenario 3		
	Average Velocity	SD Velocity	Average Absolute Acceleration
Training	B_{10} = 1/4.12, Active (M = 8.40) vs. Passive (M = 8.47)	B_{10} = 1/3.24, Active (M = 5.74) vs. Passive (M = 5.53)	B_{10} = 1/4.96, Active (M = 1.38) vs. Passive (M = 1.35)
Time	B_{10} = 1.16, Time 1 (M = 8.05) vs. Time 2 (M = 8.82)	B_{10} = 1/3.10, Time 1 (M = 5.53) vs. Time 2 (M = 5.74)	B_{10} = 3.03, Time 1 (M = 1.27) vs. Time 2 (M = 1.46)
SES	B_{10} = 1.79, High (M = 8.00) vs. Low (M = 8.87)	B_{10} = 1/1.82, High (M = 5.82) vs. Low (M = 5.45)	B_{10} = 1/4.83, High (M = 1.35) vs. Low (M = 1.38)
Time:Training	B_{10} = 1.26, Active-Time 1 (M = 7.64) vs. Passive-Time 1 (M = 8.45), Active-Time 2 (M = 9.16) vs. Passive-Time 2 (M = 8.49)	B_{10} = 1/1.76, Active-Time 1 (M = 5.47) vs. Passive-Time 1 (M = 5.59), Active-Time 2 (M = 6.01) vs. Passive-Time 2 (M = 5.47)	B_{10} = 1/2.13, Active-Time 1 (M = 1.23) vs. Passive-Time 1 (M = 1.30), Active-Time 2 (M = 1.52) vs. Passive-Time 2 (M = 1.40)
SES:Training	B_{10} = 1/2.38, High-Active (M = 8.16) vs. Low-Active (M = 8.63), High-Passive (M = 7.84) vs. Low-Passive (M = 9.11)	B_{10} = 1/2.82, High-Active (M = 6.03) vs. Low-Active (M = 5.45), High-Passive (M = 5.61) vs. Low-Passive (M = 5.45)	B_{10} = 1.1846, High-Active (M = 1.43) vs. Low-Active (M = 1.32), High-Passive (M = 1.26) vs. Low-Passive (M = 1.44)
SES:Time	B_{10} = 1/3.05, High-Time 1 (M = 7.60) vs. Low-Time 1 (M = 8.50), High-Time 2 (M = 8.40)	B_{10} = 1.8671, High-Time 1 (M = 5.43) vs. Low-Time 1 (M = 5.62), High-Time 2 (M = 6.20)	B_{10} = 1/2.00, High-Time 1 (M = 1.20) vs. Low-Time 1 (M = 1.33), High-Time 2 (M = 1.49)

Table 5 (Continued)

Scenario 3			
	Average Velocity	SD Velocity	Average Absolute Acceleration
Training:Time:SES	B_{10} = 1.35, Active-Time 1-High (M = 7.27) vs. Active-Time 1-Low (M = 8.01), Passive-Time 1-High (M = 7.93), Passive-Time 1-Low (M = 8.98), Active-Time 2-High (M = 9.06) vs. Active-Time 2-Low (M = 9.26), Passive-Time 2-High (M = 7.74) vs Passive-Time 2-Low (M = 9.23)	B_{10} = 1/2.02, Active-Time 1-High (M = 5.33) vs. Active-Time 1-Low (M = 5.61), Passive-Time 1-High (M = 5.54), Passive-Time 1-Low (M = 5.64), Active-Time 2-High (M = 6.74) vs. Active-Time 2-Low (M = 5.29), Passive-Time 2-High (M = 5.67) vs Passive-Time 2-Low (M = 5.27)	B_{10} = 1.35, Active-Time 1-High (M = 1.17) vs. Active-Time 1-Low (M = 1.30), Passive-Time 1-High (M = 1.23), Passive-Time 1-Low (M = 1.36), Active-Time 2-High (M = 1.69) vs. Active-Time 2-Low (M = 1.34), Passive-Time 2-High (M = 1.29) vs Passive-Time 2-Low (M = 1.51)

Note. Green shading indicates substantial evidence supporting the effect of interest.

Table 6

Results of the statistical analyses on the vehicle control measures for Scenario 4.

	Scenario 4		
	Average Velocity	SD Velocity	Average Absolute Acceleration
Training	B_{10} = 1/6.12, Active (M = 38.91) vs. Passive (M = 38.99)	B_{10} = 1/2.64, Active (M = 0.24) vs. Passive (M = 0.18)	B_{10} = 1/2.41, Active (M = 0.18) vs. Passive (M = 0.13)
Time	B_{10} = 1/1.36, Time 1 (M = 38.24) vs. Time 2 (M = 39.66)	B_{10} = 1/1.69, Time 1 (M = 0.17) vs. Time 2 (M = 0.25)	B_{10} = 1/1.55, Time 1 (M = 0.12) vs. Time 2 (M = 0.18)
SES	B_{10} = 1/4.70, High (M = 38.63) vs. Low (M = 39.27)	B_{10} = 1/1.95, High (M = 0.17) vs. Low (M = 0.25)	B_{10} = 1/4.63, High (M = 0.14) vs. Low (M = 0.16)
Time:Training	B_{10} = 1/2.71, Active-Time 1 (M = 37.88) vs. Passive-Time 1 (M = 38.60), Active-Time 2 (M = 39.94) vs. Passive-Time 2 (M = 39.39)	B_{10} = 1/2.89, Active-Time 1 (M = 0.19) vs. Passive-Time 1 (M = 0.14), Active-Time 2 (M = 0.30) vs. Passive-Time 2 (M = 0.21)	B_{10} = 1/3.21, Active-Time 1 (M = 0.13) vs. Passive-Time 1 (M = 0.11), Active-Time 2 (M = 0.22) vs. Passive-Time 2 (M = 0.14)
SES:Training	B_{10} = 1.45, High-Active (M = 37.70) vs. Low-Active (M = 40.11), High-Passive (M = 39.55) vs. Low-Passive (M = 38.44)	B_{10} = 1/2.28, High-Active (M = 0.18) vs. Low-Active (M = 0.31), High-Passive (M = 0.17) vs. Low-Passive (M = 0.19)	B_{10} = 1/2.33, High-Active (M = 0.15) vs. Low-Active (M = 0.21), High-Passive (M = 0.13) vs. Low-Passive (M = 0.12)
SES:Time	B_{10} = 1/1.96, High-Time 1 (M = 38.44) vs. Low-Time 1 (M = 38.04), High-Time 2 (M = 38.82) vs. Low-Time 2 (M = 40.51)	B_{10} = 1/3.44, High-Time 1 (M = 0.12) vs. Low-Time 1 (M = 0.21), High-Time 2 (M = 0.22) vs. Low-Time 2 (M = 0.28)	B_{10} = 1/2.92, High-Time 1 (M = 0.13) vs. Low-Time 1 (M = 0.12), High-Time 2 (M = 0.15) vs. Low-Time 2 (M = 0.21)

Table 6 (Continued)

Scenario 4			
	Average Velocity	SD Velocity	Average Absolute Acceleration
Training:Time:SES	B_{10} = 1/2.48, Active-Time 1-High (*M* = 37.41) vs. Active-Time 1-Low (*M* = 38.34), Passive-Time 1-High (*M* = 39.46), Passive-Time 1-Low (*M* = 37.74), Active-Time 2-High (*M* = 37.99) vs. Active-Time 2-Low (*M* = 41.88), Passive-Time 2-High (*M* = 39.65) vs Passive-Time 2-Low (*M* = 39.13)	B_{10} = 1/2.37, Active-Time 1-High (*M* = 0.10) vs. Active-Time 1-Low (*M* = 0.28), Passive-Time 1-High (*M* = 0.15), Passive-Time 1-Low (*M* = 0.14), Active-Time 2-High (*M* = 0.26) vs. Active-Time 2-Low (*M* = 0.33), Passive-Time 2-High (*M* = 0.19) vs Passive-Time 2-Low (*M* = 0.24)	B_{10} = 1/2.94, Active-Time 1-High (*M* = 0.12) vs. Active-Time 1-Low (*M* = 0.15), Passive-Time 1-High (*M* = 0.14), Passive-Time 1-Low (*M* = 0.08), Active-Time 2-High (*M* = 0.18) vs. Active-Time 2-Low (*M* = 0.26), Passive-Time 2-High (*M* = 0.13) vs Passive-Time 2-Low (*M* = 0.16)

Table 7

Results of the statistical analyses on the vehicle control measures Scenario 5.

	Scenario 5		
	Average Velocity	SD Velocity	Average Absolute Acceleration
Training	B_{10} = 1/3.83, Active (M = 28.24) vs. Passive (M = 28.67)	B_{10} = 1/1.10, Active (M = 0.86) vs. Passive (M = 1.28)	B_{10} = 3.04, Active (M = 0.34) vs. Passive (M = 0.54)
Time	B_{10} = 1/3.65, Time 1 (M = 28.24) vs. Time 2 (M = 28.68)	B_{10} = 1/3.20, Time 1 (M = 0.97) vs. Time 2 (M = 1.17)	B_{10} = 1/2.88, Time 1 (M = 0.40) vs. Time 2 (M = 0.48)
SES	B_{10} = 2.06, High (M = 29.77) vs. Low (M = 27.15)	B_{10} = 1/3.75, High (M = 0.99) vs. Low (M = 1.15)	B_{10} = 1/4.90, High (M = 0.42) vs. Low (M = 0.45)
Time:Training	B_{10} = 1/1.19, Active-Time 1 (M = 27.12) vs. Passive-Time 1 (M = 29.36), Active-Time 2 (M = 29.38) vs. Passive-Time 2 (M = 27.98)	B_{10} = 2.47, Active-Time 1 (M = 1.02) vs. Passive-Time 1 (M = 0.93), Active-Time 2 (M = 0.71) vs. Passive-Time 2 (M = 1.64)	B_{10} = 1.65, Active-Time 1 (M = 0.38) vs. Passive-Time 1 (M = 0.41), Active-Time 2 (M = 0.30) vs. Passive-Time 2 (M = 0.66)
SES:Training	B_{10} = 1/1.33, High-Active (M = 28.73) vs. Low-Active (M = 27.77), High-Passive (M = 30.80) vs. Low-Passive (M = 26.53)	B_{10} = 1/2.82, High-Active (M = 0.88) vs. Low-Active (M = 0.85), High-Passive (M = 1.11) vs. Low-Passive (M = 1.46)	B_{10} = 1/3.54, High-Active (M = 0.34) vs. Low-Active (M = 0.34), High-Passive (M = 0.51) vs. Low-Passive (M = 0.57)
SES:Time	B_{10} = 1/2.86, High-Time 1 (M = 29.77) vs. Low-Time 1 (M = 26.71), High-Time 2 (M = 29.77) vs. Low-Time 2 (M = 27.59)	B_{10} = 1/2.66, High-Time 1 (M = 0.81) vs. Low-Time 1 (M = 1.14), High-Time 2 (M = 1.18) vs. Low-Time 2 (M = 1.17)	B_{10} = 1/2.56, High-Time 1 (M = 0.35) vs. Low-Time 1 (M = 0.45), High-Time 2 (M = 0.50) vs. Low-Time 2 (M = 0.46)

Table 7 (Continued)

	Scenario 5		
	Average Velocity	SD Velocity	Average Absolute Acceleration
Training:Time:SES	B_{10} = 1/1.56, Active-Time 1-High (*M* = 28.80) vs. Active-Time 1-Low (*M* = 25.43), Passive-Time 1-High (*M* = 30.73), Passive-Time 1-Low (*M* = 27.99), Active-Time 2-High (*M* = 28.65) vs. Active-Time 2-Low (*M* = 30.1), Passive-Time 2-High (*M* = 30.88) vs Passive-Time 2-Low (*M* = 25.08)	B_{10} = 1/2.24, Active-Time 1-High (*M* = 0.88) vs. Active-Time 1-Low (*M* = 1.16), Passive-Time 1-High (*M* = 0.73), Passive-Time 1-Low (*M* = 1.12), Active-Time 2-High (*M* = 0.87) vs. Active-Time 2-Low (*M* = 0.54), Passive-Time 2-High (*M* = 1.48) vs Passive-Time 2-Low (*M* = 1.80)	B_{10} = 1/2.49, Active-Time 1-High (*M* = 0.33) vs. Active-Time 1-Low (*M* = 0.43), Passive-Time 1-High (*M* = 0.36), Passive-Time 1-Low (*M* = 0.47), Active-Time 2-High (*M* = 0.35) vs. Active-Time 2-Low (*M* = 0.25), Passive-Time 2-High (*M* = 0.66) vs Passive-Time 2-Low (*M* = 0.67)

Table 8

Results of the statistical analyses on the vehicle control measures Scenario 6.

	Scenario 6		
	Average Velocity	SD Velocity	Average Absolute Acceleration
Training	B_{10} = 1/1.88, Active (*M* = 36.40) vs. Passive (*M* = 38.03)	B_{10} = 1/2.88, Active (*M* = 0.47) vs. Passive (*M* = 0.36)	B_{10} = 1/1.57, Active (M = 0.21) vs. Passive (M = 0.15)
Time	B_{10} = 1/3.31, Time 1 (*M* = 36.77) vs. Time 2 (*M* = 37.65)	B_{10} = 1/2.55, Time 1 (*M* = 0.35) vs. Time 2 (*M* = 0.47)	B_{10} = 1/1.60, Time 1 (*M* = 0.15) vs. Time 2 (*M* = 0.21)
SES	B_{10} = 1/2.74, High (*M* = 36.67) vs. Low (*M* = 37.76)	B_{10} = 1/3.33, High (*M* = 0.38) vs. Low (*M* = 0.44)	B_{10} = 1/3.18, High (*M* = 0.17) vs. Low (*M* = 0.20)
Time:Training	B_{10} = 1/2.87, Active-Time 1 (*M* = 36.16) vs. Passive-Time 1 (*M* = 37.39), Active-Time 2 (*M* = 36.64) vs. Passive-Time 2 (*M* = 38.66)	B_{10} = 1/2.11, Active-Time 1 (*M* = 0.36) vs. Passive-Time 1 (*M* = 0.35), Active-Time 2 (*M* = 0.58) vs. Passive-Time 2 (*M* = 0.36)	B_{10} = 1/2.27, Active-Time 1 (*M* = 0.16) vs. Passive-Time 1 (*M* = 0.14), Active-Time 2 (*M* = 0.26) vs. Passive-Time 2 (*M* = 0.16)
SES:Training	B_{10} = 1/1.36, High-Active (*M* = 35.00) vs. Low-Active (*M* = 38.34), High-Passive (*M* = 37.72) vs. Low-Passive (*M* = 37.80)	B_{10} = 1/2.37, High-Active (*M* = 0.39) vs. Low-Active (*M* = 0.37), High-Passive (*M* = 0.34) vs. Low-Passive (*M* = 0.54)	B_{10} = 1/3.79, High-Active (*M* = 0.17) vs. Low-Active (*M* = 0.16), High-Passive (*M* = 0.15) vs. Low-Passive (*M* = 0.25)
SES:Time	B_{10} = 1/2.52, High-Time 1 (*M* = 35.75) vs. Low-Time 1 (*M* = 37.80), High-Time 2 (*M* = 37.58) vs. Low-Time 2 (*M* = 37.72)	B_{10} = 1/2.81, High-Time 1 (*M* = 0.37) vs. Low-Time 1 (*M* = 0.34), High-Time 2 (*M* = 0.39) vs. Low-Time 2 (*M* = 0.55)	B_{10} = 1/3.01, High-Time 1 (*M* = 0.15) vs. Low-Time 1 (*M* = 0.16), High-Time 2 (*M* = 0.18) vs. Low-Time 2 (*M* = 0.24)

Table 8 (Continued)

Scenario 6			
	Average Velocity	SD Velocity	Average Absolute Acceleration
Training:Time:SES	B_{10} = 1/1.43, Active-Time 1-High (*M* = 33.73) vs. Active-Time 1-Low (*M* = 38.58), Passive-Time 1-High (*M* = 37.78), Passive-Time 1-Low (*M* = 37.01), Active-Time 2-High (*M* = 36.27) vs. Active-Time 2-Low (*M* = 37.01), Passive-Time 2-High (*M* = 38.89) vs Passive-Time 2-Low (*M* = 38.43)	B_{10} = 1/1.41, Active-Time 1-High (*M* = 0.41) vs. Active-Time 1-Low (*M* = 0.31), Passive-Time 1-High (*M* = 0.33), Passive-Time 1-Low (*M* = 0.37), Active-Time 2-High (*M* = 0.37) vs. Active-Time 2-Low (*M* = 0.78), Passive-Time 2-High (*M* = 0.41) vs Passive-Time 2-Low (*M* = 0.32)	B_{10} = 1/1.63, Active-Time 1-High (*M* = 0.16) vs. Active-Time 1-Low (*M* = 0.17), Passive-Time 1-High (*M* = 0.14), Passive-Time 1-Low (*M* = 0.15), Active-Time 2-High (*M* = 0.19) vs. Active-Time 2-Low (*M* = 0.33), Passive-Time 2-High (*M* = 0.18) vs Passive-Time 2-Low (*M* = 0.15)

Table 9

Results of the statistical analyses on the vehicle control measures Scenario 7.

	Scenario 7		
	Average Velocity	SD Velocity	Average Absolute Acceleration
Training	B_{10} = 1/3.99, Active (M = 9.58) vs. Passive (M = 10.08)	B_{10} = 1/1.83, Active (M = 6.59) vs. Passive (M = 6.22)	B_{10} = 1.79, Active (M = 1.68) vs. Passive (M = 1.49)
Time	B_{10} = 1/4.37, Time 1 (M = 9.59) vs. Time 2 (M = 10.07)	B_{10} = 1/1.83, Time 1 (M = 6.22) vs. Time 2 (M = 6.59)	B_{10} = 46.96, Time 1 (M = 1.43) vs. Time 2 (M = 1.75)
SES	B_{10} = 1/3.14, High (M = 9.34) vs. Low (M = 10.33)	B_{10} = 1/4.04, High (M = 6.44) vs. Low (M = 6.37)	B_{10} = 1/4.11, High (M = 1.58) vs. Low (M = 1.59)
Time:Training	B_{10} = 1/3.76, Active-Time 1 (M = 9.20) vs. Passive-Time 1 (M = 9.98), Active-Time 2 (M = 9.96) vs. Passive-Time 2 (M = 10.18)	B_{10} = 1/1.73, Active-Time 1 (M = 6.25) vs. Passive-Time 1 (M = 6.18), Active-Time 2 (M = 6.92) vs. Passive-Time 2 (M = 6.25)	B_{10} = 1/1.56, Active-Time 1 (M = 1.46) vs. Passive-Time 1 (M = 1.39), Active-Time 2 (M = 1.90) vs. Passive-Time 2 (M = 1.59)
SES:Training	B_{10} = 1.36, High-Active (M = 10.03) vs. Low-Active (M = 9.14), Low-Active (M = 9.14) High-Passive (M = 8.65) vs.	B_{10} = 1/2.49, High-Active (M = 6.54) vs. Low-Active (M = 6.63), Low-Active (M = 6.63) High-Passive (M = 6.34) vs.	B_{10} = 1/3.34, High-Active (M = 1.68) vs. Low-Active (M = 1.69), High-Passive (M = 1.49) vs. Low-Passive (M = 1.49)
SES:Time	B_{10} = 1/3.62, High-Time 1 (M = 9.26) vs. Low-Time 1 (M = 9.92), High-Time 2 (M = 9.41) vs. Low-Time 2 (M = 10.73)	B_{10} = 1/3.04, High-Time 1 (M = 6.24) vs. Low-Time 1 (M = 6.20), High-Time 2 (M = 6.63) vs. Low-Time 2 (M = 6.54)	B_{10} = 1/2.95, High-Time 1 (M = 1.43) vs. Low-Time 1 (M = 1.42), High-Time 2 (M = 1.74) vs. Low-Time 2 (M = 1.75)

Table 9 (Continued)

Scenario 7			
	Average Velocity	SD Velocity	Average Absolute Acceleration
Training:Time:SES	B_{10} = 1/2.54, Active-Time 1-High (*M* = 9.93) vs. Active-Time 1-Low (*M* = 8.48), Passive-Time 1-High (*M* = 8.59), Passive-Time 1-Low (*M* = 11.36), Active-Time 2-High (*M* = 10.13) vs. Active-Time 2-Low (*M* = 9.80), Passive-Time 2-High (*M* = 8.70) vs Passive-Time 2-Low (*M* = 11.67)	B_{10} = 1/1.31, Active-Time 1-High (*M* = 6.03) vs. Active-Time 1-Low (*M* = 6.48), Passive-Time 1-High (*M* = 6.46), Passive-Time 1-Low (*M* = 5.91), Active-Time 2-High (*M* = 7.05) vs. Active-Time 2-Low (*M* = 6.79), Passive-Time 2-High (*M* = 6.22) vs Passive-Time 2-Low (*M* = 6.29)	B_{10} = 1/2.34, Active-Time 1-High (*M* = 1.44) vs. Active-Time 1-Low (*M* = 1.49), Passive-Time 1-High (*M* = 1.42), Passive-Time 1-Low (*M* = 1.35), Active-Time 2-High (*M* = 1.92) vs. Active-Time 2-Low (*M* = 1.89), Passive-Time 2-High (*M* = 1.56) vs Passive-Time 2-Low (*M* = 1.63)

Table 10

Results of the statistical analyses on the vehicle control measures Scenario 8.

	Scenario 8		
	Average Velocity	SD Velocity	Average Absolute Acceleration
Training	B_{10} = 1/4.11, Active (M = 18.11) vs. Passive (M = 17.57)	B_{10} = 1/1.34, Active (M = 2.01) vs. Passive (M = 2.53)	B_{10} = 1/2.80, Active (M = 0.86) vs. Passive (M = 0.96)
Time	B_{10} = 1/3.96, Time 1 (M = 17.59) vs. Time 2 (M = 18.10)	B_{10} = 1/4.15, Time 1 (M = 2.37) vs. Time 2 (M = 2.17)	B_{10} = 1/3.97, Time 1 (M = 0.88) vs. Time 2 (M = 0.94)
SES	B_{10} = 1/3.33, High (M = 18.16) vs. Low (M = 17.52)	B_{10} = 1/4.20, High (M = 2.34) vs. Low (M = 2.19)	B_{10} = 1/4.01, High (M = 0.93) vs. Low (M = 0.89)
Time:Training	B_{10} = 1/2.95, Active-Time 1 (M = 17.62) vs. Passive-Time 1 (M = 17.55), Active-Time 2 (M = 18.60) vs. Passive-Time 2 (M = 17.59)	B_{10} = 1/3.25, Active-Time 1 (M = 2.17) vs. Passive-Time 1 (M = 2.56), Active-Time 2 (M = 1.85) vs. Passive-Time 2 (M = 2.49)	B_{10} = 1/3.57, Active-Time 1 (M = 0.84) vs. Passive-Time 1 (M = 0.92), Active-Time 2 (M = 0.87) vs. Passive-Time 2 (M = 1.00)
SES:Training	B_{10} = 1/2.92, High-Active (M = 18.73) vs. Low-Active (M = 17.48), Low-Active (M = 17.48) High-Passive (M = 17.59) vs.	B_{10} = 1/1.74, High-Active (M = 2.30) vs. Low-Active (M = 1.72), Low-Active (M = 1.72) High-Passive (M = 2.38) vs.	B_{10} = 1/1.49, High-Active (M = 0.96) vs. Low-Active (M = 0.75), High-Passive (M = 0.90) vs. Low-Passive (M = 1.02)
SES:Time	B_{10} = 1/2.76, High-Time 1 (M = 17.58) vs. Low-Time 1 (M = 17.59), High-Time 2 (M = 18.74) vs. Low-Time 2 (M = 17.45)	B_{10} = 1/3.15, High-Time 1 (M = 2.49) vs. Low-Time 1 (M = 2.24), High-Time 2 (M = 2.19) vs. Low-Time 2 (M = 2.15)	B_{10} = 1/3.13, High-Time 1 (M = 0.91) vs. Low-Time 1 (M = 0.85), High-Time 2 (M = 0.95) vs. Low-Time 2 (M = 0.92)

Table 10 (Continued)

	Scenario 8		
	Average Velocity	SD Velocity	Average Absolute Acceleration
Training:Time:SES	B_{10} = 1/2.68, Active-Time 1-High (*M* = 17.77) vs. Active-Time 1-Low (*M* = 17.47), Passive-Time 1-High (*M* = 17.39), Passive-Time 1-Low (*M* = 17.72), Active-Time 2-High (*M* = 19.7) vs. Active-Time 2-Low (*M* = 17.5), Passive-Time 2-High (*M* = 17.78) vs Passive-Time 2-Low (*M* = 17.41)	B_{10} = 1/2.81, Active-Time 1-High (*M* = 2.43) vs. Active-Time 1-Low (*M* = 1.92), Passive-Time 1-High (*M* = 2.56), Passive-Time 1-Low (*M* = 2.56), Active-Time 2-High (*M* = 2.17) vs. Active-Time 2-Low (*M* = 1.53), Passive-Time 2-High (*M* = 2.21) vs Passive-Time 2-Low (*M* = 2.78)	B_{10} = 1/2.89, Active-Time 1-High (*M* = 0.95) vs. Active-Time 1-Low (*M* = 0.74), Passive-Time 1-High (*M* = 0.87), Passive-Time 1-Low (*M* = 0.96), Active-Time 2-High (*M* = 0.96) vs. Active-Time 2-Low (*M* = 0.77), Passive-Time 2-High (*M* = 0.93) vs Passive-Time 2-Low (*M* = 1.08)

Exploratory Analyses

Moderation analysis.

It is possible that categorizing participants into high- and low-SES groups may have reduced the statistical power to detect a potential interaction between SES and Training. Moderation analysis is a form of multiple regression that explores the conditional effects of predictors on an outcome variable by including interaction terms (Memon et al., 2019). This approach can effectively utilize continuous predictors to maintain their variability and increase the statistical power of the analysis. Thus, in this moderation analysis, SES was treated as a continuous measure.

Driver' SES level did not significantly moderate the effect of Training on HA, β = -.002, *SE* = .040, 95% CI [-.080, .077], *p* = .967, (Table 11). Consistent with the ANOVA results, the effect of Training on HA was significant, β = -.092, *SE* = .039, 95% C.I [-.169, -.016], *p* = .019, indicating the superior hazard anticipation performance in the active training group (*M* = .627) than participants in the passive training group (*M* = .541). Finally, the effect of SES on HA was not significant, β = .038, *SE* = .061, 95% CI [-.082, .158], *p* = .533.

Table 11

Results of a moderation analysis of Training and SES on HA performance

Variable	Coefficient (β)	Standard Error (SE)	t	Sig	95% CI Lower	95% CI Upper
Training	-.092	.039	-2.388	.019*	-.169	-.016
SES	.038	.061	.626	.533	-.082	.158
Training x SES	-.002	.040	-.041	.967	-.080	.077

Note. For the interaction term Training is the focal predictor and SES is the moderator. Significance levels *$p < .05$.

Logistic regression.

A follow-up logistic regression was performed to explore whether the driving scenarios differentially influenced drivers' hazard anticipation as a function of Time and SES. It is possible that different characteristics and geometric features of the tested scenarios impacted the participants' ability to anticipate hazards depending on their SES levels. Logistic regression is rooted in the odds of a two-level outcome such as a binary or dichotomous variable (Lavalley, 2008). For example, one level of the outcome variable may represent that an event of interest occurred, while the other level represents the events absence. The output of logistic regression analysis are estimates of the probability ratio of the event occurring divided by the probability of the event not occurring (LaValley, 2008). For this analysis, the raw binary measure of a "1" indicating the participant successfully anticipating the hazard, and a "0" indicating their failure to anticipate the hazard was entered as a dependent variable. The best fitting model was determined using the glmulti package in R, which determined the most parsimonious models while penalizing model complexity to avoid overfitting. The best fitting model, model 4 (Table 12), showed a strong predictive ability (C = .838), and was submitted to the logistic regression analyses using the glmer package in R.

Table 12

A list of model fits to the current data.

Model	Model Structures	AIC	Residual deviance
1	Training + Time + Scenario + Time*Training	927.5	853.4
2	Training + Time + Scenario	932.9	869.3
3	Training + SES + Time + Scenario + Time*Training + Time*SES + Scenario*Training + Scenario*SES	939.3	831.4
4	Training + SES + Time + Scenario + Time*Training + Time*SES +Scenario*Time	922.0	810.1
5	Training + SES + Time + Scenario + Time*Training +Time*SES + Scenario*Training + Scenario*Time	931.2	808.1

Consistent with the previous analysis, there was a significant effect of Time, β = 1.90, *SE* = .58, Wald's χ^2 = 10.61, p = .001, exp(β) = 6.67, 95% CI [2.13, 20.89]. The odds of successfully anticipating the hazards were 6.67 times greater during the posttest than the pretest. Once again, a significant Training by Time interaction was found, $\beta = -0.99$, $SE = .35$, Wald's $\chi^2 = 8.25$, $p = .004$, $\exp(\beta) = 0.37$, 95% CI [0.19, 0.73]. The change in the odds of anticipating the hazard from pretest to posttest was 2.70 times lower for drivers that received passive training than the change for drivers that received active training. Similar to the previous analysis, there was a significant interaction between SES and Time, $\beta = -1.14$, $SE = .35$, Wald's $\chi^2 = 10.72$, $p = .001$, $\exp(\beta) = 0.32$, 95% CI [0.16, 0.63]. The pretest-to-posttest change in the odds of anticipating the hazard was 3.13 times greater for high-SES drivers than the change in the odds of anticipating hazards for low-SES drivers.

There was a significant effect for Scenario 3, $\beta = -1.64$, $SE = .47$, Wald's $\chi^2 = 12.42$, $p < .001$, $\exp(\beta) = 0.19$, 95% CI [0.08, 0.48], indicating the odds of anticipating the hazard were 5.26 times lower in Scenario 3 than in Scenario 1. There was a significant effect for Scenario 4, $\beta = -1.81$, $SE = .48$, Wald's $\chi^2 = 14.48$, $p < .001$, $\exp(\beta) = 0.16$, 95% CI [0.06, 0.42]. Thus, the odds of anticipating the hazard were 6.25 times lower in Scenario 4 than Scenario 1. There was also a significant effect for Scenario 8, $\beta = -3.81$, $SE = .71$, Wald's $\chi^2 = 29.07$, $p < .001$, $\exp(\beta) = 0.02$, 95% CI [0.01, 0.09], indicating the odds of anticipating the hazard were 50 times lower in Scenario 8 than in Scenario 1. None of the other effects were significant (all p's > .107; Table 13).

Table 13

The results of the logistic regression analysis.

Predictor	β (SE)	Wald's χ^2	Sig	Exp(β)	95% CI Lower	95% CI Upper
Training	-0.04 (0.24)	0.02	.876	0.96	0.60	1.55
SES	0.35 (0.24)	2.11	.147	1.42	0.88	2.29
Time	1.90 (0.58)	10.61	.001**	6.67	2.13	20.89
Scenario 2	0.10 (0.46)	0.05	.827	1.11	0.45	2.74
Scenario 3	-1.64 (0.47)	12.42	<.001***	0.19	0.08	0.48
Scenario 4	-1.81 (0.48)	14.48	<.001***	0.16	0.06	0.42
Scenario 5	-0.45 (0.45)	1.01	.316	0.64	0.26	1.54
Scenario 6	0.35 (0.47)	0.54	.463	1.42	0.56	3.58
Scenario 7	0.13 (0.46)	0.08	.777	1.14	0.46	2.82
Scenario 8	-3.81 (0.71)	29.07	<.001***	0.02	0.01	0.09
Training:Time	-0.99 (0.35)	8.25	.004**	0.37	0.19	0.73
SES:Time	-1.14 (0.35)	10.72	.001**	0.32	0.16	0.63
Time:Scenario 2	-0.01 (0.72)	0.00	.986	0.99	0.24	4.03
Time:Scenario 3	-0.16 (0.66)	0.06	.811	0.85	0.23	3.14
Time:Scenario 4	-0.68 (0.67)	1.01	.315	0.51	0.14	1.90
Time:Scenario 5	-0.59 (0.67)	0.79	.374	0.55	0.15	2.04
Time:Scenario 6	-0.32 (0.72)	0.20	.655	0.72	0.17	2.99
Time:Scenario 7	-0.87 (0.68)	1.64	.200	0.42	0.11	1.58
Time:Scenario 8	1.36 (0.84)	2.60	.107	3.89	0.75	20.31

Note. Reference groups for predictors are Training-Active, SES-High, Time-Pretraining, Scenario-1. Significance levels: $^*p < .05$, $^{**}p < .01$, $^{***}p < .001$.

CHAPTER IV

DISCUSSION

The current study investigated how the effectiveness of an existing driver attention training program, RAPT, varies across different levels of SES in a high-fidelity driving simulator. Past research has shown not only that RAPT is proven effective in improving HA performance in young drivers but also that the performance benefit of RAPT substantially varies on individual differences such as a driver's sex (Thomas et al., 2016), personality traits, and driving behaviors (Zhang et al., 2018). Recently, Roberts and colleagues (2021) proposed that RAPT training may be more effective for low-SES drivers than high-SES drivers based on their reanalysis of crash data in Thomas et al. (2016). Their study used the participant's accident rates as a dependent variable rather than HA, assuming that latent hazard anticipation skills mediate the effect of training on the number of crashes, which has not been tested. Furthermore, the poverty rate of participant's reported zip codes served as a proxy to their SES levels, while a more direct measure of SES should be used to measure their SES levels. In the current driving simulator study, using a high-fidelity driving simulator and eye tracker, young drivers' (ages 18-22) latent HA performance was measured in eight driving scenarios that contained latent hazards, before and after the completion of either an active or passive training program. Instead of zip codes (Roberts et al., 2021), composite measure of each participant's SES was calculated based on self-reported parental education and family income and entered to the analysis.

First, the results suggest that drivers who completed the active training program anticipated a higher proportion of hazards than drivers that completed the passive training program, replicating the effectiveness of RAPT on latent hazard anticipation as reported in the previous on-road and simulator evaluation studies (Fisher et al, 2007; Pradhan et al., 2009; Unverricht et al., 2018). Indeed, there was no difference between training groups during the pretest, but in the posttest active-trained participants showed substantially better HA performance compared to participants exposed to the passive training. Among other simulator evaluation studies that analyzed only post-training performance, this study provides additional support that active learning of the training material via the 3M method (Mistake, Mitigate, Master) using the error-feedback mechanism is essential for improving young drivers' HA skills.

Socioeconomic Status

HA performance did not credibly vary across SES levels in the current study, indicating that, among young drivers, low-SES and high-SES individuals demonstrate measurably similar HA skills in the current simulated scenarios. Though low-SES drivers have been shown to have a higher accident rate than high-SES drivers (Sehat et al., 2012; Chen et al., 2010), the similar HA performance between low-SES and high-SES drivers found in this study suggests that HA skills may not entirely explain the SES-related disparity in accident rates as reported in Roberts et al. (2021). Surprisingly, there was also no interaction between SES and Training, suggesting that RAPT training is effective at improving HA performance regardless of SES levels. Therefore, these current results do not support the interaction between SES and training found by Roberts et al. (2021). One possibility is that the SES measure used by Roberts et al. (2021) was not valid because it was derived from the poverty rate of the zip code the participant resided in and did not include parental education data. In addition, the dependent measure used by Roberts et al., (2021) was participant's accident rate in the six months following training, not HA performance *per se*. Thus, the interaction between RAPT and accident rates may have been mediated by an unknown variable, which warrants further investigation.

The analysis revealed an unexpected, substantial interaction between SES and Time. This suggests that young drivers in the high-SES group can improve HA skills after multiple exposures to the same driving scenarios regardless of the type of training received. In contrast, low-SES drivers did not show such improvement with multiple exposures to the scenarios. It is not clear why high-SES drivers demonstrated a greater magnitude of HA improvement than low-SES drivers, from before to after completion of either type of RAPT. Among many possible explanations, one likely account is that high-SES drivers *remembered* the driving scenarios before they completed the training program when they were evaluated for their HA skills, incorporated their memory trace to their learning in the program, and demonstrated superior performance in the post-training evaluation, more than low-SES drivers. Research in Cognitive Psychology indicates that episodic memory is poorer among individuals with lower SES levels (Botdorf et al., 2022; Noble et al., 2012; Hackman & Farah, 2009). Episodic memory is a memory system that is closely associated with time and allows individuals to mentally re-experience past events along with the event's contextual and situational information (Tulving, 2002). Therefore, it is possible that high-SES drivers better contextualized scenarios they drove prior to the introduction of the training material, which led to better recollection and mental integration of the remembered scenarios to and from their learning of the training materials. This hypothesis should be tested directly in a driving simulator. Note that this episodic memory hypothesis does not necessarily explain all of these data in this study. For example, I did not observe credible interaction between SES and Training with comparable magnitude of the training effect in both SES groups. This indicates that it is possible that low-SES drivers improve their HA performance at a similar rate as high-SES drivers following the completion of the active training program, presumably unrelated to episodic memory abilities. Low-SES drivers may recruit a different mechanism that leverages elements from the active training program to offset SES related declines in episodic memory and boost their HA performance. Future research should explore how low-SES drivers may benefit more from driver training programs despite their potentially compromised episodic memory abilities. More generally, more experimentation is necessary for examining why low-SES drivers who completed RAPT may not show enhanced HA performance immediately after their completion of the training program but did show lower crash rates as reported in Roberts et al. (2021).

Vehicle Control Measures

The analysis of the vehicle control measures yielded just two effects of time, and one effect of training on average absolute acceleration. For the two effects of time, participants in the post-training session adjusted their speed more rapidly in Scenario 3 and Scenario 7 than they did during the pre-training session. Notably, Scenario 3 and Scenario 7 are the only scenarios in which the hazard was located immediately after a stop sign. Thus, this effect might have captured differences in deceleration before the stop sign or acceleration after the stop sign between the pre- and post-training sessions and thus may not be directly related to the latent hazard. The effect of training observed in Scenario 5 suggests that drivers exposed to passive training changed their speed more rapidly than active trained drivers. This was a small effect, and since there was no interaction between training and time for this measure in Scenario 5, it suggests that the training manipulation was not contributing to this effect.

Follow-up Analyses

The previous analysis showed no evidence that training effectiveness varied significantly across SES levels. However, one statistical approach with greater statistical power to investigate the hypothesis that Training effectiveness varies across levels of SES is a moderation analysis.

Moderation analyses investigate interactions such that a moderator modifies the focal predictor's effect on the outcome variable at different levels (Baron & Kenny 1986), independent of the effect of moderator on the outcome variable itself (Andersson et al., 2014). Roberts et al. (2021) argued that training was less effective for high-SES than low-SES drivers, as high-SES drivers "may have already been exposed to HA examples that were in RAPT because they were more likely to have taken driver education and to have driven with their parents." (Roberts et al., p. 458). This argument implies that SES modifies the main relationship between Training and accident rates by influencing the level of previous driving experience and training that drivers have before taking RAPT. Thus, in the current study, hypothesis 3 may have been better evaluated by testing a moderation effect of SES (moderator) on the effect of Training (focal predictor) on latent hazard anticipation (outcome variable).

Consistent with the previous analysis, though, SES was not shown to moderate the effect of Training on the HA performance of drivers. The results of this more powerful analysis suggest that RAPT training is similarly effective for drivers across SES levels. Thus, despite low-SES drivers being less likely to have access to driver training (Curry et al., 2012), low-SES drivers showed similar HA performance at the outset of training and receive measurably similar HA performance improvements after training.

Why do the results of the current study and a previous study (Roberts et al., 2021) differ on the impact of SES on the effectiveness of RAPT? First, it is possible that the measure that Roberts et al. (2021) used may not be the most suited for validly measuring SES. As stated previously, the interaction reported by Roberts et al. (2021) may be mediated by an unknown third variable rather than by HA. Second, it is also possible that the current experiment did not have sufficient power to detect the impact of SES. Given the observed variability of SES scores in the current sample, a measure of SES that is more accepted in the literature, and the observed data patterns, though, it is unlikely that the current experiment was substantially under-powered. Lastly, an interaction between SES and Training on HA performance reported in Roberts et al. (2021) may be present among novice drivers within the first six months of licensure, which was not observable in the 18-22 age group sampled here. Low-SES drivers sampled by Roberts et al., (2021) may have possessed worse HA skills before training and their HA performance deficits may have been offset by training. In contrast, the older drivers in the current study, aged 18-22, may have eliminated initial HA performance deficits with age as they accumulated driving experience. This was supported by Pradhan et al., (2005) who found HA performance improves with age; drivers aged 16-17 years with less than 6 months of driving experience exhibited the poorest HA skills, and drivers aged 60-75 years old demonstrated the best HA performance. These points imply that the reported effect of SES on the effectiveness of RAPT should be taken with caution.

The original analysis did not reveal the three-way interaction among Training, SES, and Time, while the Training by Time and SES by Time interactions were significant. Anecdotally, and observed in previous research (Pradhan et al., 2006), driving scenarios modeled in a driving simulator led to a broad range of hazard anticipation performance indicating different levels of difficulty across the scenarios tested. To explore this possibility, a logistic regression that included Scenario as a predictor of a binary response of HA.

Participants anticipated significantly fewer hazards in Scenario 3, Scenario 4, and Scenario 8, compared to the reference group, Scenario 1. There may be many reasons for participants poor performance in Scenario 4. One potential explanation is that, in Scenario 4, the hazard precursors were not as effective in cuing participants to the presence of the hazard as the other scenarios, whereas in Scenario 3 and Scenario 8, poor performance may be an artifact of the HA measure. According to Crundall et al. (2012; also Yahoodik & Yamani, 2021), drivers use their knowledge of the contextual structure of the *environment*, known as environmental precursors, to predict where potential hazards will emerge. For instance, drivers may anticipate that a high-sided stationary vehicle could mask a pedestrian, or a smaller vehicle if the obscured area contains another lane, and drivers use these precursors to predict the locations of a latent hazard (Crundall, 2016). Note that perception of a high-sided vehicle and an obscured lane are both necessary contextual cues that signal the driver of the presence of a potential latent hazard. In driving simulators, drivers only receive monocular cues like optic flow, relative size, and linear perspective to judge relative distance between objects in the simulated environment. However, binocular cues, such as visual disparity and certain monocular cues like motion parallax from head movements are missing, which is known to cause drivers to underestimate relative distances between objects in driving simulators (Schmieder & Schoener 2016; Kemeny & Panerai, 2003). Without these cues, drivers may have perceived the bus as filling the entire space between the centerline and curb and inaccurately perceived that the bus was within a two-lane road, rather than a four-lane road (see Figure 9). Thus, the driver would not have been cued to monitor the far front side of the bus for a vehicle to emerge.

Figure 9

Scenario 4 – Latent hazard obscured by bus.

Note. Scenario 4 from perspective view from within launch zone (top), and the lane obscured by the bus (bottom).

The poor HA performance in Scenario 3 and Scenario 8 may have been an artifact from the way HA is measured. For example, in Scenario 3 the target zone was located just after a stop sign, and the launch zone ended just before the stop sign. Because participants either slowed or came to a complete stop before reaching the crosswalk, they may not have prioritized checking for pedestrians emerging from the obscured crosswalk entrance. If participants checked the target zone for an emerging pedestrian by creeping forward past the stop sign, then it would not have been counted as a successful anticipation of the hazard because they would have been outside of the launch zone. In Scenario 8, the launch zone was quite small relative to the other driving scenarios. In this scenario, a truck in the left opposing lane obscured the right opposing lane where the latent hazard could emerge. The launch zone begins when drivers initiate the left-hand turn and ends when they crossed the path of the right lane of the opposing road where an obscured vehicle may emerge. Thus, the driver may not have had sufficient time to glance at the target zone while they were traversing the small launch zone. Future research may benefit from pilot testing scenarios to identify design issues and optimize their structure for exploring HA performance.

The results were consistent with the previous analysis that found an interaction between Training and Time, such that drivers exposed to the active RAPT training performed better than those that received passive training on the immediate evaluation. Thus, these data strongly support that RAPT training improves HA skills in young drivers. In addition, consistent with the previous analysis, the results showed an interaction between Time and SES. This interaction suggests that high-SES drivers were able to improve HA performance in the post-training evaluation after being exposed to the scenarios in the pre-training evaluation, whereas low-SES drivers were not able to improve performance from multiple exposures to simulated driving scenarios.

None of the Time by Scenario interactions were significant, and the best fitting model did not include the Training by Scenario interaction term. In addition, the best fitting model did not include the Scenarios by Training interaction term. Collectively, these results imply that it is unlikely that scenario difficulties, if any, impact hazard anticipation performance differently across either time points of evaluation or the types of driver training programs. Instead, different characteristics of driving scenarios tested in the virtual environment may influence, or determine, latent hazard anticipation performance regardless of the time and training factors tested here.

Theoretical and Practical Contributions

The current research has novel theoretical and practical implications for the domain of training and surface transportation. First, the results empirically demonstrate the superiority of the 3M training method that promotes active learning of HA skills compared to the passive training program. Past HA research utilized a placebo training program in which drivers were exposed to information about traffic safety laws (Yahoodik & Yamani, 2021; Taylor et al., 2011; Pollatsek et al., 2006; Pradhan et al., 2006). Due to the lack of pre-training performance data, the researchers necessarily assume that participant assignment to the training or placebo group did not have influence on the differences in HA performance in the post-training simulator evaluation. Additionally, a comparison between the training and placebo programs did not allow a direct test of whether the 3M method or the training material itself enhanced HA performance. This study addressed this gap by using a placebo training program that included information about HA, but participants were not induced to practice their HA skills, nor did they receive error feedback. The substantial improvements in HA performance that drivers exposed to active training showed, in contrast to the negligible improvements for drivers exposed to passive training, demonstrates the critical role of error feedback in learning higher cognitive skills. Thus, this study makes clear that error-based feedback of the sort provided by the 3M method is an effective means of improving higher cognitive skills like HA.

A practical implication of this study is that it demonstrates that RAPT training is equally beneficial for drivers across the socioeconomic spectrum. Low-SES drivers showed substantial improvements after being exposed to active training, an effect that was also observed for high-SES drivers. This insight may be particularly relevant for driving instructors and educators, as it suggests they can enhance the quality of the driver training they provide by implementing the RAPT training program into their education programs regardless of the SES background of their students. However, this implication should be taken with some caution that there may exist mechanisms that allow low-SES drivers to offset performance losses due to known differences in psychological mechanisms among individuals across SES levels such as episodic memory system.

Limitations

As with any driving simulator study, the results of the current study do not necessarily generalize to latent hazard anticipation in real-world driving environments. Given the observed variability in scenario difficulties, more optimized scenario design and rigorous testing of the scenarios are necessary for further elucidating the impact of the driver training program in young drivers. In particular, low-SES individuals may be underrepresented in the current sample, and therefore the results may not necessarily generalize to the general population of lower-SES drivers. The sample of drivers in this study was drawn from a university population where individuals typically have a higher SES than the general population, and low-SES individuals are less likely to attend college than individuals with a medium- and high-SES (Sewell & Shaw, 1967).

CHAPTER V

CONCLUSIONS

This study evaluated the effectiveness of an active driver attention training program, RAPT, compared to the passive training program in a high-fidelity driving simulator using eye tracking technology. Further, I examined how the impact of RAPT varies across different levels of SES for drivers. Results show that drivers who completed the existing active training program, which employs the 3M (Mistake, Mitigate, and Master) training mechanism, identified latent hazards in more simulated scenarios than those who completed the passive training program which did not use the 3M method. Unexpectedly, the effectiveness of the training programs was comparable for drivers across the SES spectrum. These data contribute to the theory of HA training by supporting an active training approach using error-based feedback as the training mechanism, as opposed to a passive training approach that simply exposes trainees to training material without the opportunity to make and correct mistakes via specific error feedback. Further, the results imply that the training programs can be equally effective to trainees in different SES groups. Yet, this conclusion should be interpreted with caution given that the current study used only a small sample of the university students and that there exist other unexplored psychological mechanisms such as episodic memory that are implicated to operate differently across individuals with different SES backgrounds. However, it is noteworthy that the effect of the existing training program, regardless of if it is active or passive, does not diminish in low-SES drivers, and this point can be incorporated into driver education programs to improve the HA performance of young drivers (cf. Thomas et al., 2016).

REFERENCES

Agrawal, R., Knodler, M., Fisher, D. L., & Samuel, S. (2018). Virtual reality headset training: Can it be used to improve young drivers' latent hazard anticipation and mitigation skills. *Transportation Research Record*, *2672*(33), 20-30. https://doi.org/10.1177/0361198118758311

Andersson, U., Cuervo-Cazurra, A., & Nielsen, B. B. (2014). From the Editors: Explaining interaction effects within and across levels of analysis. *Journal of International Business Studies*, *45*(9), 1063–1071. https://doi.org/10.1057/jibs.2014.50

Arnett, J. (1994). Sensation seeking: A new conceptualization and a new scale. *Personality and individual differences*, *16*(2), 289-296. https://doi.org/10.1016/0191-8869(94)90165-1

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173–1182. https://doi.org/10.1037//0022-3514.51.6.1173

Botdorf, M., Dunstan, J., Sorcher, L., Dougherty, L. R., & Riggins, T. (2022). Socioeconomic disadvantage and episodic memory ability in the ABCD sample: Contributions of hippocampal subregion and subfield volumes. *Developmental Cognitive Neuroscience*, *57*, 101138. https://doi.org/10.1016/j.dcn.2022.101138

Braitman, K. A., Kirley, B. B., McCartt, A. T., & Chaudhary, N. K. (2008). Crashes of novice teenage drivers: Characteristics and contributing factors. *Journal of safety research*, *39*(1), 47-54. https://doi.org/10.1016/j.jsr.2007.12.002

Buss, A. H., & Perry, M. (1992). The aggression questionnaire. *Journal of personality and social psychology*, *63*(3), 452. https://doi.org/10.1037/0022-3514.63.3.452

Chen, H. Y., Senserrick, T., Martiniuk, A. L. C., Ivers, R. Q., Boufous, S., Chang, H. Y., & Norton, R. (2010). Fatal crash trends for Australian young drivers 1997-2007: Geographic and socioeconomic differentials. *Journal of Safety Research*, *41*(2), 123–128. https://doi.org/10.1016/j.jsr.2009.12.006

Curry, A. E., Hafetz, J., Kallan, M. J., Winston, F. K., & Durbin, D. R. (2011). Prevalence of teen driver errors leading to serious motor vehicle crashes. *Accident Analysis & Prevention*, *43*(4), 1285-1290. https://doi.org/10.1016/j.aap.2010.10.019

Curry, A. E., Hafetz, J., Kallan, M. J., Winston, F. K., & Durbin, D. R. (2011). Prevalence of teen driver errors leading to serious motor vehicle crashes. *Accident Analysis & Prevention*, *43*(4), 1285–1290. https://doi.org/10.1016/j.aap.2010.10.019

Crundall, D. (2016). Hazard prediction discriminates between novice and experienced drivers. *Accident Analysis & Prevention*, *86*, 47–58. https://doi.org/10.1016/j.aap.2015.10.006

Crundall, D., Chapman, P., Trawley, S., Collins, L., van Loon, E., Andrews, B., & Underwood, G. (2012). Some hazards are more attractive than others: Drivers of varying experience respond differently to different types of hazard. *Accident Analysis & Prevention*, *45*, 600–609. https://doi.org/10.1016/j.aap.2011.09.049

Crundall, D. E., & Underwood, G. (1998). Effects of experience and processing demands on visual information acquisition in drivers. *Ergonomics*, *41*(4), 448–458. https://doi.org/10.1080/001401398186937

Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. *Human factors*, *37*(1), 32-64. https://doi.org/10.1518/001872095779049543

Ensminger, M. E., Forrest, C. B., Riley, A. W., Kang, M., Green, B. F., Starfield, B., & Ryan, S. A. (2000). The Validity of Measures of Socioeconomic Status of Adolescents. *Journal of Adolescent Research*, *15*(3), 392–419. https://doi.org/10.1177/0743558400153005

Fisher, D. L., Pollatsek, A. P., & Pradhan, A. (2006). Can novice drivers be trained to scan for information that will reduce their likelihood of a crash? *Injury Prevention*, *12*(Suppl 1), i25–i29. https://doi.org/10.1136/ip.2006.012021

Fisher, D. L., Pradhan, A. K., Pollatsek, A., & Knodler, M. A. (2007). Empirical Evaluation of Hazard Anticipation Behaviors in the Field and on Driving Simulator Using Eye Tracker. *Transportation Research Record: Journal of the Transportation Research Board*, *2018*(1), 80–86. https://doi.org/10.3141/2018-11

Fisher, D. L., Narayanaan, V., Pradhan, A., & Pollatsek, A. (2004). Using eye movements in driving simulators to evaluate effects of PC-based risk awareness training. *In Proceedings of the Human Factors and Ergonomics Society Annual Meeting 48*(19), 2266-2270. https://doi.org/10.1177/154193120404801913

Foss, R., Masten, S., & Martell, C. (2014). *Examining the Safety Implications of Later Licensure: Crash Rates of Older vs. Younger Novice Drivers Before and After Graduated Driver Licensing*. https://trid.trb.org/View/1345927

Garay-Vega, L., Fisher, D. L., & Pollatsek, A. (2007). Hazard Anticipation of Novice and Experienced Drivers: Empirical Evaluation on a Driving Simulator in Daytime and Nighttime Conditions. *Transportation Research Record*, *2009*(1), 1–7. https://doi.org/10.3141/2009-01

Grayson, G. B., & Sexton, B. F. (2002). *The development of hazard perception testing*.

Hackman, D. A., & Farah, M. J. (2009). Socioeconomic status and the developing brain. *Trends in Cognitive Sciences*, *13*(2), 65–73. https://doi.org/10.1016/j.tics.2008.11.003

Harper, S., Charters, T. J., & Strumpf, E. C. (2015). Trends in socioeconomic inequalities in motor vehicle accident deaths in the United States, 1995–2010. *American journal of epidemiology*, *182*(7), 606-614. https://doi.org/10.1093/aje/kwv099

Horswill, M., & McKenna, F. (2004). Drivers' hazard perception ability: situation awareness on the road. In S. Banbury & S. Tremblay (Eds.), A cognitive approach to situation awareness (pp. 155–175). Ashgate.

Insurance Institute for Highway Safety (IIHS). Fatality Facts (2022) - Yearly Snapshot. May 2022. https://www.iihs.org/topics/fatality-statistics/detail/yearly-snapshot.

Jeffreys, H. (1998). *The theory of probability*. OuP Oxford.

Krishnan, A., Samuel, S., Yamani, Y., Romoser, M. R. E., & Fisher, D. L. (2019). Effectiveness of a strategic hazard anticipation training intervention in high risk scenarios. *Transportation Research Part F: Traffic Psychology and Behaviour*, *67*, 43–56. https://doi.org/10.1016/j.trf.2019.10.004

Kemeny, A., & Panerai, F. (2003). Evaluating perception in driving simulation experiments. *Trends in Cognitive Sciences*, *7*(1), 31–37. https://doi.org/10.1016/S1364-6613(02)00011-6

LaValley, M. P. (2008). Logistic Regression. *Circulation*, *117*(18), 2395–2399. https://doi.org/10.1161/CIRCULATIONAHA.106.682658

Males, M. A. (2009). Poverty as a determinant of young drivers' fatal crash risks. *Journal of safety research*, *40*(6), 443-448. https://doi.org/10.1016/j.jsr.2009.10.001

Crick, J., & McKenna, F. P. (1992). Hazard perception: Can it be trained? In *Behavioural research in road safety II. Proceedings of a seminar, 17-18 September 1991, Manchester University (TRL Published Article PA 2193/92).*

Mckenna, F. P., & Crick J. (1997). *Developments in Hazard Perception*. https://doi.org/10.13140/RG.2.1.1014.7680

Mourant, R. R., & Rockwell, T. H. (1970). Mapping Eye-Movement Patterns to the Visual Scene in Driving: An Exploratory Study. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *12*(1), 81–87. https://doi.org/10.1177/001872087001200112

McKnight, A. J., & McKnight, A. S. (2003). Young novice drivers: Careless or clueless? *Accident Analysis & Prevention*, *35*(6), 921–925. https://doi.org/10.1016/S0001-4575(02)00100-8

Memon, M. A., Cheah, J.-H., Ramayah, T., Ting, H., Chuah, F., & Cham, T. H. (2019). Moderation analysis: Issues and guidlines. *Journal of Applied Structural Equation Modeling*, *3*(1), i–xi. https://doi.org/10.47263/JASEM.3(1)01

Noble, K. G., Houston, S. M., Kan, E., & Sowell, E. R. (2012). Neural correlates of socioeconomic status in the developing human brain. Developmental Science, *15*(4), 516–527. https://doi.org/10.1111/j.1467-7687.2012.01147.x

Pelz, D. C., & Krupat, E. (1974). Caution profile and driving record of undergraduate males. *Accident Analysis & Prevention*, *6*(1), 45–58. https://doi.org/10.1016/0001-4575(74)90015-3

Pollatsek, A., Fisher, D. L., & Pradhan, A. (2006). Identifying and remedying failures of selective attention in younger drivers. *Current Directions in Psychological Science*, *15*(5), 255-259. https://doi.org/10.1111/j.1467-8721.2006.00447.x

Pollatsek, A., Narayanaan, V., Pradhan, A., & Fisher, D. L. (2006). Using Eye Movements to Evaluate a PC-Based Risk Awareness and Perception Training Program on a Driving Simulator. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *48*(3), 447–464. https://doi.org/10.1518/001872006778606787

Pradhan, A. K., Fisher, D. L., & Pollatsek, A. (2006). Risk Perception Training for Novice Drivers: Evaluating Duration of Effects of Training on a Driving Simulator. *Transportation Research Record: Journal of the Transportation Research Board*, *1969*(1), 58–64. https://doi.org/10.1177/0361198106196900108

Pradhan, A. K., & Crundall, D. (2016). Hazard avoidance in young novice drivers: Definitions and a framework. *In Handbook of teen and novice drivers*, 81-94. CRC Press. https://doi.org/10.1177/107118132064147

Pradhan, A. K., Hammel, K. R., DeRamus, R., Pollatsek, A., Noyce, D. A., & Fisher, D. L. (2005). Using Eye Movements To Evaluate Effects of Driver Age on Risk Perception in a Driving Simulator. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *47*(4), 840–852. https://doi.org/10.1518/001872005775570961

Roberts, S. C., Zhang, F., Fisher, D., & Vaca, F. E. (2021). The effect of hazard awareness training on teen drivers of varying socioeconomic status. *Traffic injury prevention*, *22*(6), 455-459. https://doi.org/10.1080/15389588.2021.1940984

Rouder, J. N., & Morey, R. D. (2012). Default Bayes factors for model selection in regression. *Multivariate Behavioral Research*, *47*(6), 877-903. https://doi.org/10.1080/00273171.2012.734737

Sackett, P. R., Kuncel, N. R., Arneson, J. J., Cooper, S. R., & Waters, S. D. (2009). Does socioeconomic status explain the relationship between admissions tests and postsecondary academic performance? Psychological Bulletin, *135*(1), 1–22. https://doi.org/10.1037/a0013978

Sackett, P. R., Kuncel, N. R., Beatty, A. S., Rigdon, J. L., Shen, W., & Kiger, T. B. (2012). The Role of Socioeconomic Status in SAT-Grade Relationships and in College Admissions Decisions. Psychological Science, *23*(9), 1000–1007. https://doi.org/10.1177/0956797612438732

Sehat, M., Naieni, K. H., Asadi-Lari, M., & Foroushani, A. R. (2012). Socioeconomic Status and Incidence of Traffic Accidents in Metropolitan Tehran: A Population-based Study. *International Journal of Preventive Medicine*, *3*(3).

Schöner, H.-P., Schmieder, H., Chardonnet, J.-R., Colombet, F., & Kemeny, A. (2022). *Verification of Stereoscopic Projection Systems for Quantitative Distance and Speed Perception Tasks*.

Sewell, W. H., & Shah, V. P. (1967). Socioeconomic Status, Intelligence, and the Attainment of Higher Education. Sociology of Education, *40*(1), 1. https://doi.org/10.2307/2112184

Slamecka, N. J. , & Graf, P. (1978). The generation effect: Delineation of a phenomenon. Journal of Experimental Psychology: Human Learning, Memory, and Cognition, *4*, 592–604.

Snow, R. W. (2000). 1999 National Highway Safety Survey: Monitoring Americans' Attitudes, Opinion, and Behaviors (No. 2000-1). http://www.ssrc.msstate.edu/publications

Spicer, R. A. (1964). *Human factors in traffic accidents. Final report*. Department of Health, Honolulu, Hawaii.

Sweller, J. Element Interactivity and Intrinsic, Extraneous, and Germane Cognitive Load. Educ Psychol Rev 22, 123–138 (2010). https://doi.org/10.1007/s10648-010-9128-5

Taylor, T. G. G., Masserang, K. M., Pradhan, A. K., Divekar, G., Samuel, S., Muttart, J. W., Pollatsek, A., & Fisher, D. L. (2011). Long Term Effects of Hazard Anticipation Training on Novice Drivers Measured on the Open Road. *Proceedings of the ... International Driving Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design*, *2011*, 187–194.

Tefft, B. C., Williams, A. F., & Grabowski, J. G. (2014). Driver licensing and reasons for delaying licensure among young adults ages 18-20, United States, 2012. *Injury Epidemiology*, *1*(1), 4. https://doi.org/10.1186/2197-1714-1-4

Thomas, F. D., Rilea, S., Blomberg, R. D., Peck, R. C., & Korbelak, K. T. (2016). Evaluation of the safety benefits of the risk awareness and perception training program for novice teen drivers (No. DOT HS 812 235). Dunlap and Associates, Inc.. https://doi.org/10.21949/1525804

Underwood, G., Chapman, P., Brocklehurst, N., Underwood, J., & Crundall, D. (2003). Visual attention while driving: sequences of eye fixations made by experienced and novice drivers. Ergonomics, *46*(6), 629-646. https://doi.org/10.1080/0014013031000090116

Underwood, G., Crundall, D., & Chapman, P. (2002). Selective searching while driving: The role of experience in hazard detection and general surveillance. Ergonomics, *45*(1), 1–12. https://doi.org/10.1080/00140130110110610

Unverricht, J., Samuel, S., & Yamani, Y. (2018). Latent hazard anticipation in young drivers: Review and meta-analysis of training studies. *Transportation research record*, *2672*(33), 11-19. https://doi.org/10.3141/2009-0

Wickens, C., Hutchins, S., Carolan, T., & Cumming, J. (2011). Investigating the Impact of Training on Transfer: A Meta-Analytic Approach. *Proceedings of the Human Factors* *and Ergonomics Society Annual Meeting*, *55*(1), 2138–2142. https://doi.org/10.1177/1071181311551446

Wickens, C. D., Hutchins, S., Carolan, T., & Cumming, J. (2013). Effectiveness of Part-Task Training and Increasing-Difficulty Training Strategies: A Meta-Analysis Approach. *Human Factors*, *55*(2), 461–470. https://doi.org/10.1177/0018720812451994

Yahoodik, S., & Yamani, Y. (2020, December). Attentional control in young drivers: Does training impact hazard anticipation in dynamic environments?. *In Proceedings of the Human Factors and Ergonomics Society Annual Meeting 64*(1), 1986-1990. https://doi.org/10.1177/1071181320641478

Yahoodik, S., & Yamani, Y. (2021). Effectiveness of risk awareness perception training in dynamic simulator scenarios involving salient distractors. Transportation Research Part F: Traffic Psychology and Behaviour, *81*, 295–305. https://doi.org/10.1016/j.trf.2021.06.009

Yamani, Y., Samuel, S., Knodler, M. A., & Fisher, D. L. (2016). Evaluation of the effectiveness of a multi-skill program for training younger drivers on higher cognitive skills. *Applied Ergonomics*, *52*, 135–141. https://doi.org/10.1016/j.apergo.2015.07.005

Yamani, Y., Samuel, S., Yahoodik, S., & Fisher, D. L. (2022). Identifying and remedying failures of hazard anticipation in novice drivers. Theoretical issues in ergonomics science, *23*(3), 333-346. https://doi.org/10.1080/1463922X.2021.1971323

Yamani, Y., Glassman, J., Alruwaili, A., Yahoodik, S. E., Davis, E., Lugo, S., Xie, K., & Ishak, S. (2023). Post Take-Over Performance Varies in Drivers of Automated and Connected Vehicle Technology in Near-Miss Scenarios. *Human Factors: The Journal of the Human*

Factors and Ergonomics Society, 00187208231219184. https://doi.org/10.1177/00187208231219184

Zhang, T., Hajiseyedjavadi, F., Wang, Y., Samuel, S., Qu, X., & Fisher, D. (2018). Training interventions are only effective on careful drivers, not careless drivers. *Transportation Research Part F: Traffic Psychology and Behaviour*, *58*, 693–707. https://doi.org/10.1016/j.trf.2018.07.004

APPENDIX A

INFORMED CONSENT DOCUMENT

OLD DOMINION UNIVERSITY

PROJECT TITLE: Analyzing driving behaviors using a driving simulator with automated features

INTRODUCTION

The purposes of this form are to give you information that may affect your decision whether to say YES or NO to participation in this research, and to record the consent of those who say YES. This research project, *Analyzing driving behaviors using a driving simulator with automated features,* will be conducted in Driving Simulator Laboratory (ECSB 1001) at Old Dominion University.

RESEARCHERS

Yusuke Yamani, Ph.D., Associate Professor, College of Sciences, Department of Psychology, Principal Investigator
Sarah Yahoodik, M.S., Ph.D. Candidate, College of Sciences, Department of Psychology
James Unverricht, M.S., Ph.D. Candidate, College of Sciences, Department of Psychology
Jeffrey Glassman, B.S., Ph.D. Student, College of Sciences, Department of Psychology

DESCRIPTION OF RESEARCH STUDY

This research is designed to investigate drivers' behaviors when using a driving simulator with automated driving features. We are specifically interested in how drivers control the vehicle with varying levels of support from automated driving systems in safety-critical situations including intersections and highway on-ramp merging scenarios.

EXCLUSIONARY CRITERIA

All participants in this research study must be at least 18 years of age with normal or corrected-to-normal visual acuity and normal color perception.

RISKS AND BENEFITS

RISKS: You will not be subject to any risks or discomforts in this experiment.

BENEFITS: You may not benefit directly from the present study. However, your participation in the study will serve to enhance our understanding of drivers' use of automated driving features.

COSTS AND PAYMENTS

The researchers want your decision about participating in this study to be absolutely voluntary. The main benefit to you for participating in this study is the extra credit or course credit points that you will earn for your class. Although they are unable to give you payment for participating in this study, if you decide to participate in this study, you will receive 1 Psychology Department research credit per hour of participation, which may be applied to course requirements or extra credit in certain Psychology courses. Equivalent credits may be obtained in other ways. You do not have to participate in this study, or any Psychology Department study, to obtain this credit.

CONFIDENTIALITY

The researchers will take reasonable steps to keep private information confidential. The researchers will keep any record of your participation in locked storage in the psychology department. Furthermore, individual participants results will not be distributed in any form. The results of the study aggregated across participants will be published in professional journals and/or book chapters.

WITHDRAWAL PRIVILEGE

It is OK for you to say NO. Even if you say YES now, you are free to say NO later, and walk away or withdraw from the study at any time. Your decision will not affect your relationship with Old Dominion University, or otherwise cause a loss of benefits to which you might otherwise be entitled.

COMPENSATION FOR ILLNESS AND INJURY

If you say YES, then your consent in this document does not waive any of your legal rights. However, in the event of illness arising from this study, neither Old Dominion University nor the researchers are able to give you any money, insurance coverage, free medical care, or any other compensation for such injury. In the event that you suffer injury as a result of participation in any research project, you may contact Dr. Yusuke Yamani at 757-683-4457 or Dr. Tancy Vandecar-Burdin the current IRB chair at 757-6833802 (or at tvandeca@odu.edu) at Old Dominion University, or the Old Dominion University Office of Research at 757-683-3460 who will be glad to review the matter with you.

VOLUNTARY CONSENT

By verbally agreeing to this form, you are saying several things. You are saying that you have read this form or have had it read to you, that you are satisfied that you understand this form, the research study, and its risks and benefits. The researchers should have answered any questions you may have had about the research. If you have any questions later on, then the researchers should be able to answer them:

If at any time you feel pressured to participate, or if you have any questions about your rights or this form, then you should call Dr. Vandecar-Burdin, the current IRB chair, at 7576833802, or the Old Dominion University Office of Research, at 7576833460.

And importantly, by verbally agreeing, you are telling the researcher that you DO agree to participate in this study.

APPENDIX B

APPLIED COGNITIVE PERFORMANCE LAB
DRIVING HISTORY QUESTIONNAIRE

This is a ***strictly confidential*** questionnaire. Only a randomly generated participant ID number, assigned by the research administrator, will be on this questionnaire. No information reported by you here will be traced back to you personally in any way. **You can skip any questions you do not feel comfortable answering.**

Section 1: Demographics

Sex: □ Male □ Female

Date of Birth: (Month / Day / Year): _______ / _______ / _______ Age: ___________

Race / Ethnicity: (check all that apply)
□ Black / African American
□ Caucasian
□ Hispanic / Latino
□ Asian
□ American Indian / Native Alaskan
□ Other

Have you participated in a study at this laboratory in the past? □ Yes □ No

Section 2: Driving History

Approximately how long have you had your driver's license? _______ years _______ months

About how many miles did you drive since your licensure? ____________ miles

Does your license require you to wear glasses or contacts while driving? □ Yes, eyeglasses □ Yes, contacts □ No

Do you have any other restrictions on your driver's license? □ Yes □ No

If yes, please describe: ____

Are you currently on any over-the-counter or prescription medications that make it difficult to drive? □ Yes □ No

If yes, please describe: ____

Section 2: Driving History (continued)

Do you think text messaging while driving could affect your driving performance? □ Yes □ Maybe □ No

How frequently do you text message in a day? □ Over 20 □ 10 - 20 □ 5 - 10 □ Less than 5 □ Never

Within the last three years, have you had any moving violations? □ Yes □ No

If so, what type and how many?

□ Speeding How many times? _____
□ Running red light How many times? _____
□ Running stop sign How many times? _____
□ Failure to yield How many times? _____
□ Other ______________ How many times? _____

Within the last three years, have you been involved in any automobile crashes? □ Yes □ No

If so, what type of crashes(s)? (Please check all that apply)

□ Head-on collision (front of car to front of car contact)
□ Rear-end collision (front of car to rear of car contact)
□ Side impact or angled collision (front of car to side of car contact)
□ Sideswipe (door to door contact)
□ Single car accident (struck tree, sign, pedestrian)
□ Multiple car accident (more than two cars involved)
□ Other
□ I don't remember

APPENDIX C

DEMOGRAPHIC INFORMATION SHEET

Demographic Information Sheet

Office Use	Study ID:________
Near Vision: _______ Far: _____ Color______	

Applied Cognitive Performance Laboratory

Date of Birth: _____________ Age: ___

Health: 1 2 3 4 5
Poor -> Excellent (circle one)

Gender: ☐Male ☐Female

Race: _________________________

Native Language: ______________________ Second Language: _________________

How many years of education has your father completed? _________ years

How many years of education has your mother completed? _________ years

What was your family's total yearly income growing up? _________

Please circle True/False for the following.

Do you wear Glasses/Contacts on a regular basis? True False
Have you been diagnosed with any neuropsychological dysfunction? True False
If so, are you currently taking any medication for this? True False

How many years of education have you completed (Please record a number)? ____
Please note: grade school through high school is usually 12 years in the US, if needed, add on how many years of college you have completed.

APPENDIX D

BAYES FACTOR DESIGN ANALYSIS

Sample Code (Fixed-n design)

```
sim <- BFDA.sim(expected.ES = rnorm(10000, 0.95, .1), type = "t.paired", n.max = 48,stepsize
= 1, design = "fixed.n", B = 10000, alternative = "two.sided", verbose = FALSE, cores = 1)

BFDA.analyze(sim, design = "fixed", n= 48, boundary = c(1/3,3))
```

VITA

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Education

Bachelor of Arts: Psychology, May 2021 (*Summa Cum Laude*)
University of Connecticut, Storrs, CT

Publications

Glassman, J,. Yahoodik, S., Samuel, S., Young, J., Knodler, M., Zhang, L., Fisher, D., & Yamani, Y. (2022). Booster dose of driver training program for young novice drivers: A longitudinal driving simulator evaluation study. *Human Factors.*

Yamani, Y., **Glassman, J**., Alruwaili, A., Yahoodik, S. E., Davis, E., Lugo, S., Xie, K., & Ishak, S. (2023). Post Take-Over Performance Varies in Drivers of Automated and Connected Vehicle Technology in Near-Miss Scenarios. *Human Factors.*

Conference Proceedings

Glassman, J., Yamani, Y., Politowicz, M., Transfer and retention: A systematic exploration of the effect of a driver attention training program. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, Atlanta, Georgia.

Glassman, J,. Yahoodik, S., Samuel, S., Young, J., Knodler, M., Zhang, L., Fisher, D., Yamani, Y. (2022) A driving simulator evaluation of second dose of an integrated driver training program. Presented at Applied Human Factors and Ergonomics Conference, Manhattan, New York.

Experience

2021 – present Graduate Research Assistant, Applied Cognitive Performance Laboratory, Old Dominion University. (Dr. Yusuke Yamani)

2024 – present SONA Administrator Old Dominion University

2023 NSF Research Experience for Undergraduates (REU) Mentor, Old Dominion University.

2022 NSF Research Experience for Undergraduates (REU) Mentor Old Dominion University.

2019 – 2021 Undergraduate Research Assistant University of Connecticut. (Dr. Janet Barnes-Farrel)

2019 Undergraduate Research Assistant, University of Connecticut. (Dr. Alexandra Paxton)