

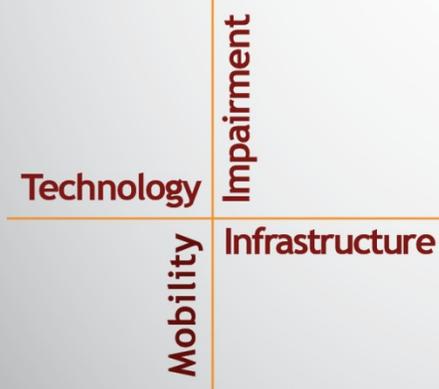
NSTSCCE

National Surface Transportation Safety Center for Excellence

An On-Road Evaluation of the Impact of Explicit and Implicit Cognitive Training Protocols on Safety-Related Senior Driver Behaviors

Jon Antin, Ph.D., CHFP • Justin Owens, Ph.D. • Brian Wotring

Submitted: April 21, 2017



ACKNOWLEDGMENTS

The authors of this report would like to acknowledge the support of the stakeholders of the National Surface Transportation Safety Center for Excellence (NSTSCE): Tom Dingus from the Virginia Tech Transportation Institute, John Capp from General Motors Corporation, Lincoln Cobb from the Federal Highway Administration, Chris Hayes from Travelers Insurance, Martin Walker from the Federal Motor Carrier Safety Administration, and Cathy McGhee from the Virginia Department of Transportation and the Virginia Transportation Research Council.

The NSTSCE stakeholders have jointly funded this research for the purpose of developing and disseminating advanced transportation safety techniques and innovations.

The project team wishes to gratefully acknowledge the contributions of several individuals to this research effort. Drs. Kazu Ebe and James Foley (Toyota Collaborative Safety Research Center) and Kenji Kimura-san (Toyota Motor Corp.) provided support and guidance on the project design. Jeremy Sudweeks provided expert advice regarding the statistical analyses. Additional project personnel included Jennifer Mullen, Laurel Marburg, and Naomi Dunn, Ph.D.

ABSTRACT

This study presents a long-term examination of the effects of two types of perceptual-cognitive brain training programs on senior driver behavior and on-road driving performance. Seniors over the age of 69 engaged in either a Toyota-designed in-vehicle training program based on implicit learning principles or a commercially available computer-based training program developed by Posit Science®. Another group served as a control group and received no training; total enrollment was 55 participants. Participants completed a series of four experimental sessions: (1) baseline pre-training, (2) immediate post-training, (3) 6–9 months post-training, and (4) 12–16 months post-training. Experimental metrics taken at each session included a laboratory metrics portion, a target-detection performance on a closed-road course, and a public-road portion examining vehicle control and glance behavior. These sessions were designed to examine not only whether training provided immediate benefit to senior drivers, but also whether any improvements persisted after training or precluded decrements in performance found in untrained individuals. The results found few statistically significant improvements in performance with either type of training. However, there were non-significant trends toward improved glance behavior at risky intersections for participants in the Car Training group, suggesting that this might be a valuable target of future research using experimental designs with increased statistical power. In addition, several tests of training improvements examined by individual differences suggested that drivers with particular deficits on physical and cognitive metrics could benefit differentially from this type of training, leading to future research questions on appropriate targeting and the potential benefits of refresher training.

TABLE OF CONTENTS

LIST OF FIGURES.....	v
LIST OF TABLES.....	xi
LIST OF ABBREVIATIONS AND SYMBOLS	xiii
CHAPTER 1. INTRODUCTION.....	1
BACKGROUND	1
<i>Self-Restriction</i>	2
<i>Functional Impairment</i>	2
BRAIN TRAINING.....	2
TRAINING METHODS	5
<i>Toyota In-Vehicle</i>	5
CHAPTER 2. METHODS	7
TRAINING PROGRAMS.....	7
<i>In-Vehicle Training</i>	7
<i>Computer Training</i>	10
<i>Control Group</i>	14
EXPERIMENTAL DESIGN	14
DEPENDENT MEASURES	15
PARTICIPANTS.....	16
<i>Recruitment</i>	16
<i>Screening</i>	16
APPARATUS	19
<i>Vision Tester</i>	19
<i>Experimental Vehicle and Onboard Data Acquisition System</i>	19
<i>Peripheral Detection Tasks (PDT)</i>	22
EXPERIMENTAL PROCEDURES.....	23
<i>Experimental Sessions</i>	24
CHAPTER 3. RESULTS.....	35
ON-ROAD METRICS	35
<i>Standard Deviation of Speed</i>	35
<i>Standard Deviation of Lane Position</i>	38
<i>Glance Entropy</i>	39
<i>Intersection Glance Entropy</i>	40
<i>Road Segment Glance Entropy</i>	42
TEST TRACK METRICS	44
<i>Roadside Object Detection Distance</i>	44
<i>Vehicle-Centric Detection Task</i>	46
<i>Driver-Centric Peripheral Detection Task</i>	51
DIFFERENTIAL EFFECTS OF TRAINING BASED ON INDIVIDUAL DIFFERENCES	56
CHAPTER 4. RESULTS SUMMARY	61
DRIVER BEHAVIOR ON PUBLIC ROADS	61
<i>Standard Deviation of Speed</i>	61
<i>Standard Deviation of Lane Position</i>	61
<i>Glance Behavior: Intersections</i>	61
<i>Glance Behavior: Road Segments</i>	62
DRIVER VISUAL PERFORMANCE ON CLOSED COURSE.....	62
<i>Roadside Object Detection</i>	62
<i>Vehicle-Centric Detection Task</i>	63

<i>Driver-Centric Peripheral Detection Task</i>	63
<i>Training Effects by Individual Differences</i>	63
CHAPTER 5. DISCUSSION	65
OVERVIEW	65
REASONS FOR GENERAL LACK OF FINDINGS	65
FUTURE RESEARCH	67
GENERAL CONCLUSION	68
APPENDIX A. QUESTIONNAIRE ITEMS	71
APPENDIX B. STANDARDIZED PREDICTOR GRAPHS	85
ON-ROAD METRICS	85
<i>Physical Dimension</i>	85
<i>Visual Dimension</i>	91
<i>Cognitive Dimension</i>	97
SMART ROAD METRICS	103
<i>Physical Dimension</i>	103
<i>Visual Dimension</i>	107
<i>Cognitive Dimension</i>	112
REFERENCES	117

LIST OF FIGURES

Figure 1. Chart. Population percentage projections by age group (U.S. Census Bureau, 2012). 1

Figure 2. Illustration. Study overview..... 7

Figure 3. Photo. Green LED embedded in dashboard and aimed up at the windshield..... 8

Figure 4. Photo. Green training stimuli. 8

Figure 5. Photo. Testing red hood-mounted LEDs. 9

Figure 6. Photo. Finger-mounted PDT response button. 9

Figure 7. Chart. DriveSharp training process (6 to 15 weeks total training time per participant). 11

Figure 8. Screen capture. Example Visual Sweeps sine wave grating test image. 12

Figure 9. Screen capture. Example Visual Sweeps participant response options..... 12

Figure 10. Screen capture. Example Target Tracker screen with yellow arrows added to point out the target bubbles; all others are distractors. 13

Figure 11. Screen capture. Example Double Decision test image showing the central car icon as well as the peripheral target and distractor images..... 14

Figure 12. Photo. Optec 6500P vision tester. 19

Figure 13. Photo. Study vehicle: 2012 Toyota Camry SE, pictured here with dGPS antenna affixed to the roof and the vehicle-centric PDT stalks affixed to the hood..... 20

Figure 14. Photo. VTTI Next-Gen DAS (grey box in back) and dGPS receiver (on metal plate)..... 20

Figure 15. Screen Capture. Video streams captured (from left moving clockwise: participant’s face, forward roadway, pedal interactions, rear roadway, and over-the-shoulder). 21

Figure 16. Photo. Emergency passenger-side brake..... 21

Figure 17. Photo. Vehicle-centric PDT apparatus. 22

Figure 18. Photo. Driver-centric PDT..... 23

Figure 19. Diagram. Example VMI test; the rightmost image matches the target image at top..... 25

Figure 20. Diagram. Illustration of the VS:A task..... 25

Figure 21. Diagram. Illustration of the VS:B task..... 26

Figure 22. Screen capture. The stimulus image flashed briefly on the screen (left) followed by the response screen (right) for the processing speed UFOV subtest. 26

Figure 23. Screen capture. Divided Attention UFOV subtest. The stimulus image (left) followed by the response screen (right). (#2 is the correct peripheral location choice)..... 27

Figure 24. Screen capture. Selective attention subtest showing distractor triangles..... 27

Figure 25. Photo. Illustration of Rapid Pace Walk.....	28
Figure 26. Photo. Depictions of the neck and torso flexibility tests. The left image shows rotation with the back flat on the chair; the right image shows the participant twisting through the torso.....	28
Figure 27. Diagram. The Virginia Smart Road.	30
Figure 28. Illustration. Instances of object categories.	31
Figure 29. Photo. Example location of a Sign object.	31
Figure 30. Map. Route driven during the public road driving segment of the study.....	32
Figure 31. Illustration. Some of the glance locations coded during data reduction.	33
Figure 32. Photo. Examples of the three road segments.	35
Figure 33. Chart. Standard deviation of speed for rural road segment.	36
Figure 34. Chart. Standard deviation of speed for the highway road segment.	37
Figure 35. Chart. Standard deviation of speed for the neighborhood road segment.	37
Figure 36. Chart. Standard deviation of lane position for the rural road segment.....	38
Figure 37. Chart. Standard deviation of lane position for highway road segment.....	39
Figure 38. Photo. Examples of intersection types.	40
Figure 39. Diagram. Example of reduction protocol for intersections.	40
Figure 40. Chart. Average glance entropy for unprotected left-turn intersection.	41
Figure 41. Chart. Average glance entropy for sign-protected left-turn intersection.....	41
Figure 42. Chart. Average glance entropy for signal-protected left-turn intersection.	42
Figure 43. Chart. Average glance entropy for 10s rural driving segment.....	43
Figure 44. Chart. Average glance entropy for 10s neighborhood driving segment.....	43
Figure 45. Chart. Average glance entropy for 10-s highway driving segment.....	44
Figure 46. Chart. Mean roadside object recognition distance.....	45
Figure 47. Chart. Mean roadside object recognition hit rate.	45
Figure 48. Chart. RT for vehicle-centric detection task combined.	47
Figure 49. Chart. RT for the left vehicle-centric detection task.....	47
Figure 50. Chart. RT for the center vehicle-centric detection task.....	48
Figure 51. Chart. RT for the right vehicle-centric detection task.....	48
Figure 52. Chart. Reaction time by light location.....	49
Figure 53. Chart. HR for the vehicle-centric detection task combined.	49
Figure 54. Chart. HR for the left vehicle-centric detection task.	50
Figure 55. Chart. HR for the center vehicle-centric detection task.	50

Figure 56. Chart. HR for the right vehicle-centric detection task.....	51
Figure 57. Chart. RT for the driver-centric PDT.....	52
Figure 58. Chart. RT for left driver-centric PDT.....	52
Figure 59. Chart. RT for the center driver-centric PDT.....	53
Figure 60. Chart. RT for the right driver-centric PDT.....	53
Figure 61. Chart. Reaction time by light location for driver-centric PDT.....	54
Figure 62. Chart. HR for the driver-centric PDT.....	54
Figure 63. Chart. HR for the left driver-centric PDT.	55
Figure 64. Chart. HR for the center driver-centric PDT.	55
Figure 65. Chart. HR for the right driver-centric PDT.	56
Figure 66. Chart. Average reaction time for the vehicle-centric detection task for the computer training group by z-score on physical metrics.....	58
Figure 67. Chart. Average reaction time for the vehicle-centric detection task for the car training group by z-score on cognitive metrics.	58
Figure 68. Chart. Average entropy for the car training group for straight road segments grouped by z-score on physical metrics.	59
Figure 69. Chart. Average lane variability for the control group by z-score on physical metrics.....	85
Figure 70. Chart. Average lane variability for the car training group by z-score on physical metrics.....	85
Figure 71. Chart. Average lane variability for the computer training group by z-score on physical metrics.....	86
Figure 72. Chart. Average speed variability for the control group by z-score on physical metrics.....	86
Figure 73. Chart. Average speed variability for the car training group by z-score on physical metrics.....	87
Figure 74. Chart. Average speed variability for the computer training group by z-score on physical metrics.....	87
Figure 75. Chart. Average entropy for the control group for straight road segments grouped by z-score on physical metrics.	88
Figure 76. Chart. Average entropy for the car training group for straight road segments grouped by z-score on physical metrics.	88
Figure 77. Chart. Average entropy for the computer training group for straight road segments grouped by z-score on physical metrics.....	89
Figure 78. Chart. Average entropy for the control group for intersections grouped by z-score on physical metrics.....	89

Figure 79. Chart. Average entropy for the car training group for intersections grouped by z-scores on physical metrics.....	90
Figure 80. Chart. Average entropy for the computer training group for intersections grouped by z-scores on physical metrics.....	90
Figure 81. Chart. Average lane variability for the control group by z-score on visual metrics.....	91
Figure 82. Chart. Average lane variability for the car training group by z-score on visual metrics.....	91
Figure 83. Chart. Average lane variability for the computer training group by z-score on visual metrics.....	92
Figure 84. Chart. Average speed variability for the control group by z-score on visual metrics.....	92
Figure 85. Chart. Average speed variability for the car training group by z-score on visual metrics.....	93
Figure 86. Chart. Average speed variability for the computer training group by z-score on visual metrics.....	93
Figure 87. Chart. Average entropy for the control group on straight road segments grouped by z-score on visual metrics.	94
Figure 88. Chart. Average entropy for the car training group for straight road segments grouped by z-score on visual metrics.	94
Figure 89. Chart. Average entropy for the computer training group for straight road segments grouped by z-score on visual metrics.....	95
Figure 90. Chart. Average entropy for the control group for intersections grouped by z-score on visual metrics.....	95
Figure 91. Chart. Average entropy for the car training group for intersections grouped by z-score on visual metrics.	96
Figure 92. Chart. Average entropy for the computer training group for intersections grouped by z-score on visual metrics.	96
Figure 93. Chart. Average lane variability for the control group by z-score on cognitive metrics.....	97
Figure 94. Chart. Average lane variability for the car training group by z-score on cognitive metrics.....	97
Figure 95. Chart. Average lane variability for the computer training group by z-score on cognitive metrics.....	98
Figure 96. Chart. Average speed variability for the control group by z-score on cognitive metrics.....	98
Figure 97. Chart. Average speed variability for the car training group by z-score on cognitive metrics.....	99

Figure 98. Chart. Average speed variability for the computer training group by z-score on cognitive metrics.	99
Figure 99. Chart. Average entropy for the control group for straight road segments grouped by z-score on cognitive metrics.	100
Figure 100. Chart. Average entropy for the car training group for straight road segments grouped by z-score on cognitive metrics.	100
Figure 101. Chart. Average entropy for the computer training group for straight road segments grouped by z-score on cognitive metrics.	101
Figure 102. Chart. Average entropy for the control group for intersections grouped by z-score on cognitive metrics.	101
Figure 103. Chart. Average entropy for the car training group for intersections grouped by z-score on cognitive metrics.	102
Figure 104. Chart. Average entropy for the computer training group for intersections grouped by z-score on cognitive metrics.	102
Figure 105. Chart. Average reaction time for the vehicle-centric detection task for the control group by z-score on physical metrics.	103
Figure 106. Chart. Average reaction time for the vehicle-centric detection task for the car training group by z-score on physical metrics.	103
Figure 107. Chart. Average reaction time for the vehicle-centric detection task for the computer training group by z-score on physical metrics.	104
Figure 108. Chart. Average reaction time for the driver-centric peripheral detection task for the control group by z-score on physical metrics.	104
Figure 109. Chart. Average reaction time for the driver-centric peripheral detection task for the car training group by z-score on physical metrics.	105
Figure 110. Chart. Average reaction time for the driver-centric peripheral detection task for the computer training group by z-score on physical metrics.	105
Figure 111. Chart. Average object recognition distance for the control group by z-score on physical metrics.	106
Figure 112. Chart. Average object recognition distance for the car training group by z-score on physical metrics.	106
Figure 113. Chart. Average object recognition distance for the computer training group by z-score on physical metrics.	107
Figure 114. Chart. Average reaction time for the vehicle-centric detection task for the control group by z-score on visual metrics.	107
Figure 115. Chart. Average reaction time for the vehicle-centric detection task for the car training group by z-score on visual metrics.	108
Figure 116. Chart. Average reaction time for the vehicle-centric detection task for the computer	108

Figure 117. Chart. Average reaction time for the driver-centric peripheral detection task for the control group by z-score on visual metrics..... 109

Figure 118. Chart. Average reaction time for the driver-centric peripheral detection task for the car training group by z-score on visual metrics. 109

Figure 119. Chart. Average reaction time for the driver-centric peripheral detection task for the computer training group by z-score on visual metrics..... 110

Figure 120. Chart. Average object recognition distance for the control group by z-score on visual metrics..... 110

Figure 121. Chart. Average object recognition distance for the car training group by z-score on visual metrics..... 111

Figure 122. Chart. Average object recognition distance for the computer training group by z-score on visual metrics. 111

Figure 123. Chart. Average reaction time for the vehicle-centric detection task for the control group by z-score on cognitive metrics..... 112

Figure 124. Chart. Average reaction time for the vehicle-centric detection task for the car training group by z-score on cognitive metrics..... 112

Figure 125. Chart. Average reaction time for the vehicle-centric detection task for the computer training group by z-score on cognitive metrics..... 113

Figure 126. Chart. Average reaction time for the driver-centric peripheral detection task for the control group by z-score on cognitive metrics. 113

Figure 127. Chart. Average reaction time for the driver-centric peripheral detection task for the car training group by z-score on cognitive metrics. 114

Figure 128. Chart. Average reaction time for the driver-centric peripheral detection task for the computer training group by z-score on cognitive metrics. 114

Figure 129. Chart. Average object recognition distance for the control group by z-score on cognitive metrics. 115

Figure 130. Chart. Average object recognition distance for the car training group by z-score on cognitive metrics. 115

Figure 131. Chart. Average object recognition distance for the computer training group by z-score on cognitive metrics. 116

LIST OF TABLES

Table 1. Summary of Training Methods.....	5
Table 2. In-vehicle training schedule.	10
Table 3. Planned experimental design for each training group.....	14
Table 4. Summary of Driver Performance Metrics.	15
Table 5. Participant Requirements by Type.....	16
Table 6. In-person screening criteria.	18
Table 7. Participant age demographics by training group and gender.	18
Table 8. Participant recruitment and retention.	19
Table 9. Approximate specifications for driver-centric PDT LED locations relative to participant.	23
Table 10. Object types and descriptions used for the object identification task.....	30
Table 11. Construction of predictor variables.	57

LIST OF ABBREVIATIONS AND SYMBOLS

ACTIVE	Advanced Cognitive Training for Independent and Vital Elderly
AMTS	Abbreviated Mental Test Score
CAN	Controller Area Network
DAS	Data Acquisition System
dGPS	Differential Global Positioning System
DHI	Driving Health Inventory
DMB	Department of Motor Vehicles
IADL	Important Activities Of Daily Living
IIHS	Insurance Institute for Highway Safety
IRB	Institutional Review Board
LTAP	Left Turn Across Path
PDT	Peripheral Detection Task
VS:A	Visual Search Trail Making Task Part A
VS:B	Visual Search Trail Making Task Part B
VMI	Visualizing Missing Information

CHAPTER 1. INTRODUCTION

BACKGROUND

A series of findings issued by the Insurance Institute for Highway Safety (IIHS) shows that over the past decade or so, both crash and traffic fatality rates for seniors have declined to a substantial degree, and at an even more dramatic pace than that of younger drivers, whose rates have also been decreasing (Cheung, McCartt, & Braitman, 2008; Cheung & McCartt, 2011; Cicchino & McCartt, 2014). Despite this positive trend, crash rates for seniors in 2008, using mileage as the metric of exposure, were still on the order of two to three times higher for those aged 80+ compared with the lowest risk middle-aged group (Cicchino & McCartt, 2014). Thus, senior crash rates are likely to remain a serious and growing concern, as our society's current aging trend is expected to continue well past the middle of this century (U.S. Census Bureau, 2012). As illustrated in Figure 1, the proportion of the total population represented by each of the younger age groups is projected to *decrease* by anywhere from 3.6% to more than 13% from 2015 to 2060, whereas the proportion of those aged 65+ is projected to *increase* by more than 47% over that same time period.

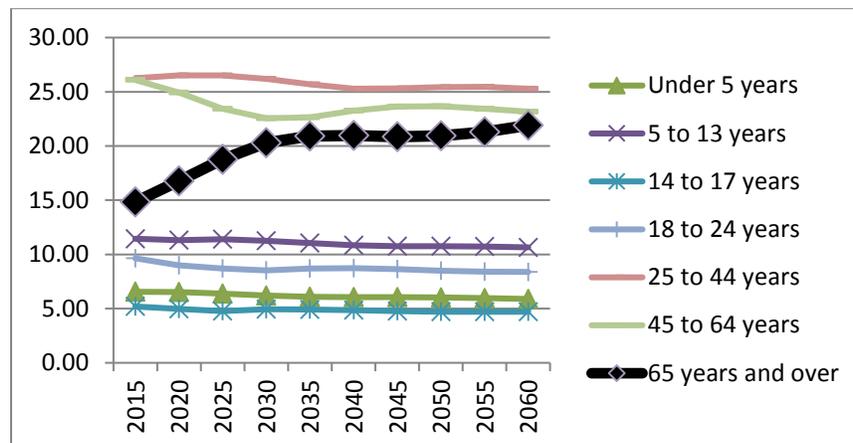


Figure 1. Chart. Population percentage projections by age group (U.S. Census Bureau, 2012).

This aging trend, due largely to the baby boom generation, will undoubtedly place severe strains on, and test the resiliency of, all of society's institutions, with transportation being one of the most affected. Colli, Sharp, & Giesbrecht (2003) determined from 2001 National Household Travel Survey data that nearly 80% of individuals over 65 still drove; more than a decade later these numbers remain unchanged (IIHS, 2014). As long as the private vehicle continues to be the overwhelming transportation modality of choice for seniors and the proportion of senior drivers continues to grow, any issues confronting society related to senior drivers are expected to remain a serious source of concern for some time to come. Although the advent of increasing vehicle connectivity and automation may have a significant positive impact on senior mobility, it is impossible to say at this juncture when such technologies may be robust enough—and sufficiently well accepted by the general public—for full and broad-scale implementation.

Self-Restriction

Seniors tend to drive substantially less than middle-aged drivers (45% fewer miles; IIHS, 2014) and in less-demanding situations (e.g., avoiding nighttime driving and bad weather; Molnar & Eby, 2008). However, Molnar & Eby (2008) also found that only 25% of senior drivers surveyed indicated that they engaged in self-restriction. They also note that the proportion of seniors reporting self-restriction may vary widely from study to study, depending on the particular population and the specific questions asked. Regardless, the degree of restriction is not sufficient to alter the large-scale pattern noted above: the oldest senior drivers still have a substantially higher crash rate per mile driven than the safest group of middle-aged drivers. Ball et al. (1998) found that older drivers with visual and/or attentional impairments reported more avoidance of difficult driving scenarios than those free of impairments; the most impaired reported avoiding a wider variety of difficult situations than other less-impaired drivers.

Functional Impairment

There is evidence that functional impairments typically associated with the aging process can lead to a variety of self-imposed driving restrictions. These dimensions of functional ability include cognition, perception, psycho-motor ability, and physical ability (e.g., strength, flexibility, stability, and stamina). Along this same line of reasoning, there is also evidence that such impairment, especially cognitive-related impairment in seniors, can have an impact on traffic safety outcomes. Owsley et al. (1991) found that older drivers with a visual attentional disorder or with poor scores on a mental status test had significantly more intersection-related crashes than those without these problems. Stutts, Stewart, & Martell (1998) used a retrospective approach and found that seniors in the bottom 10th percentile of cognitive test scores were 50% more likely to have been in a crash than those in the top 10th percentile.

One metric of functional ability has probably had more research confirming its relationship to driving safety outcomes than any other: useful field of view (UFOV[®]), defined fundamentally as the greatest breadth of visual field from which one can gather meaningful information in a single glance without head or eye movement (Ball et al., 1988). Ball & Owsley (1993) developed a method to assess and train useful field of view that also incorporates higher order attentional and processing speed components: the UFOV[®]. Roenker et al. (2003) found that UFOV[®] training resulted in better performance in a driving simulator and fewer dangerous maneuvers in an on-road driving evaluation. Mathias & Lucas (2009) performed a meta-analysis evaluating cognitive predictors of unsafe driving in seniors. They found that a wide variety of screening approaches were successful at predicting either on-road or simulated driving performance, or the presence of driving problems. However, the only cognitive test that was successful at predicting performance for all three performance categories or environments was the UFOV[®]. For an overview of the wide variety of studies supporting the relationship between the UFOV[®] metric and driving safety and other meaningful outcomes, consult Ross et al. (2011).

BRAIN TRAINING

There is ample evidence that functional impairments can have a deleterious effect on senior driver safety. One approach to reducing risk for senior drivers is to address the salient functional impairment(s). If there is a strength or stability deficit, it is possible that physical exercise can

restore functionality or reduce future declines. If there is a perceptual deficit, perhaps a new eyewear prescription or the elimination of night driving can reduce that driver's risk. Similarly, if there is a cognitive-related deficit, there is substantial evidence that improvement can be achieved in a variety of ways via one or more forms of brain training.

Brain training has been defined as the improvement of cognitive function through the regular use of computerized tests (Owen et al., 2010). However, Owen and his colleagues remain skeptical of the ability of such tests to transfer their benefits to broad and/or meaningful improvements in trainees' ability to succeed in their daily activities. A more refined perspective on brain or cognitive training can be specifically defined both in terms of the type or aspect of cognition being trained (e.g., memory or processing speed) as well as the specific task or activity for which the transfer of training is intended or purported to take effect (e.g., driving safety).

Also, while some brain training may be focused on teens or middle-aged adults, one often-targeted demographic is seniors. A key question for this group is whether the senior brain can still be changed (i.e., develop new and reliable response patterns) in a relatively permanent way as a result of training. If not, then all such efforts may be wasted on this particular demographic. The concept of *brain-* or *neuro-*plasticity asserts the concept that the human brain is structurally and functionally malleable such that learning and positive change can occur in the context of specific training, and that this plasticity endures throughout the lifespan (Draganski et al., 2004; O'Connell & Robertson, 2012).

Buitenweg, Murre, & Ridderinkhof (2012) performed a literature review to determine what was currently known about the ability of brain training to counter the cognitive deficits normally associated with aging. They found that, broadly speaking, the results are neither substantial nor reliable, and that transfer effects are limited. However, they also discussed several specific findings that are encouraging. For instance, Cassavaugh & Kramer (2009) showed that computer-based variable priority training on tasks combining manual control, visual attention, and working memory resulted in seniors demonstrating significant improvement on simulated driving tasks related to maintaining lane position and pedal response time. These results demonstrate that computer-based training of seniors on relatively simple perceptual and cognitive tasks only grossly related to driving can still produce significant improvements in selected aspects of performance in a simulated driving environment. Thus, while a generic brain training approach may have little transfer to one or more instrumental activities of daily living (IADL), a training approach that is targeted to address particular deficits may succeed.

In our conceptual model for the efficacy of brain training, the senior driver starts with a particular level of skill or ability in a particular cognitive dimension related to driving safety. Brain training targeted to improving that particular dimension is applied, and because of the brain's durable neuroplasticity, learning and skill level improvement take place, leading to reduced risk while driving. If particular aging-related cognitive deficits can be identified up front in a fitness-to-drive screening, and these deficits are amenable to improvement via training, then brain training can become an efficient, effective, and viable means of helping seniors remain mobile and independent as drivers aging in place.

One of the most far-reaching scientific studies of brain training to date is the Advanced Cognitive Training for Independent and Vital Elderly (ACTIVE) trial, which was a study designed to determine whether cognitive training approaches including memory, reasoning, and speed of information processing could improve seniors' measures of daily functioning that relate to these constructs, including outcome metrics related to driving safety (Jobe et al., 2001). In particular, the ACTIVE training incorporated elements of UFOV training that had been previously found to be associated with improved driving safety. Ball, Edwards, Ross, and McGwin (2010) in a six-year follow-up on ACTIVE trial participants found that both speed-of-processing (UFOV) and reasoning training resulted in an approximately 50% reduction in rates of at-fault crashes compared with the control group. The crash rate reduction observed in the ACTIVE trial for two of the targeted brain training approaches is remarkable both in degree as well as the durability of the training transfer effect. However, there are no direct data available to suggest what, in terms of specific driving-related behaviors or skills, was changed or improved in order to bring about these results.

The possibility of senior drivers deriving long-term safety-related benefits from different forms of brain training has significant appeal. One of the largest studies to date supporting the viability of this approach is the ACTIVE trial, and while the long-term reduction in crash rate observed in that study was an extremely promising finding, the lack of identified functional mechanisms of driver improvement left open a number of research questions that could lead to a better understanding of the benefits of training and improved training protocols. The current research project was developed to identify specific safety-related aspects of driving behavior that may be improved or maintained by a commercial brain training product, as well as a novel brain training product based on implicit learning principles and developed to be implemented in vehicles. The two tested systems are summarized in Table 1 and the following section, and they are detailed in the Methods section. Driving performance before and after training was compared between the two groups and with a third no-contact control group (i.e., not only did the control group receive no training, but they also were not asked to participate in any other non-training-related activities).

Table 1. Summary of Training Methods

Training Method	<i>PositScience DriveSharp®</i>	<i>Toyota In-Vehicle</i>
Training Type	Computer-Based	In-Vehicle
Theoretical Underpinning	Improved peripheral vision, speed of processing, divided attention, object tracking, and dynamic contrast sensitivity	Implicit improvement in central as well as peripheral monitoring behavior
Training Frequency	Self-Paced (Recommended 1 hour 3x/week)	3-5x/week, 0.5 hour/session, with breaks between weeks
Training Duration	10 hours (Recommended 3-5 weeks total; maximum 15 weeks)	7 weeks

TRAINING METHODS

A brief overview of the two methods of brain training included in this research effort are presented here and detailed in the Methods section following.

PositScience DriveSharp®

DriveSharp® is commercially available, computer-based brain-training software designed to improve seniors' driving skills by specifically targeting cognitive skills important for driving. The software is based on three self-paced components, which are presented in the form of mini-games. The component games include UFOV training, multiple object tracking, and visual grating discrimination. Participants were able to complete this training at home if they had a compatible computer, or in the laboratory if not; all but two participants completed training at home. As training was self-paced, participants who lagged behind the expected pace were gently reminded to continue training, but were not dismissed from the study unless their training extended beyond 15 weeks.

Toyota In-Vehicle

This system represents an in-vehicle approach developed by Toyota Engineers designed to improve seniors' driving skills by using an implicit learning paradigm. The fundamental concept is similar to UFOV, in that it is designed to improve visual attention to peripheral stimuli while still requiring the driver to maintain central focus. It is intended to be implemented in a driving context. The training system incorporates two distinct phases, the "Training" phase and the "Response" phase. During the Training phase, trainees simply drive as usual (in this case, on a closed track) while a set of dashboard-mounted lights illuminate and reflect off the windshield. As this is an implicit learning paradigm, no participant response is required during this phase. During the Response phase, trainees are instructed to press a finger-switch as quickly as possible

in response to a different set of flashing LED lights that are mounted to the hood of the vehicle. Training for this group followed a strict 7-week schedule detailed in the following section.

CHAPTER 2. METHODS

This study compared the effects of two approaches to cognitive training on senior driver performance and safety. Training effects were examined both in the short term and up to 12 months after completion of training. Both training programs were compared with a no-contact control group to account for any inherent task improvement *not* attributable to either training program. All study protocols were approved by Virginia Tech's Institutional Review Board (IRB) prior to the start of either participant recruitment or data collection. Figure 2 provides an overview of the study; details are described below.

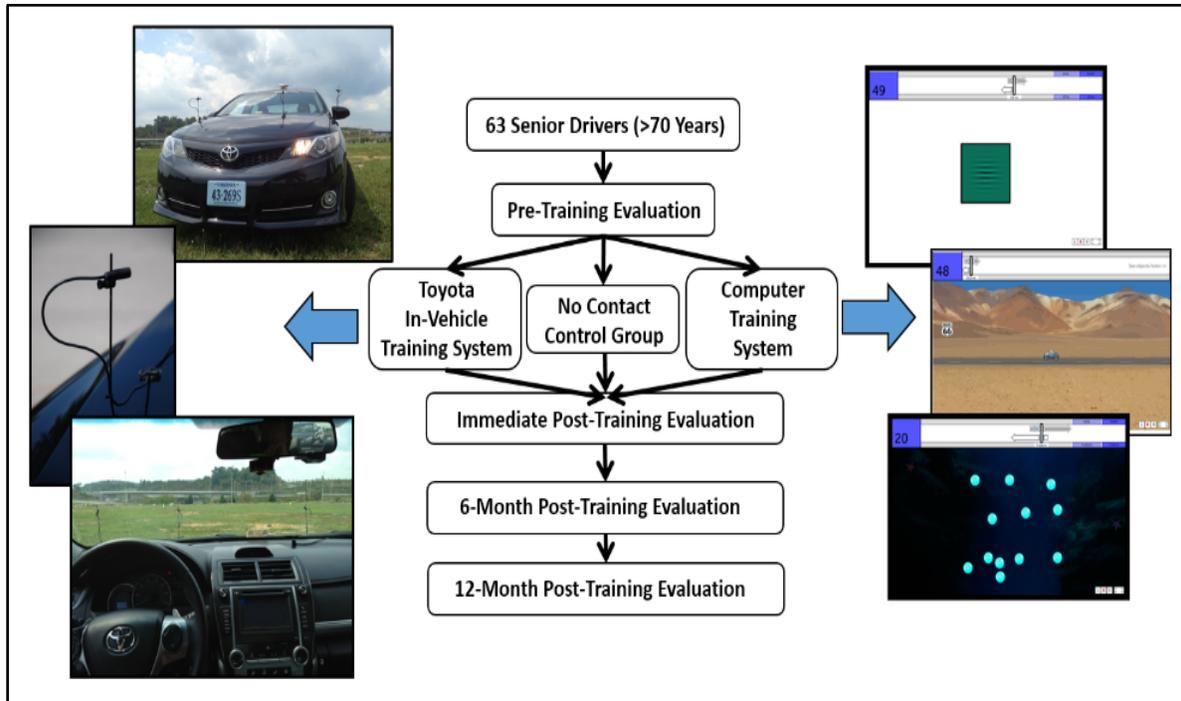


Figure 2. Illustration. Study overview.

TRAINING PROGRAMS

In-Vehicle Training

This training approach was developed by Toyota engineers and implemented by Virginia Tech Transportation Institute (VTTI) staff in the experimental vehicle, a 2012 Toyota Camry SE. Training involved asking the participant to drive laps for 10 minutes at 40 mph (64 km/h) on a closed-to-traffic test track, the Virginia Smart Road, while being exposed to three green LED lights blinking in a random pattern for 50 ms every 2 s. As this approach was based on an implicit learning model, no participant responses to these stimuli were required during the training phase of each session. These lights were embedded in the vehicle's dashboard and aimed upward, and thus seen only as virtual images reflected off the vehicle's windshield as illustrated in Figure 3. These stimuli were positioned at approximately 20 degrees to the left of the driver's center and at 1 degree and 40 degrees to the right as illustrated in Figure 4.



Figure 3. Photo. Green LED embedded in dashboard and aimed up at the windshield.



Figure 4. Photo. Green training stimuli.

Each in-vehicle training session consisted of two phases: an implicit learning/training portion as described above and a response phase utilizing a set of red LED lights mounted on stalks on the vehicle's hood, which were positioned individually for each participant so that the red lights would be seen in the same locations as the reflected green stimuli (Figure 5).

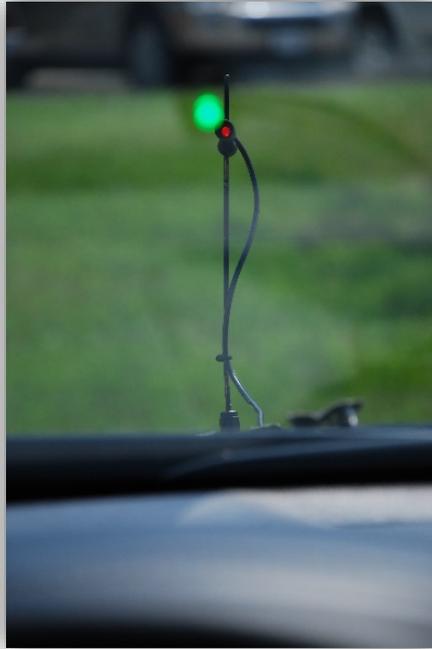


Figure 5. Photo. Testing red hood-mounted LEDs.

In the response phase, while the participant drove on the closed test track, the red LEDs illuminated for 1 s at variable random intervals from 5 s to 9 s. Participants were asked to respond to these stimuli as quickly as possible by pressing a finger-mounted switch (Figure 6).



Figure 6. Photo. Finger-mounted PDT response button.

Vehicle training sessions occurred three to five times a week during each week of training (e.g., Train-W1), with each week of training separated by two weeks with no study-related activities (e.g., No Contact-W2&3, Table 2). Each training session lasted approximately 20 minutes.

Table 2. In-vehicle training schedule.

Train-Week 1	No Contact-Weeks 2 & 3	Train-Week 4	No Contact-Weeks 5 & 6	Train-Week 7
3-5 training sessions	0 training sessions	3-5 training sessions	0 training sessions	3-5 training sessions

Computer Training

The other training program used commercially available software, DriveSharp, developed by Posit Science, as a computer-based program designed specifically to enhance cognitive skills important for senior drivers. These skills included speed of visual processing, useful field of view, and divided attention. DriveSharp included three training subcomponents: Visual Sweeps, Target Tracker, and Double Decision. DriveSharp was developed by Posit Science in conjunction with authors of the Ball et al. (2010) ACTIVE study.

The training performance criterion was that each participant had to complete 10 stages for each of the three subcomponents. A trainee had to complete the current stage for each of the three subcomponents in order to be permitted to proceed to the next stage. For each subcomponent, there were two or three levels per stage depending on component. It was generally expected that it would take approximately one hour to complete a stage and, thus, approximately 10 total hours to complete the entire computer training program, though this varied from participant to participant. Recommended total training time was 6 weeks, but as training was self-paced participants were allowed up to 15 weeks to complete training. Seven participants were dismissed from the study for failing to complete training within 15 weeks; reasons for this varied and included busy schedules, medical issues, vacations, and loss of interest.

The DriveSharp training process is illustrated in Figure 7.

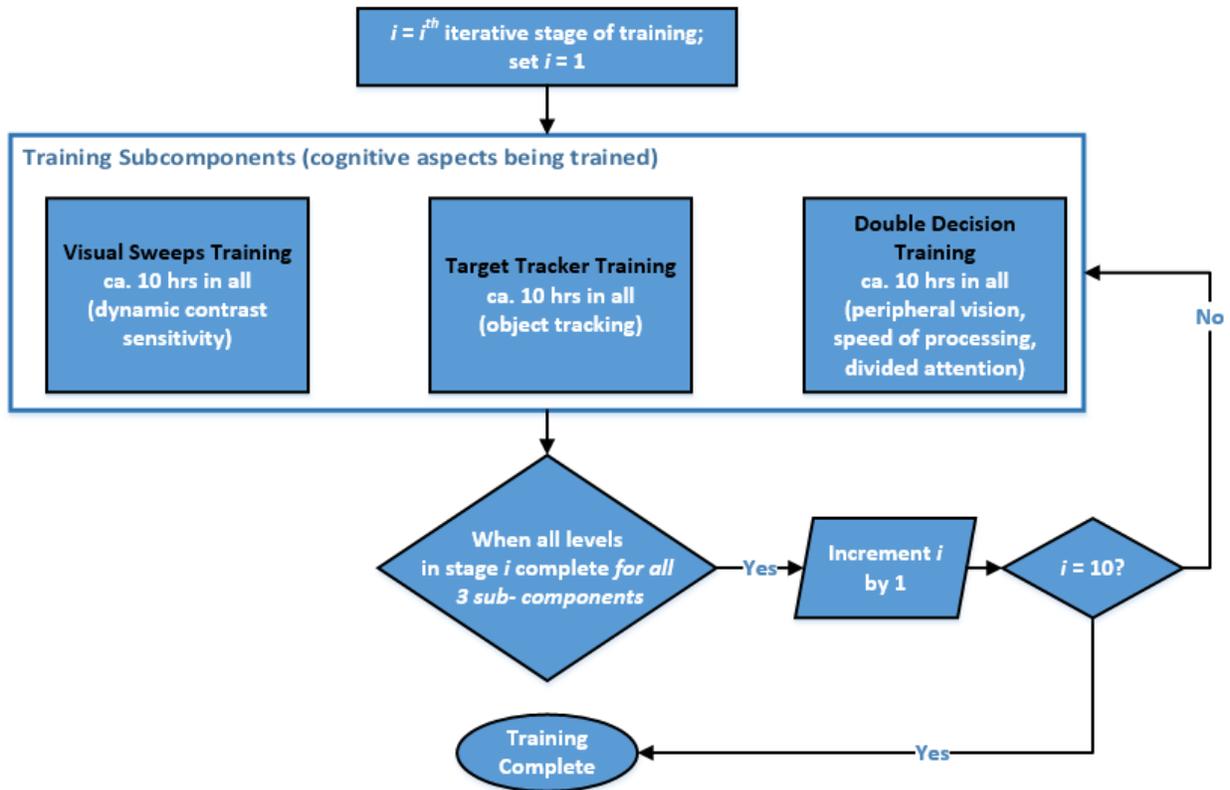


Figure 7. Chart. DriveSharp training process (6 to 15 weeks total training time per participant).

Subcomponents

The [Visual Sweeps](http://www.brainhq.com/why-brainhq/about-the-brainhq-exercises/brainspeed/visual-sweeps) training subcomponent aims to improve participants' visual processing speed using sine wave gratings of different colors that appear to sweep in inward or outward directions from different orientations (i.e., horizontally, vertically, or diagonally; Figure 8 and Figure 9; detailed information can be found at <http://www.brainhq.com/why-brainhq/about-the-brainhq-exercises/brainspeed/visual-sweeps>). The sweeps change in color/luminance, spatial frequency, and orientation from trial to trial to target a variety of visual receptor cell types. The trainee's role is to determine the direction of two sweeps presented in rapid succession.

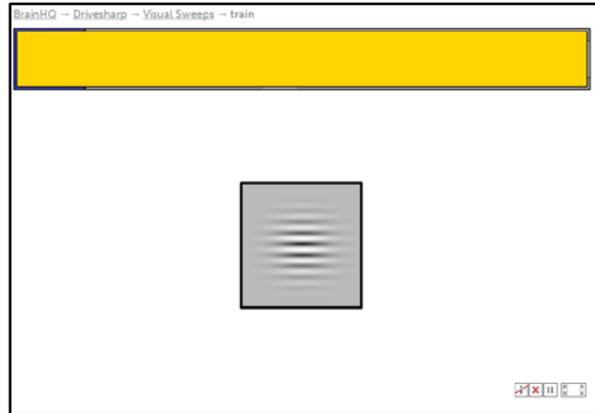


Figure 8. Screen capture. Example Visual Sweeps sine wave grating test image.

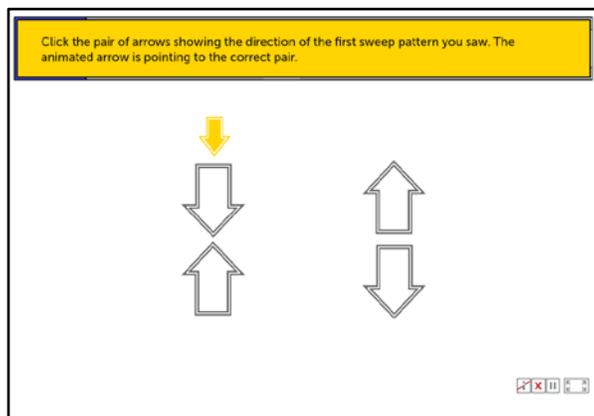


Figure 9. Screen capture. Example Visual Sweeps participant response options.

The [Target Tracker](http://www.brainhq.com/why-brainhq/about-the-brainhq-exercises/attention/target-tracker) training subcomponent aims to improve trainees' divided attention skills by having them track target objects moving among identical distractor objects and identify them after a period of movement (detailed information about the Target Tracker subtask can be found at <http://www.brainhq.com/why-brainhq/about-the-brainhq-exercises/attention/target-tracker>). The task gets successively more difficult in a variety of ways: objects move faster, for longer durations, and over greater areas; object-background contrast decreases; and the exercise adapts to the trainee's skill level by adding to the number of tracked objects if successful and subtracting if the trainee is performing at a lower skill level.

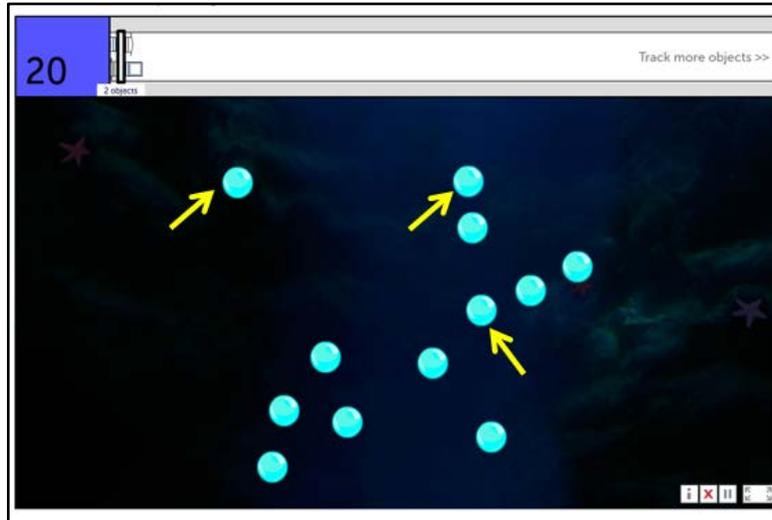


Figure 10. Screen capture. Example Target Tracker screen with yellow arrows added to point out the target bubbles; all others are distractors.

The [Double Decision](http://www.brainhq.com/why-brainhq/about-the-brainhq-exercises/attention/double-decision) training subcomponent aims to expand trainees' useful field of view and speed of visual processing using the UFOV™ approach (detailed information about the Double Decision subtask can be found at <http://www.brainhq.com/why-brainhq/about-the-brainhq-exercises/attention/double-decision>). That is, it focuses the trainee's visual attention on a task in the middle of the screen. For this task, the trainee must determine which of two vehicles was presented tachistoscopically in the middle of the screen, and simultaneously must also determine where in the periphery a Route 66 road sign appears among distractor peripheral images (Figure 11). Images are presented for briefer and briefer time periods until performance deteriorates below a set criterion.



Figure 11. Screen capture. Example Double Decision test image showing the central car icon as well as the peripheral target and distractor images.

Control Group

Those individuals in the control group received neither training nor any similar placebo-based contact; however, they were tested in the same way and on the same basic schedule as those in the two training groups to help to account for the potentially confounding effects of simply participating in the study itself.

EXPERIMENTAL DESIGN

The planned experimental design is shown in Table 3. It shows training group as the between-subjects variable and training session as the within-subject variable (where P = participant number). The planned experimental design called for a total of 63 participants between the ages of 69 and 85.

Table 3. Planned experimental design for each training group.

Training Session	Control Group	In-Vehicle Training	Computer Training
Pre-Training	P1–P21	P22-P42	P43-P63
Immediate Post-Training	P1–P21	P22-P42	P43-P63
6–9 Months Post-Training	P1–P21	P22-P42	P43-P63
12–18 Months Post-Training	P1–P21	P22-P42	P43-P63

DEPENDENT MEASURES

Driver performance was assessed on both public roads and a closed-road course. Dependent measures assessed vehicle control and information gathering on the public roads. For the closed-road course, dependent measures assessed task performance. Public-road metrics included measures of driver workload for representative driving segments and information gathering for both driving segments and specific intersections. These metrics were intended to identify specific improvements in the workload necessary to maintain vehicle control and gather information, particularly in situations such as unprotected left-hand turns that have been shown to pose specific risk for senior drivers. If brain training increases senior drivers' ability to efficiently obtain information about the environment, which is core to the UFOV concept, we predicted that this will manifest during driving in improved glance behavior and better longitudinal and lateral vehicle control, indicating that the driver is experiencing a lower overall workload (Angell et al., 2006).

Closed-road metrics included the distance at which drivers could identify and respond to relevant (potentially hazardous) roadside stimuli, as well as drivers' ability to notice and quickly react to nonspecific (illuminating) peripheral stimuli. Again, if brain training enables drivers to more effectively sample information in their environment, we predicted that participants would be able to identify relevant roadside stimuli from further distances, as well as respond more quickly and more accurately to illuminating nonspecific stimuli. These metrics are summarized in Table 4.

Table 4. Summary of driver performance metrics.

Location	Metric	Construct Measured	Expected Results
Public-Road	Standard Deviation of Speed	Driver workload	Decrease in SD Speed post-training for training groups
	Standard Deviation of Lane Position	Driver workload	Decrease in SD Lane Position post-training for training groups
	Glance Entropy	Degree of glance dispersion across predefined glance locations inside and outside the vehicle	Increase in entropy post-training for training groups
Test Track	Detection Distance: Roadside Objects	Ability to identify relevant peripheral stimuli	Increase in distance at which stimuli are identified post-training for training groups
	Vehicle-Centric PDT: Reaction	Ability to rapidly and accurately respond to nonspecific central and peripheral stimuli	Increase in hit rate and decrease in reaction time

Location	Metric	Construct Measured	Expected Results
	Time and Hit Rate		post-training for training groups
	Participant-Centric PDT: Reaction Time and Hit Rate	Ability to rapidly and accurately respond to nonspecific peripheral stimuli	Increase in hit rate and decrease in reaction time post-training for training groups

PARTICIPANTS

Recruitment

Participants who had previously expressed interest in participating in studies at VTTI and who fit the project age criteria were recruited over the phone from a pool of seniors in the New River Valley area of Virginia near Virginia Tech. A total of 74 individuals were recruited, resulting in 55 participants who completed the 6–9 months Post-Training session or beyond. Nineteen exited the study early due to a variety of reasons.

Screening

Those contacted for recruitment were required to pass a set of phone screening criteria equal to or stricter than the requirements set forth by the Virginia Department of Motor Vehicles, including the requirements set forth in Table 5. Note that some requirements may be appropriate for more than one requirement type; for example, minimum visual performance would be both DMV-related and safety-related. In these cases, the requirement is assigned to the most-appropriate column.

Table 5. Participant Requirements by Type.

	DMV-Mandated	Legal (Institutionally Required)	Safety-Related	Experimental Control
Screening Requirement	Possess a valid United States driver's license	U.S. citizen or hold green card	Be judged by researchers competent to provide informed consent	Between ages of 69-85
	Not have currently impaired field of view	Be able to read and understand forms and instructions provided in English	Not report being diagnosed with Alzheimer's Disease	Drive at least once per week

	DMV-Mandated	Legal (Institutionally Required)	Safety-Related	Experimental Control
		Be willing to provide Social Security Number or Virginia Tech ID number for payment	Report having normal (or corrected to normal) hearing	Not have engaged in formal “brain training” within the past five years
			Be able to drive without assistive devices	Not report having more than two moving violations in the past three years
			Not have lingering effects of heart condition, surgery, brain damage from stroke, tumor, or head injury/recent concussion.	
			If participant has had eye injury/surgery, must be informed of increased risk and given opportunity to decline participation.	
			Not have had epileptic seizures or lapses of consciousness, uncontrolled current respiratory disorders, motion sickness, inner ear problems, dizziness, vertigo, balance problems, uncontrolled diabetes that requires insulin, chronic migraine or tension headaches in last 12 months.	
			Not currently be taking any substances/medications or undergoing treatments that interfere with driving ability, cause drowsiness, or impair motor abilities.	

	DMV-Mandated	Legal (Institutionally Required)	Safety-Related	Experimental Control
			Provide a satisfactory answer to the screening question, “Are there any other conditions that may affect your ability to drive safely?”	

For potential participants who indicated interest in participating and who passed each of the phone screening criteria listed above, additional laboratory-based screening protocols were administered at the outset of participation. First, the participant was asked to produce in person his/her current, valid license. Shortly after the informed consent form was signed by the participant, additional screening measures were applied; any participant who failed any of these tasks was politely excused from further study participation. Laboratory-based screening criteria are delineated in Table 6.

Table 6. In-person screening criteria.

Screening Task/Element	Criterion
Corrected binocular visual acuity (daylight)	20/40
Peripheral vision (both eyes)	85 degrees in at least one eye
Abbreviated Mental Test Score	At least 7 of 10 correct (see Appendix A)

Participant age demographics are delineated in Table 7 for each of the three training groups, broken out by gender. All participants but one were Caucasian, with the exception being an African American male. To contribute to the data represented in Table 7, the participant had to remain active in the study at least through the first post-training experimental session.

Table 7. Participant age demographics by training group and gender.

	Control Group		In-Vehicle Training		Computer Training	
	Male	Female	Male	Female	Male	Female
N	11	11	11	9	8	7
Mean Age (S.D.)	73.7 (3.6)	73 (2.9)	74.4 (3.5)	72.6 (4.4)	71.8 (2.4)	72 (2.5)
Range	70-81	69-77	69-79	69-81	70-76	70-77

Table 8 indicates the actual number of participants that were recruited into each group as well as the number who continued at least through the 6–9 month test session.

Table 8. Participant recruitment and retention.

	Control Group		In-Vehicle Training		Computer-Training	
	Recruited	Completed 6–9 month+	Recruited	Completed 6–9 month+	Recruited	Completed 6–9 month+
Female	12	10	14	11	10	6
Male	12	11	13	9	12	8
Total	24	21	27	20	22	14

APPARATUS

Study apparatus included the vision tester and the instrumented experimental vehicle.

Vision Tester

All visual tests were completed using the Optec 6500P (Figure 12).



Figure 12. Photo. Optec 6500P vision tester.

Experimental Vehicle and Onboard Data Acquisition System

The experimental vehicle was a 2012 Toyota Camry SE (Figure 13) instrumented with a VTTI Next-Gen data acquisition system (DAS) and a differential Global Positioning System (dGPS) receiver (Figure 14). In addition to controlling the various training and testing, the DAS provided a comprehensive suite of kinematic sensors and five continuous video channels. Sensors provided vehicle position using highly accurate dGPS, acceleration in three axes, continuous audio recording, and access to several variables on the vehicle's network, including speed, throttle, brake pedal activations, and steering wheel angle. Data were recorded on a solid-state hard drive and were transferred to a secure database following each data collection session.



Figure 13. Photo. Study vehicle: 2012 Toyota Camry SE, pictured here with dGPS antenna affixed to the roof and the vehicle-centric PDT stalks affixed to the hood.



Figure 14. Photo. VTTI Next-Gen DAS (grey box in back) and dGPS receiver (on metal plate).

Five channels of continuous video were recorded, including the participant's face, the forward and rear roadway, an over-the-shoulder view of the driver's interactions with the center stack, and video of the participant's interactions with the pedals (Figure 15).



Figure 15. Screen capture. Video streams captured (from left moving clockwise: participant's face, forward roadway, pedal interactions, rear roadway, and over-the-shoulder).

The vehicle was also equipped with a passenger-side brake so that the onboard experimenter could stop the vehicle in a perceived emergency (Figure 16).



Figure 16. Photo. Emergency passenger-side brake.

Peripheral Detection Tasks (PDTs)

A peripheral detection task (PDT) typically presents a randomly timed series of brief light stimuli in a single area within the participant's peripheral field of view; the participant's task is to respond by pressing a button as soon as the stimulus is seen. Metrics can include response latency and proportion of stimuli missed. Two PDTs were implemented in this study: vehicle-centric and driver-centric. In both cases, stimuli were presented in three visual locations.

Vehicle-Centric PDT

The vehicle-centric PDT placed red LEDs on wire stalks affixed by magnets to the hood of the vehicle (Figure 17). The stalks allowed the images to be adjusted up and down, as well as rotated about the wire for precise orientation for each participant in line with the green LEDs as described in the vehicle-based training approach above.



Figure 17. Photo. Vehicle-centric PDT apparatus.

The red LEDs flashed for a duration of 1 s in a random location (left, center, or right) with a variable inter-flash interval of 5 to 9 s. With this PDT approach, the stimuli retained their orientation to *the vehicle*, regardless of the participant's head movement or location.

Driver-Centric Peripheral Response Task

The final Smart Road portion of the study, a driver-centric PDT, was very similar to the hood-mounted light task above. The primary difference was that the stimuli were provided by three red LEDs mounted with formable metal rods to an adjustable headband that was worn by the participant (Figure 18). The driver-centric PDT red LEDs also flashed for a duration of 1 s in a random location (left, center, or right) with a variable inter-flash interval of 5 to 9 s.



Figure 18. Photo. Driver-centric PDT.

With this PDT approach, the stimuli retained their orientation to the *participant's field of view*, regardless of the participant's head movement or location. Specifications for placement of the LED lights relative to the driver are presented in Table 9.

Table 9. Approximate specifications for driver-centric PDT LED locations relative to participant.

	Left	Center	Right
Lateral angle	+50°	0°	+50°
Elevation angle	+20°	+30°	+20°
Distance from bridge of nose	150 mm	130 mm	150 mm

EXPERIMENTAL PROCEDURES

All participants completed a pre-training experimental data collection session; this was followed by approximately seven weeks of training (or an equivalent period of no contact for the control group), after which participants completed three additional experimental data collection sessions. These three post-training sessions were scheduled as follows: within a week after the completion of training, at 6–9 months post-training, and at 12–18 months post-training.

Experimental Sessions

Laboratory Portion

Study Intake: Upon arrival at VTTI, participants were escorted to a private room where all of the intake, screening, and assessments took place. At the start of the intake process, each participant was asked to present a current and valid driver's license. Participants were then asked to read and sign the IRB-approved consent form, which detailed all of the responsibilities and risks of participation, and also informed the participants that they could discontinue participation at any time. Due to the semi-lengthy nature of the study, participants were required to review and sign the consent form each time they returned to VTTI for subsequent sessions. During their first visit, participants also completed tax forms for Virginia Tech and a form allowing researchers access to Department of Motor Vehicles (DMV) driving records.

Assessments: After completion of the intake process, participants began a series of physical, cognitive, and survey assessments. On average, assessments took an hour to complete, and a researcher was always present to administer the specific task or to answer any questions that arose. Participants were free to take a break at any point.

Vision Testing: Vision tests included binocular visual acuity, contrast sensitivity (simulated day and night conditions), and peripheral vision (simulated day and night conditions). Acuity served as a screening metric as described above, and the additional visual tests were included to serve as potential predictors of driver performance.

Abbreviated Mental Test Score (AMTS): The AMTS is a brief assessment of a person's cognitive fitness and was used as an additional screening metric. The researcher asked participants a series of 10 basic questions to assess their general mental fitness and/or detect signs of dementia. These questions ranged from asking the participants' age to asking participants to identify the jobs of people in a picture (Appendix A). Any potential participant who missed three or more answers would have been dismissed from the study; however, this was not the case for any participants.

Visual-Cognitive Assessments: The Driving Health Inventory (DHI) is a series of computerized assessments that evaluates several abilities related to seniors' driving ability. In this study, participants completed a subset of these tests that involved visualizing missing information (VMI) and two visual search tasks: Trail Making Parts A (VS:A) and B (VS:B). Responses were combined with the UFOV test to act as a predictive metric for driver performance.

All responses were collected via the use of a touch screen monitor to eliminate any bias from unfamiliarity with a computer mouse. The VMI task required participants to view a completed line drawing of a figure (such as a picnic table or bicycle) and identify from a selection of incomplete figures which single one could be completed to look like the example figure without erasing any portion (Figure 19). Trials increased in complexity, and the final score was the number of incorrect responses.

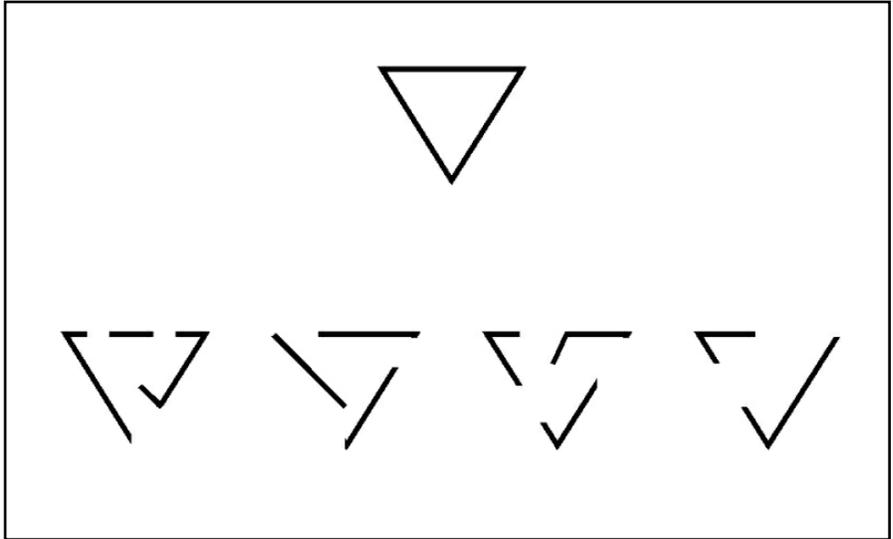


Figure 19. Diagram. Example VMI test; the rightmost image matches the target image at top.

The Trail Making task required participants to connect circles arranged in a grid sequentially from first to last. Part A (VS:A) included only numbers (Figure 20).

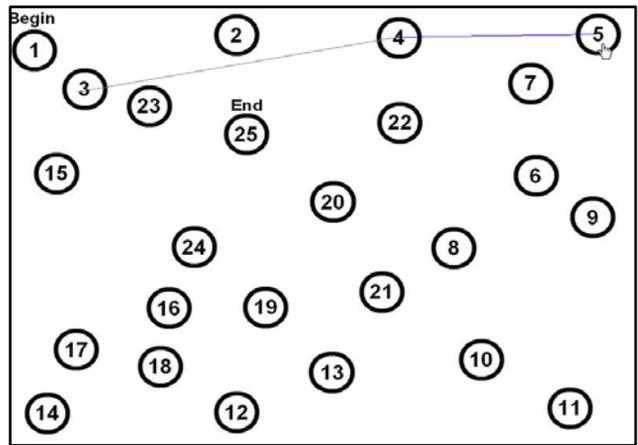


Figure 20. Diagram. Illustration of the VS:A task.

In the more challenging Part B (VS:B), participants were asked to alternate between numbers and letters. For example, in Figure 21 the initial desired trace would be “1-A-2-B-3-C” and so forth. For both visual search tasks, the score was the total time required to complete the test.

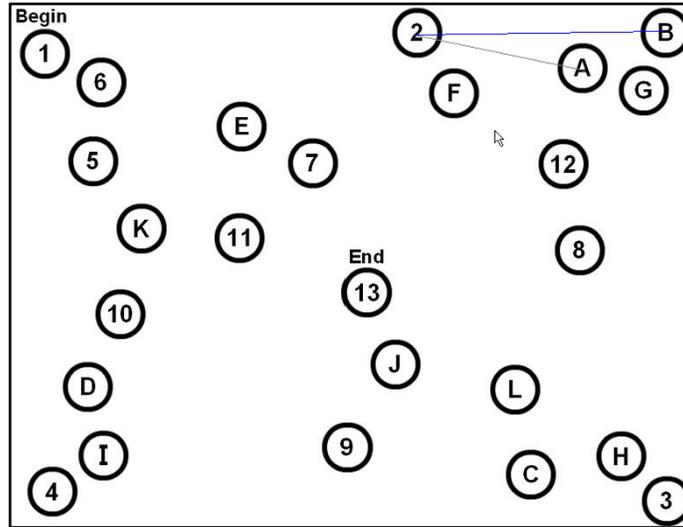


Figure 21. Diagram. Illustration of the VS:B task.

*UFOV*TM: The *UFOV*TM assessment was comprised of three subtests: processing speed, divided attention, and selective attention. For all three subtests, the score was the minimum amount of time the test images needed to be displayed on the monitor for the participant to achieve a preset success-rate criterion. *UFOV* scores were combined with subsets of the DHI to act as predictors of driving performance. The processing speed subtest presented the participant with an image of either a car or a truck in the center of the screen. The image was presented tachistoscopically for briefer and briefer periods, with the participants' task being to identify whether the image present was a car or a truck (Figure 22).

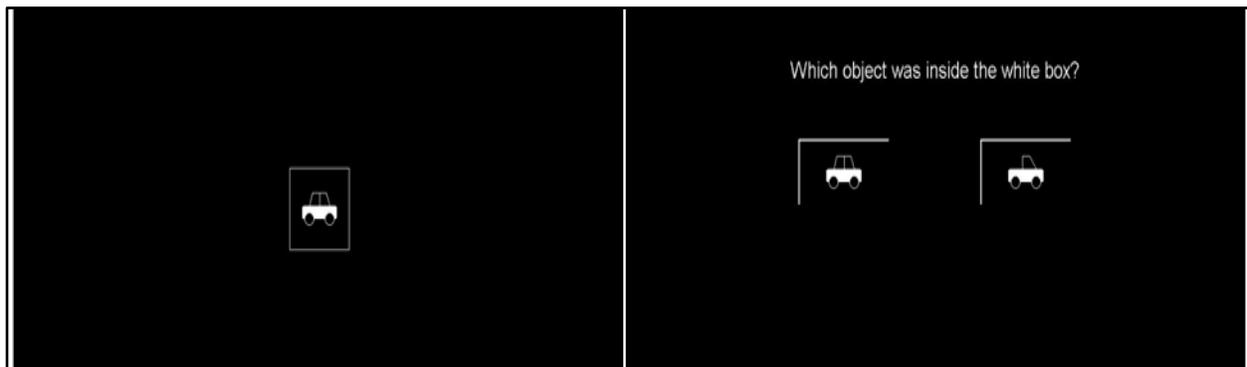


Figure 22. Screen capture. The stimulus image flashed briefly on the screen (left) followed by the response screen (right) for the processing speed *UFOV* subtest.

The divided attention subtest introduced the presence of a secondary vehicle, which was presented along a radial axis simultaneously with the vehicle in the center. The participants' task was now twofold: first, as before, to identify which type of vehicle was present in the center of the screen, and, second, to determine on which radial axis the second vehicle appeared (Figure 23).

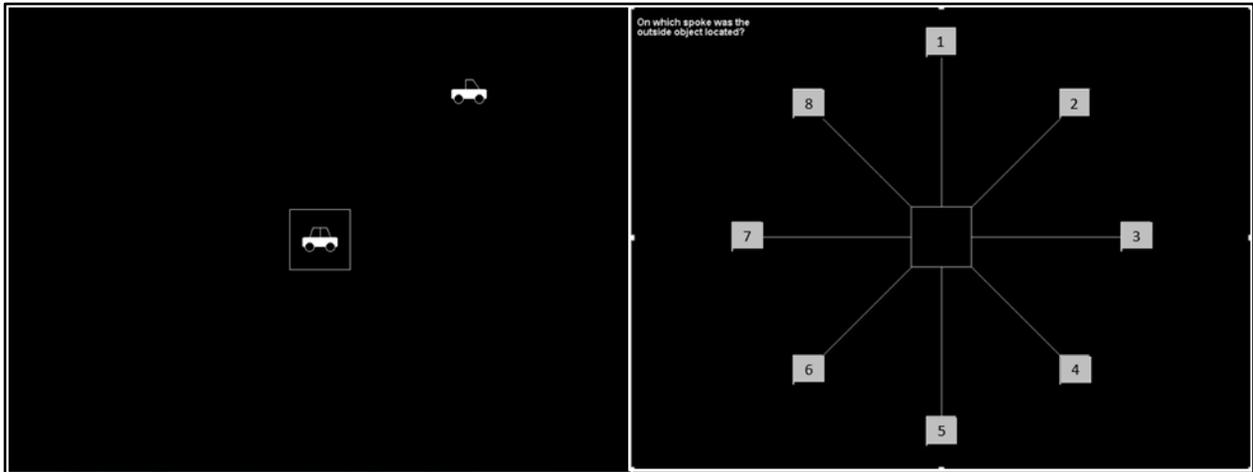


Figure 23. Screen capture. Divided Attention UFOV subtest. The stimulus image (left) followed by the response screen (right). (#2 is the correct peripheral location choice).

The selective attention subtest was identical to the divided attention subtest, with the exception that the selective attention subtest added a field of distractor triangles (Figure 24).

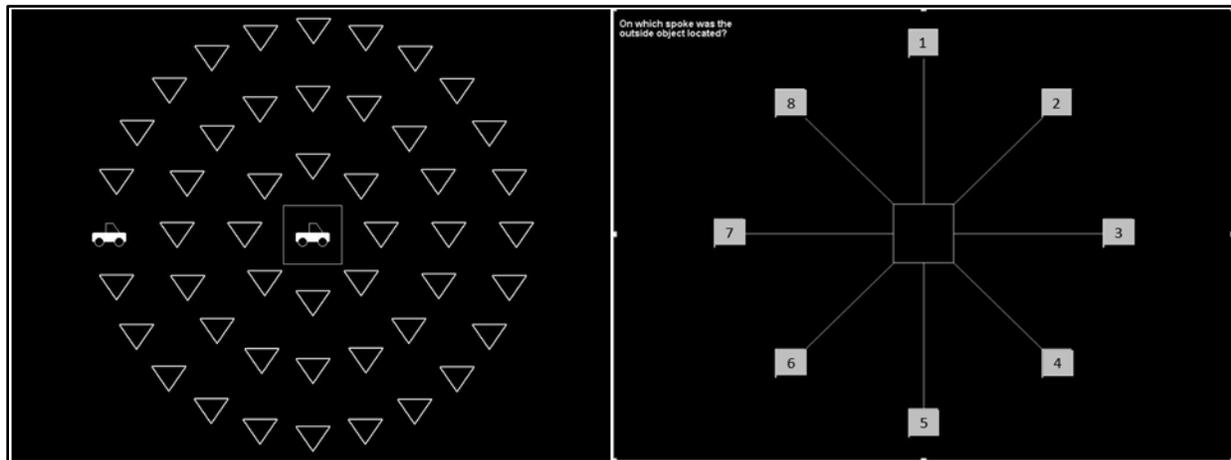


Figure 24. Screen capture. Selective attention subtest showing distractor triangles.

Rapid Pace Walk: The rapid pace walk assessment included a marked section of the floor 10 feet in length (Staplin, Lococo, Gish, & Decina, 2003). Participants were asked to walk the length of the marked section, turn around, and walk back as fast as they safely could without hurting themselves or without worry of falling or tripping (Figure 25). For participants' safety, the researcher always stood near enough to provide assistance if necessary, and the space was cleared of potentially hazardous objects.



Figure 25. Photo. Illustration of Rapid Pace Walk.

Neck and Torso Flexibility: The neck and torso flexibility assessment was conducted by asking the participant to sit in a fixed-base chair in a specific location within the room. While in this chair, participants were fitted with a helmet that had a laser pointer mounted to the side in such a fashion that it pointed in the direction of participants' heads. This allowed a mark to be projected onto the wall that moved in conjunction with the participants' head rotation and which could be easily noted and recorded. Participants completed two separate tasks: (1) one which specifically assessed neck flexibility where they were asked to keep their shoulders against the chair while turning as far as they comfortably could, and (2) one where participants were allowed to move their shoulders off the chair during the rotation exercise but not use their hands or arms to help twist (Figure 26).



Figure 26. Photo. Depictions of the neck and torso flexibility tests. The left image shows rotation with the back flat on the chair; the right image shows the participant twisting through the torso.

In both cases, participants were asked to rotate to the left and to the right. The score was the furthest point on the tape measure where participants could consistently shine the laser without bouncing or artificially increasing their range of motion.

Health and Lifestyle Questionnaires: The final assessment participants completed prior to entering the vehicle for the on-road portion of the study involved the administration of several surveys (Appendix A): Demographics, Technology Use, Vehicle Details and Features, Health Assessment, WHO (Five) Well-Being Index (1998 version), Major (ICD-10) Depression Inventory, and Activity Level.

In-Vehicle Protocols

After finishing the laboratory portion of the study, participants were offered a break. Once they were ready to proceed, participants were escorted to the study vehicle. Due to the population being examined, and mobility issues that may have been encountered with this group, the vehicle was always parked near the door.

The researcher then gave participants an introduction to the vehicle's controls and the various adjustments that could be made to the seats, side and rear-view mirrors, etc., that they would need to be comfortable and safely operate the vehicle. Next, the researcher gave a high-level overview of tasks to be completed while in the car. Safety considerations were also thoroughly discussed, including instructions that participants must wear a safety belt at all times, follow speed limits, and refrain from engaging in secondary tasks such as mobile phone use during the course of the study. Participants were also informed that a secondary braking system was installed on the passenger's floorboard, which the researcher explained was only for use if they detected an imminent danger.

Smart Road: After completing the laboratory portions of the session, participants completed a series of driving segments on the Virginia Smart Road, a 2.2-mile section of highway-grade roadway test track closed to outside traffic (Figure 27). Participants were given a brief introduction to the layout of the Smart Road and were informed that they should drive as close to 40 mph as possible for the duration of this portion of the study. Once participants felt comfortable with the rules and requirements of driving on the road, they completed a practice lap on the road, which allowed the researcher to point out turn-around locations and familiarize participants with the physical layout of the road. For safety reasons, we exclusively used road locations between the Top Turn and Turn 3 to avoid the bridge located between Turn 3 and the Bottom Turn.

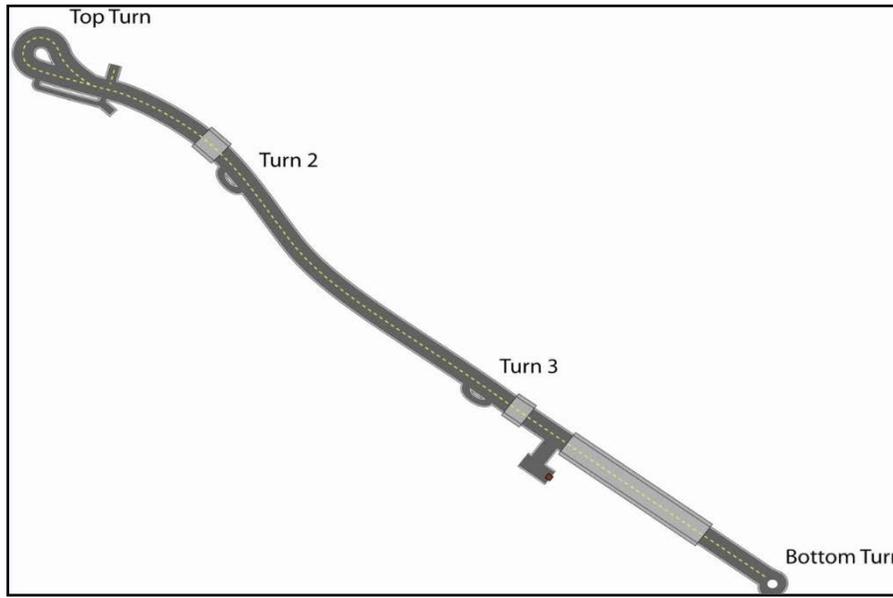


Figure 27. Diagram. The Virginia Smart Road.

Smart Road Tasks:

The participants’ first task on the Smart Road was to identify objects located on the side of the roadway that could indicate the presence of children. Participants completed this task while driving two full laps. These objects fell into five categories: signs, strollers, balls, dolls, and tricycles (Table 10). Each category contained several object instances to avoid repetition (Figure 28), and presentation location, order, and object instances were counterbalanced across participants and sessions. Figure 29 illustrates an example placement on the test course of the Sign object.

Table 10. Object types and descriptions used for the object identification task.

Object	Description	Type
Signs	A metal sign that was mounted at the top of a black metal pole with an overall height of 48 inches. Signs were a yellow background with black text and pictures, and measured 12 inches by 18 inches.	Caution Children at Play, Slow Kids at Play, Slow Children at Play, Drive Slow
Strollers	Simple small stroller with different patterns on the fabric.	Dinosaurs, X’s and O’s, Monkeys, Circles
Balls	Visually distinct play-balls of roughly the same size.	Kickball, Volleyball, Basketball, Soccer Ball
Tricycles	A small tricycle-type ride-on.	Traditional Red Metal, Blue and Red Big Wheel, Green and Blue Big Wheel, All Red Big Wheel
Dolls	A realistic child-sized mannequin 33 inches in height that wore different colored shirts.	Brown, Khaki, Dark Blue, Light Gray

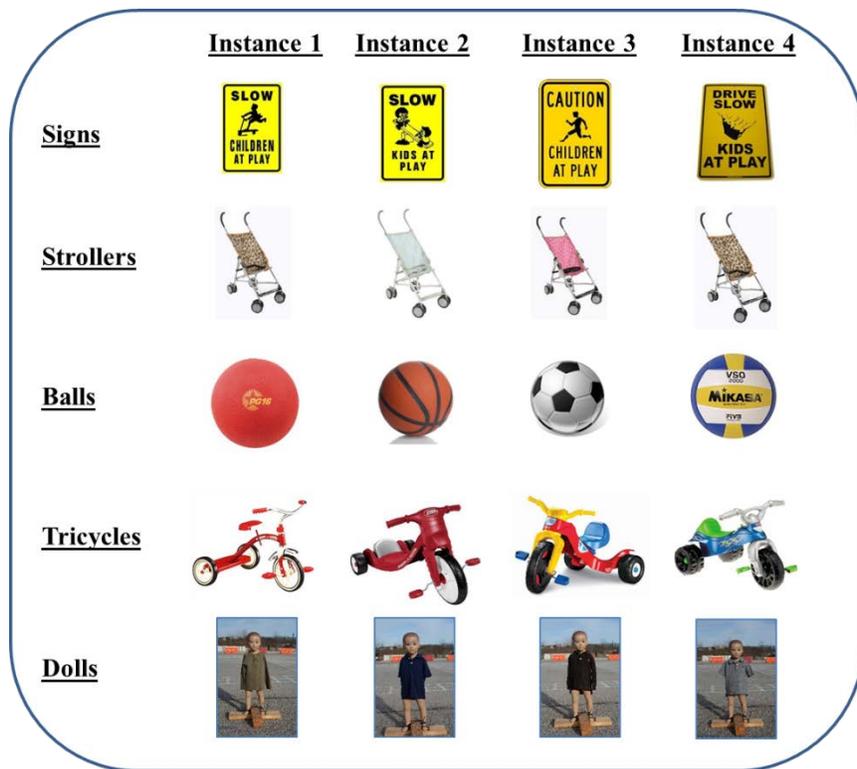


Figure 28. Illustration. Instances of object categories.



Figure 29. Photo. Example location of a Sign object.

Participants were instructed to call out the name of each object alongside the road as soon as they could identify it. Emphasis was placed on identifying the name of the object (stroller, ball, etc.) rather than vague terms (toy, thing) to enable accurate determination of identification distance. Each segment (“leg”) of each lap contained a single object at a given location, except for one segment that contained two objects. When a participant noted an object by name, or passed an object without reporting it, the researcher flagged the data stream by clicking an inconspicuous button. This flag assisted in data reduction. The dependent measure for this task was the distance at which the participant correctly identified each potential hazard.

Participants then drove approximately 2.5 laps of the Smart Road course while responding to the vehicle-centric PDT. Finally, participants drove an additional lap while performing the driver-centric PDT.

Public Road Section: Finally, participants were asked to drive a route on public roads in Blacksburg, VA, which took approximately 20 minutes. The route contained a mix of suburban, rural, and highway roads, and included several features such as unprotected left turns across path (LTAP) that are a source of major concern from a senior driver safety perspective.

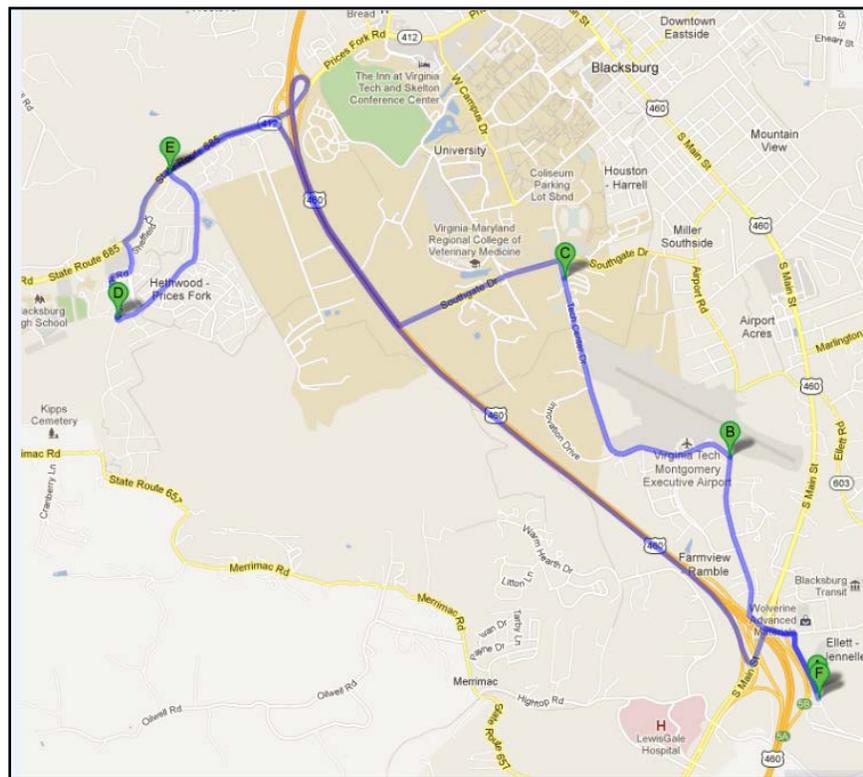


Figure 30. Map. Route driven during the public road driving segment of the study.

The experimenter rode with participants at all times to provide route guidance and ensure participant safety, which was facilitated by a passenger-side brake. Dependent measures for the public road route included glance entropy at specified locations (Figure 31), as well as vehicle control metrics, including the standard deviations of speed and lane position.

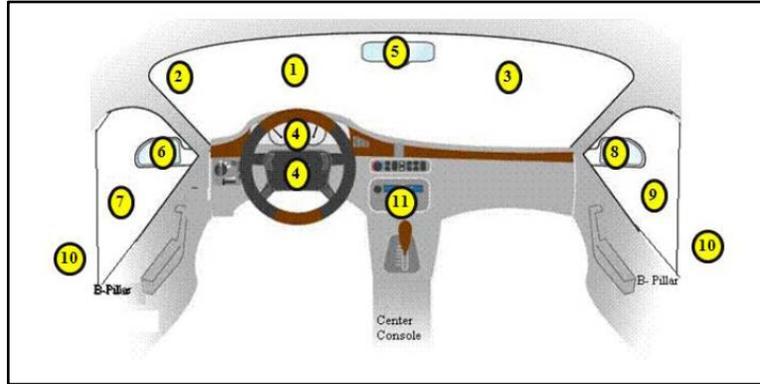


Figure 31. Illustration. Some of the glance locations coded during data reduction.

Glance entropy, or degree of dispersion in the pattern of glances is defined as follows:

$$\text{Glance Entropy} = -\sum_{i=1}^n p_i \log p_i$$

Where:

- p_i = probability of the i^{th} glance location
- n = number of possible glance locations

Note that for any $p_i = 0$, we define $p_i \log p_i = 0$, which is consistent with the well-known limit of this equation as p_i approaches zero.

Upon arrival back at VTTI, participants were paid in cash, signed an acknowledgment of receipt of money, and received a receipt for their time spent in the study.

CHAPTER 3. RESULTS

Results are presented first for metrics derived from the naturalistic driving segment, then for metrics derived from tasks performed on the Smart Road. On-road metrics included speed and lane position maintenance as well as glance entropy, all collected at each of several different types of roadway segments or scenarios. Metrics collected from participants' performance on a variety of experimental tasks performed within the controlled environment of the Smart Road included those related to roadside object detection distance, driver-centric PDT, and vehicle-centric detection task performance.

ON-ROAD METRICS

Standard Deviation of Speed

Standard deviation of speed was calculated for three 10-s windows of driving at different locations on the public road portion of the study. These locations represented a two-lane rural road with a speed limit of 35 mph, a neighborhood with a speed limit of 25 mph, and a four-lane divided highway with a speed limit of 65 mph (these segments are illustrated in Figure 32). Speed data were calculated using the vehicle network (recording at 50 Hz), or single-position GPS (1 Hz) on rare occasions when the network speed became unavailable due to technical issues. A mixed-design analysis of variance (ANOVA) was conducted using SAS on the standard deviation of speed for the first three experimental sessions for each public-road location, comparing the Control, Car Training, and Computer Training groups. It was predicted that speed variance, as a measure of driver workload, would decrease after training for the brain training groups but not for the control group, and that this difference would persist across subsequent follow-on sessions.



Figure 32. Photo. Examples of the three road segments.

The fourth experimental session was not included in the omnibus ANOVA due to the small number of Computer Training participants who completed this session as of the writing of this report; however, to evaluate the fourth session data for the two groups who did complete the study, a paired-comparison *t*-test was conducted for each location comparing the standard deviation for the Control and Car Training groups for the fourth and final experimental session. This approach was applied throughout the analysis process.

Mean standard deviations of speed and standard errors for the rural segment of roadway are shown in Figure 33. There was a marginal difference among training groups, $F(2, 50.4) = 2.48$, $p = 0.09$, but no significant difference across sessions, $F(2, 47.6) = 0.55$, $p > .05$, or interaction effect, $F(4, 56.3) = 0.36$, $p > .05$, was found. (Note: As F -values were calculated using a mixed-model in SAS, degrees of freedom were output in the more precise decimal notation, reflecting an increase in precision relative to more traditional methods.) An independent samples t -test found no significant difference between the Control and Car Training groups for the Session 4, $t(30) = 1.34$, $p > .05$.

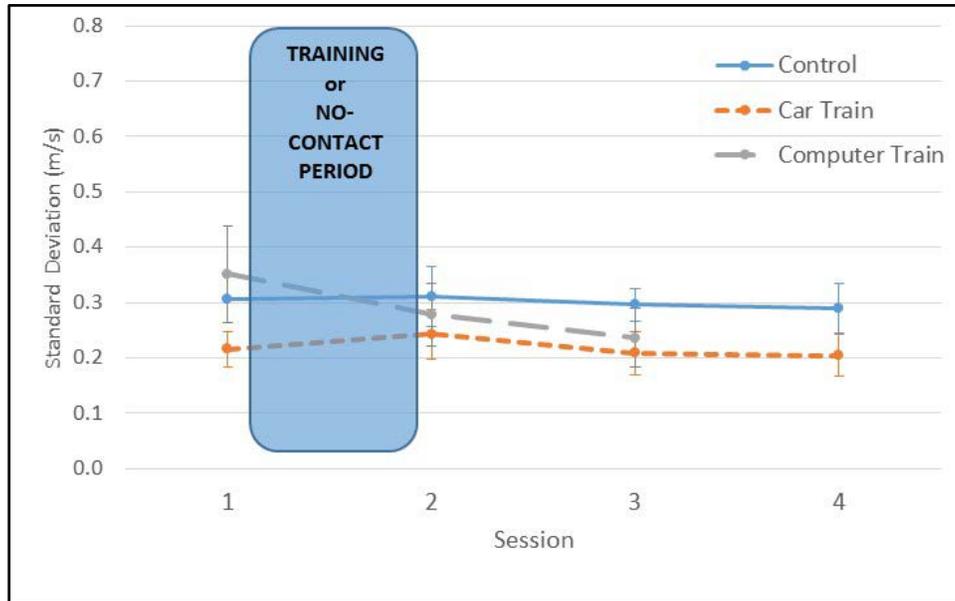


Figure 33. Chart. Standard deviation of speed for rural road segment.

Mean standard deviations of speed and standard errors for the highway segment of roadway are shown in Figure 34. There were no significant main effects for either training group $F(2, 46.8) = 0.65$, $p > .05$, or session, $F(2, 42.6) = 1.30$, $p > .05$, and no significant interaction among conditions $F(4, 49.8) = 0.60$, $p > .05$. An independent samples t -test found no significant difference between the Control and Car Training groups for Session 4, $t(30) = 0.65$, $p > .05$.

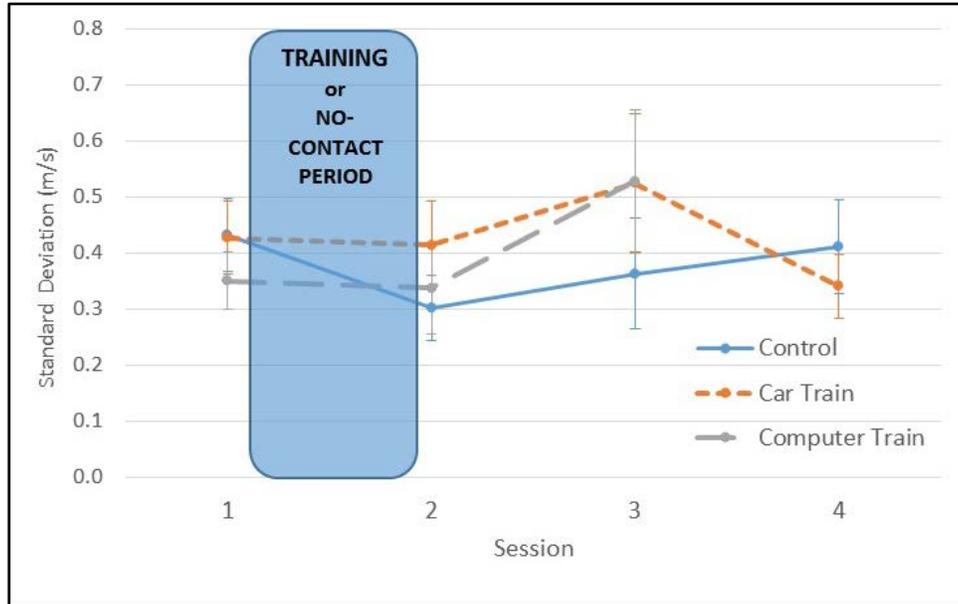


Figure 34. Chart. Standard deviation of speed for the highway road segment.

Mean standard deviations of speed and standard errors for the neighborhood roadway segment are shown in Figure 35 below. There was a marginal effect of Session, $F(2, 42.2) = 2.47$, $p = 0.097$, that may reflect a general increase in variance for all groups between sessions Post 1 and Post 2, but no effect of Group, $F(2, 46.5) = 1.41$, $p > .05$, or interaction between Group and Session, $F(4, 49.3) = 0.78$, $p > .05$. An independent samples t -test found no significant difference between the Control and Car Training groups for Session 4, $t(30) = 1.88$, $p > .05$.

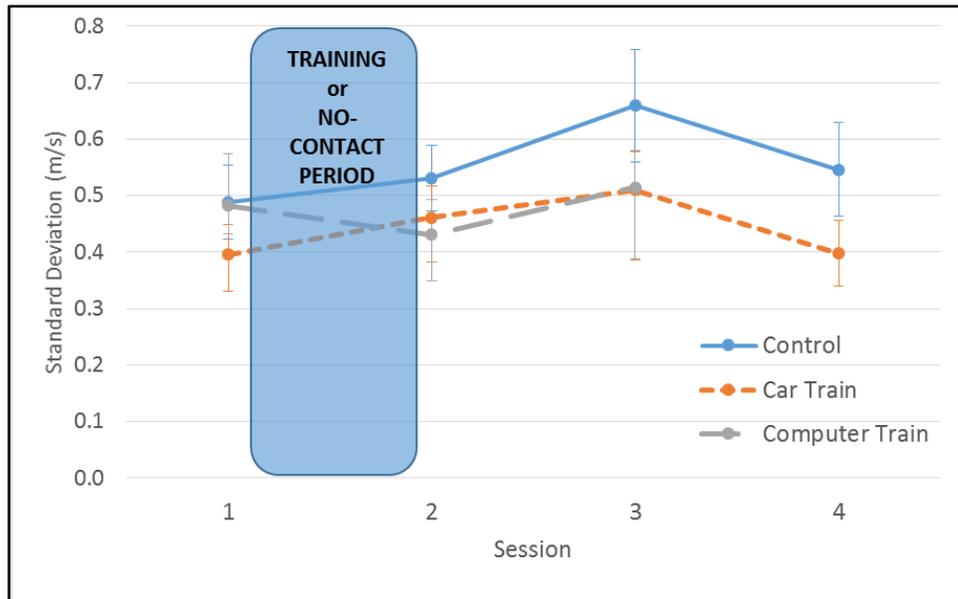


Figure 35. Chart. Standard deviation of speed for the neighborhood road segment.

Standard Deviation of Lane Position

Lane position was recorded using VTTI's Road Scout machine-vision software, which utilizes the forward view of the roadway and detectable lane lines to generate this metric. Standard deviation of lane position was calculated for two 10-s windows of driving at different locations on the public road portion of the study comprising a two-lane rural road with a speed limit of 35 mph and a four-lane divided highway with a speed limit of 65 mph. Since there were no lane lines for the neighborhood portion of the drive, it was not possible to calculate position variability for this section. A mixed-design ANOVA was conducted on the standard deviation of position for the first three experimental sessions for each public-road location, comparing the Control, Car Training, and Computer Training groups. A paired-comparison *t*-test was conducted for each location comparing the standard deviation for the Control and Car Training groups for the fourth and final experimental session. It was predicted that lane position variance, as a measure of driver workload, would decrease after training for the brain training groups but not for the control group, and that this difference would persist across subsequent follow-on sessions.

Mean standard deviations of lane position and standard errors for the rural segment of roadway are shown in Figure 36 below. There were no significant differences in lane position among training groups, $F(2, 48.1) = 0.35, p > .05$, or across sessions, $F(2, 48.7) = 0.47, p > .05$; there was also no interaction effect, $F(4, 56.8) = 0.72, p > .05$. No significant difference was found between the Control and Car Training groups in Session 4, $t(30) = -1.39, p > .05$.

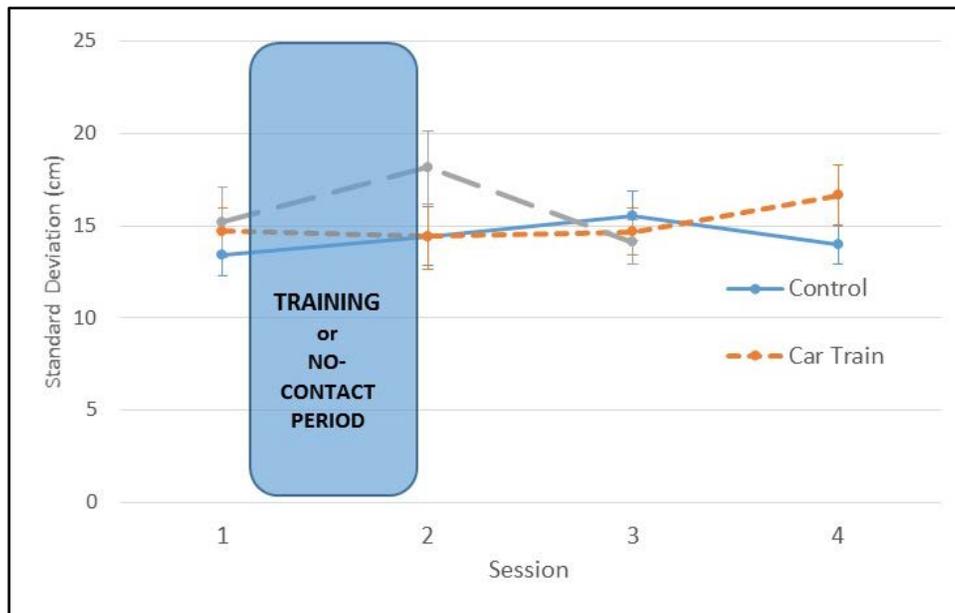


Figure 36. Chart. Standard deviation of lane position for the rural road segment.

Mean standard deviations of lane position and standard errors for the highway segment of roadway are shown in Figure 37 below. There were no significant differences in lane position found among training groups, $F(2, 41.1) = 0.14, p > .05$, or across sessions, $F(2, 43.3) = 0.54, p > .05$; however, there was a marginal interaction found between Group and Session,

$F(4, 49.1) = 0.72, p = 0.09$; this may simply reflect the large degree of variability in lane position for the Car Training group, particularly in Session 2. An independent samples t -test found no significant difference between the Control and Car Training groups for Session 4, $t(30) = -1.38, p > .05$.

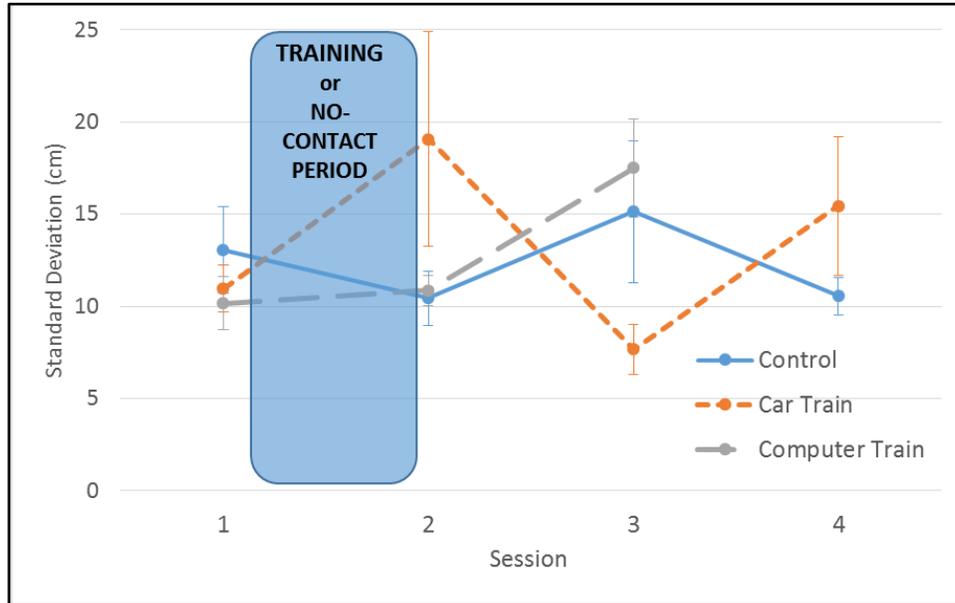


Figure 37. Chart. Standard deviation of lane position for highway road segment.

Glance Entropy

Glance entropy, or amount of dispersion displayed in the pattern of glances during a period of time, was calculated for three intersections at which participants made left-hand turns during the public-road portion of the experimental sessions. This metric can be used as a way to investigate the degree to which drivers are sampling from a broad array of information sources (i.e., greater degree of entropy) vs. focusing on a more narrowly scoped set. As described above, we predicted that drivers in the training groups would show increased glance entropy post-training compared to the control group, and that this difference would persist across all post-training sessions.

These three intersections represented a signal-protected turn, an unprotected turn with a turning lane, and a sign-protected turn. As these intersections contain distinct features and driver requirements, they are presented separately here. These intersections are illustrated in Figure 38.



Figure 38. Photo. Examples of intersection types.

Glance location was determined by trained reductionists viewing drivers' faces and noting where they were looking during each frame recorded at 10 Hz (Figure 31).

Intersection Glance Entropy

For intersections, glance was analyzed from the period starting 5 s prior to when drivers entered the intersection (Figure 39, point A) until they exited the conflict zone (Figure 39, point C). This standardized the amount of time prior to intersection entrance while incorporating both the drivers' glances when they made the decision to turn and the entirety of the intersection conflict zone.

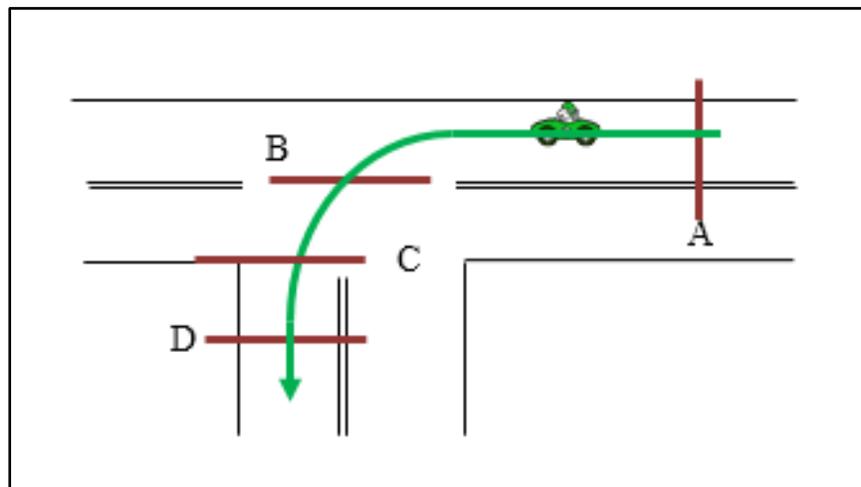


Figure 39. Diagram. Example of reduction protocol for intersections.

Mean entropy and standard errors across groups for the unprotected left-turn intersection are presented in Figure 40 below. No main effects were found for Group, $F(2, 52.2) = 0.71, p > .05$, or Session, $F(2, 49.6) = 0.05, p > .95$, nor was a significant interaction effect found for Group*Session, $F(4, 57.4) = 1.58, p > .05$. An independent samples t -test found no significant difference in entropy scores between the Control and Car Training groups for Session 4, $t(33) = -0.9, p > .05$. While not statistically significant, there was a trend in the data for the Car

Training group to have increased entropy after training, and to maintain this at a higher entropy than the Control group across sessions. This suggests that there may be some benefit from the Car Training in terms of enhanced glance strategy at unprotected intersections, but at a level that this study design did not have sufficient statistical power to detect.

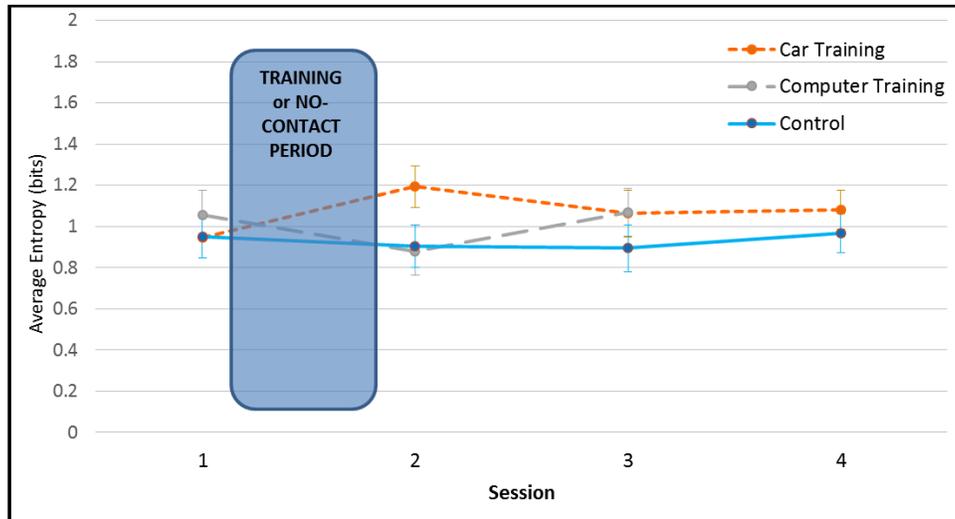


Figure 40. Chart. Average glance entropy for unprotected left-turn intersection.

Mean entropy and standard errors across groups for the sign-protected left-turn intersection are presented in Figure 41. No main effects were found for Group, $F(2, 50.7) = 2.19, p > .05$, or Session, $F(2, 49.8) = 0.05, p > .95$, nor was a significant interaction effect found for Group*Session, $F(4, 57.7) = 1.48, p > .05$. An independent-samples t -test found no significant difference between Control and Car Training group scores for Session 4, $t(33) = -0.06, p > .05$.

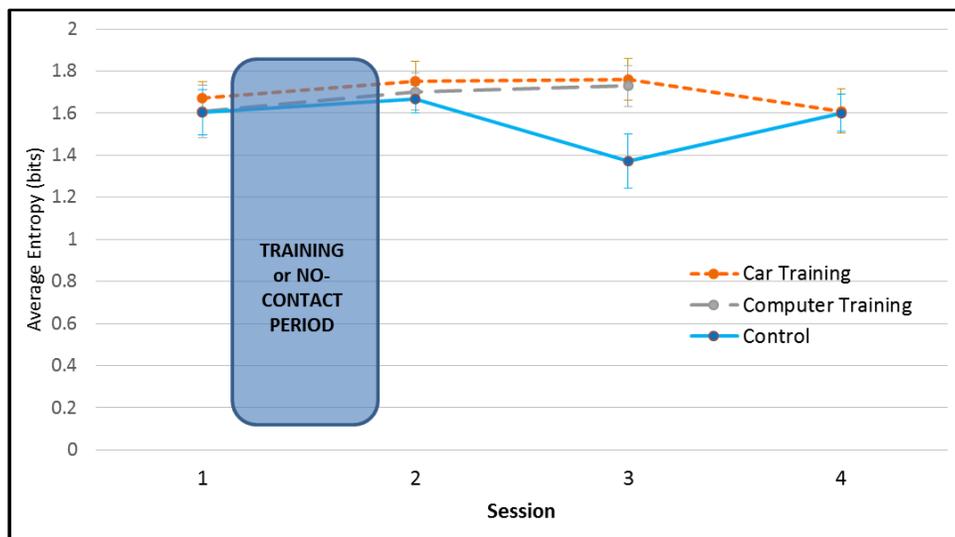


Figure 41. Chart. Average glance entropy for sign-protected left-turn intersection.

Mean entropy and standard errors across groups for the signal-protected left-turn intersection are presented in Figure 42 below. No main effects were found for Group, $F(2, 50.7) = 0.20, p > .05$, or Session, $F(2, 48.6) = 0.23, p > .95$, nor was a significant interaction effect found for Group*Session, $F(4, 56.7) = 0.09, p > .05$. An independent samples t -test found no significant difference in entropy scores between the Control and Car training groups for Session 4, $t(33) = 0.2, p > .05$.

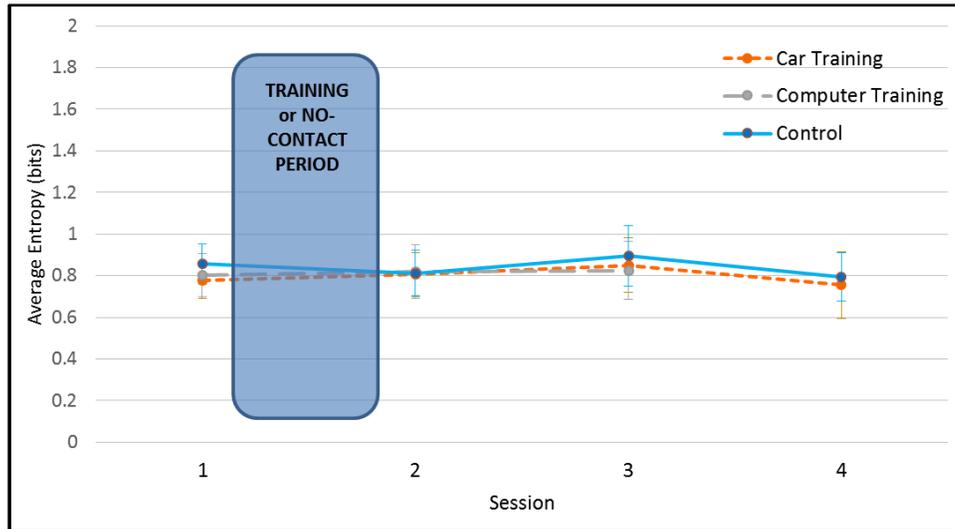


Figure 42. Chart. Average glance entropy for signal-protected left-turn intersection.

Road Segment Glance Entropy

In addition to intersections, glance entropy was analyzed for three sections of public road driving. These road segments are the same as those introduced in the Speed and Lane Position data above: rural, neighborhood, and highway. Each of these segments was 10 s in duration, initiated at a common landmark. As before, a mixed-design ANOVA was conducted on only the first three sessions, and an independent-samples t -test was conducted to determine if there was a difference in scores between the Control and Car Training groups for the fourth session.

Mean entropy and standard deviations for the rural driving segment for all training groups are illustrated in Figure 43 below. There were no significant main effects of Group, $F(2, 50.2) = 0.30, p > .05$ or Session, $F(2, 48.1) = 0.62, p > .05$, or for the interaction of Group*Session, $F(4, 55.8) = 1.25, p > .05$. An independent-sample t -test found no significant difference in scores between Control and Car Training groups for Session 4, $t(33) = -0.36, p > .05$.

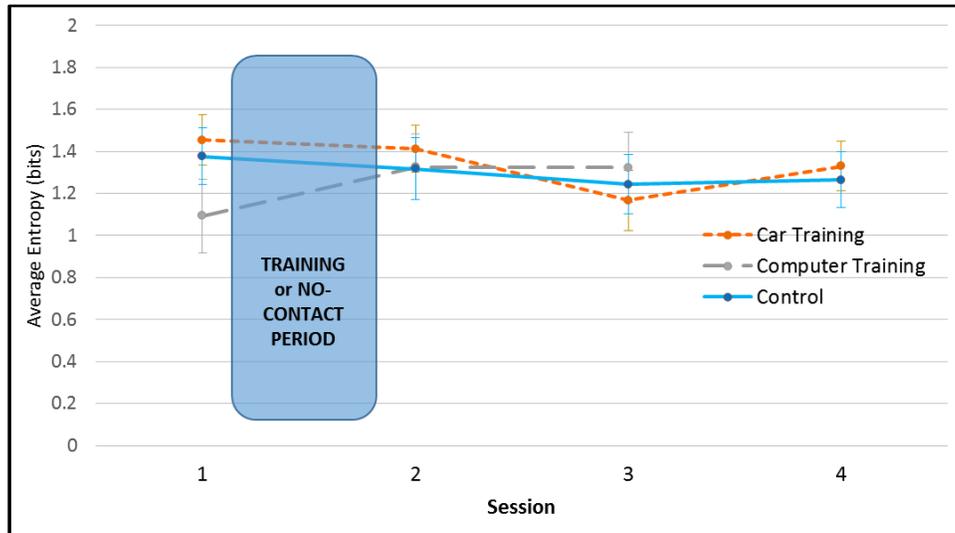


Figure 43. Chart. Average glance entropy for 10-s rural driving segment.

Mean entropy and standard deviations for the neighborhood driving segment for all training groups are illustrated in Figure 44 below. There was a marginally significant main effect for Group, $F(2, 49.7) = 2.52, p = .09$, but no main effect of Session, $F(2, 48.9) = 0.57, p > .05$, or for the interaction of Group*Session, $F(4, 56.9) = 0.65, p > .05$. A Tukey-Kramer adjusted post hoc test for Group found that the Car Training group scored marginally higher than the Control group, $p = .09$. An independent-sample t -test found no significant difference in scores between Control and Car Training groups for Session 4, $t(33) = -1.16, p > .05$.

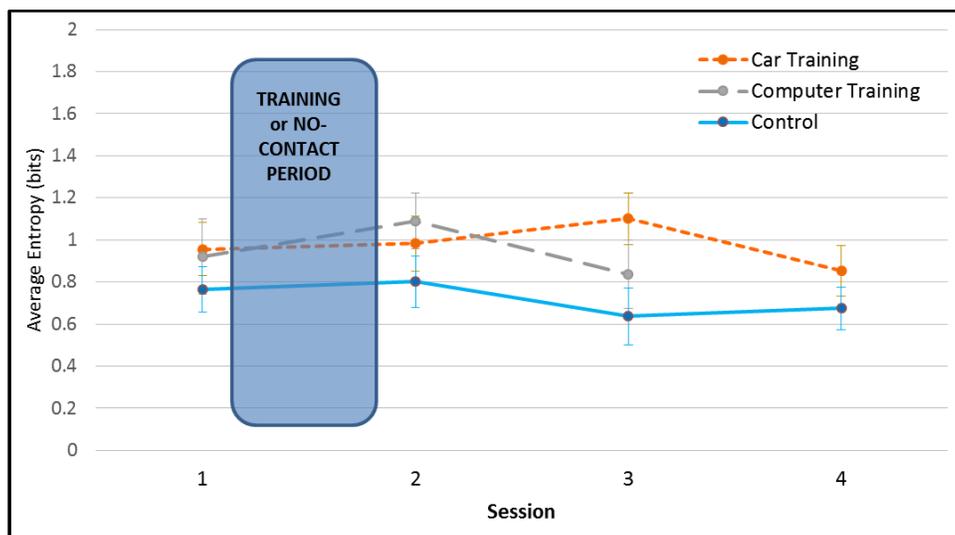


Figure 44. Chart. Average glance entropy for 10-s neighborhood driving segment.

Mean entropy and standard deviations for the highway driving segment for all training groups are illustrated in Figure 43 below. There were no significant main effects of Group, $F(2, 49) = 0.173, p > .05$, or Session, $F(2, 49.3) = 0.13, p > .05$. There was a marginally significant Group*Session interaction, $F(4, 56.7) = 2.12, p = .09$. An independent-sample t -test

for Session 4 alone found that the mean entropy of the Car Training group was significantly higher than that of the Control group, $t(33) = -2.70, p < .05$.

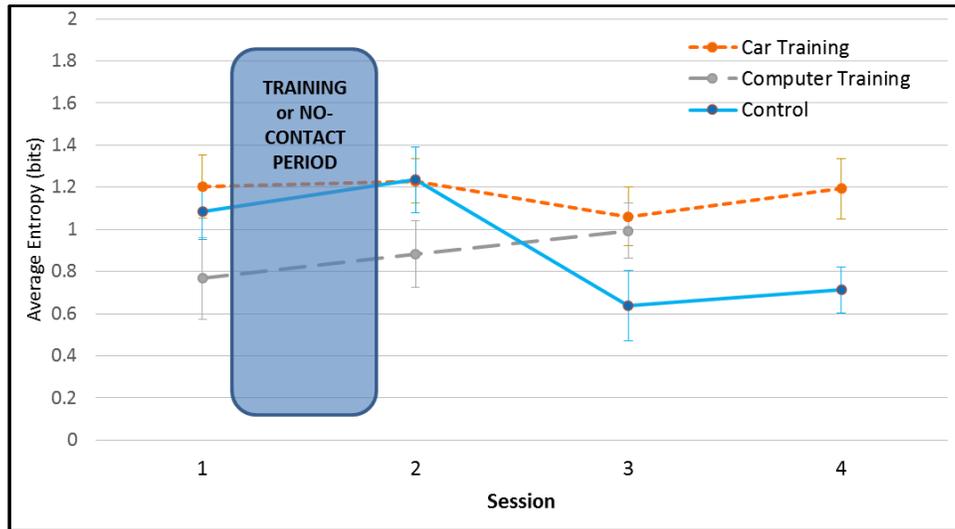


Figure 45. Chart. Average glance entropy for 10-s highway driving segment.

TEST TRACK METRICS

Roadside Object Detection Distance

While driving on the closed-road course, participants were asked to identify roadside objects that may have indicated the presence of children, including signs, balls, strollers, tricycles, and dolls (Figure 28). There were five objects in each session, spread over the course of two laps of the course (one object on each course leg, with one leg having two objects). We predicted that participants who participated in brain training, which is designed to attune drivers to peripheral stimuli, would exhibit the ability to detect relevant objects from a farther distance relative to the control group, and that this difference would persist across post-training sessions.

Mean recognition distance and standard error in meters for participants in all three groups are shown in Figure 46. A marginal effect was found for Training Group, $F(2, 49.4) = 2.38, p = .10$, with the Control group scoring higher on average than the Car Training group. There was a significant effect of Session, $F(2, 46.3) = 6.75, p = .002$; Tukey-Kramer adjusted post hoc tests showed that Session 1 showed a significantly shorter recognition distance (i.e., worse performance) than Session 2, $t(52) = -2.46, p = 0.04$, and Session 3, $t(45.1) = -3.47, p = .003$, while there was no significant difference between the mean recognition distances for Group 2 and Group 3 ($p > .05$). An independent-samples t -test found no significant difference in scores between the Control and Car Training groups for Session 4, $t(34) = 0.44, p > .05$.

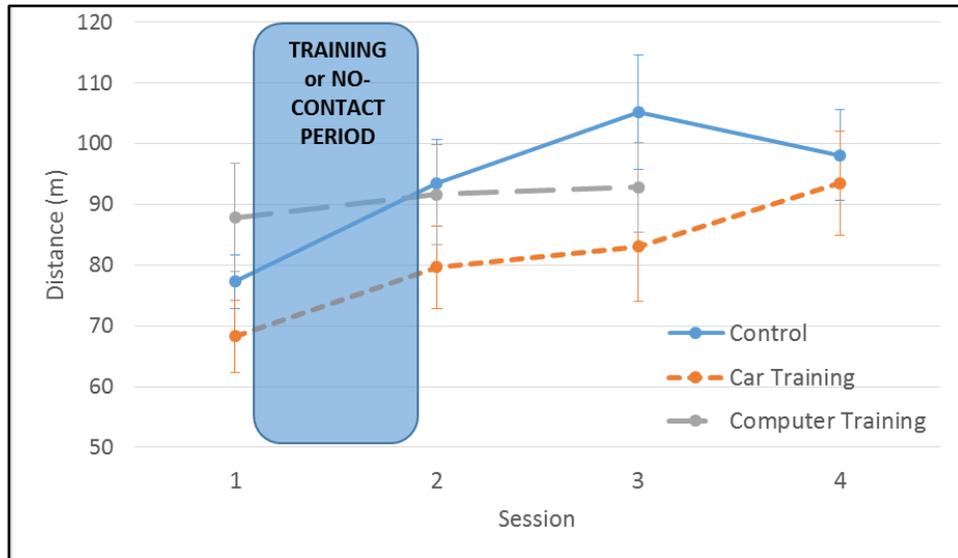


Figure 46. Chart. Mean roadside object recognition distance.

Mean object detection hit rates (correct object identifications/total object identification opportunities) and standard deviations are shown in Figure 47 below. A mixed-design ANOVA found no significant difference among Groups, $F(2, 51.2) = 1.14, p > .05$, or across Sessions, $F(2, 51.6) = 1.49, p > .05$, nor was a significant Group*Session interaction effect found, $F(4, 57.2) = 0.89, p > .05$. An independent-samples t -test found no significant difference between Control and Car Training hit rates for Session 4, $t(32) = 1.52, p > .05$.

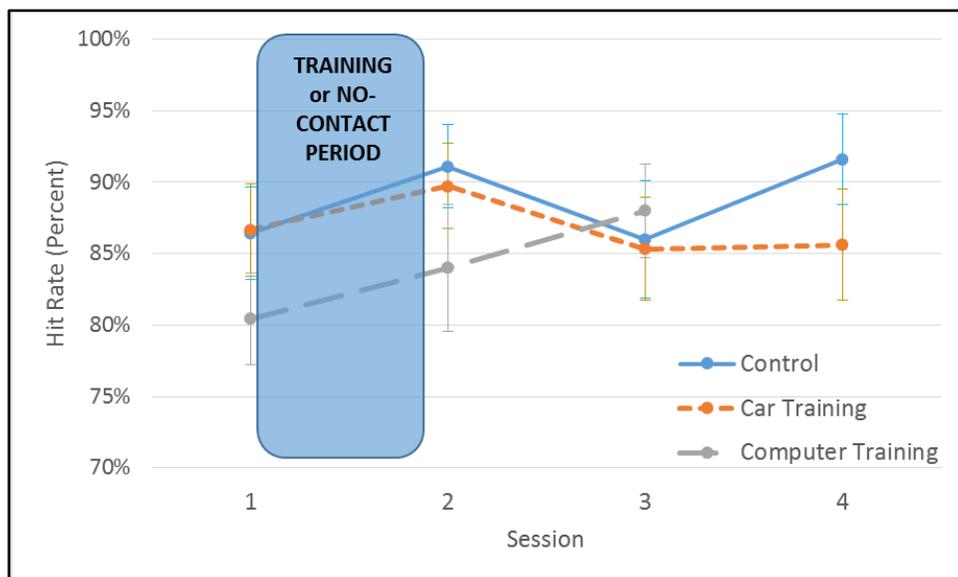


Figure 47. Chart. Mean roadside object recognition hit rate.

Vehicle-Centric Detection Task

During the closed-road course portion of the study, participants were asked to respond as quickly as possible to three randomly illuminating LED lights mounted on stalks on the hood of the test vehicle using a finger-mounted switch (Figure 6). The following graphs illustrate response times and hit rates for each of the three lights. We predicted that participants in the brain training groups, which were designed to attune drivers to peripheral stimuli, would exhibit faster responses and higher accuracy than the control group, and that this difference would persist across post-training sessions. One omnibus ANOVA was conducted to determine the effects of Gender, Session, and Light Location (Left, Center, or Right) on response time, and another ANOVA was conducted on the same variables for hit rate.

Figure 48 shows mean reaction times and standard deviations in milliseconds for all Groups across all Sessions, combined across lights. Figure 49, Figure 50, and Figure 51 illustrate mean reaction times and standard errors in milliseconds for all Groups across Sessions, for the Left, Center, and Right light, respectively. The omnibus ANOVA found main effects of Session, $F(2, 64.4) = 38.88, p < .0001$, and Light Location, $F(2, 47.5) = 36.01, p < .0001$, but no significant effect of Group, $F(2, 47.7) = 0.19, p > .05$. Significant interactions were found for Group*Session, $F(4, 65.1) = 2.54, p = .048$, and Group*Light Location, $F(4, 50.3) = 5.01, p = .002$. No significant interaction was found for Session*Light Location, $F(4, 50.3) = 1.27, p > .05$, and no significant three-way interaction was found, $F(8, 57.9) = 1.74, p = 0.11$.

The significant main effect of Session suggests that reaction times tended to improve over time, which can be seen in Figure 48. Tukey-Kramer corrected tests found that Session 3 had a lower mean response latency than Sessions 1 and 2, $p < .0001$ for both, although there was no significant difference between Sessions 1 and 2, $p > .05$. The main effect of Light Location suggests that some lights elicited faster response time than others; this is illustrated in Figure 52, where the left light is associated with the longest reaction time, particularly for the Control and Computer Training groups. Post hoc tests also found that response times for all light locations were significantly different from one another, $p < .01$ in all cases. The interaction between Group and Session can be seen in a significant decrease in reaction time (RT) between Sessions 1 and 3 for Control and Car Training groups, but not the Computer Training group, and a significant decrease in RT between Sessions 1 and 2 for the Control group but no other groups. These results reveal little of scientific interest. An ANOVA testing the independence of Control and Car Training mean reaction times for Session 4 revealed no significant effects of Group, $F(1, 49) = 0.84, p > .05$, Light Location, $F(2, 49) = 1.55, p > .05$, or interaction between Group*Light Location, $F(1, 49) = 0.97, p > .05$.

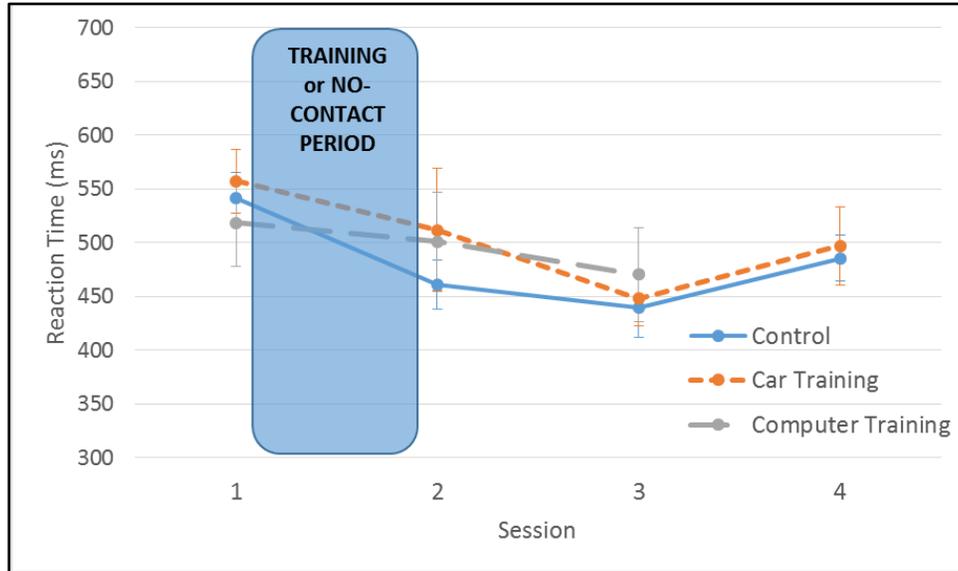


Figure 48. Chart. RT for vehicle-centric detection task combined.

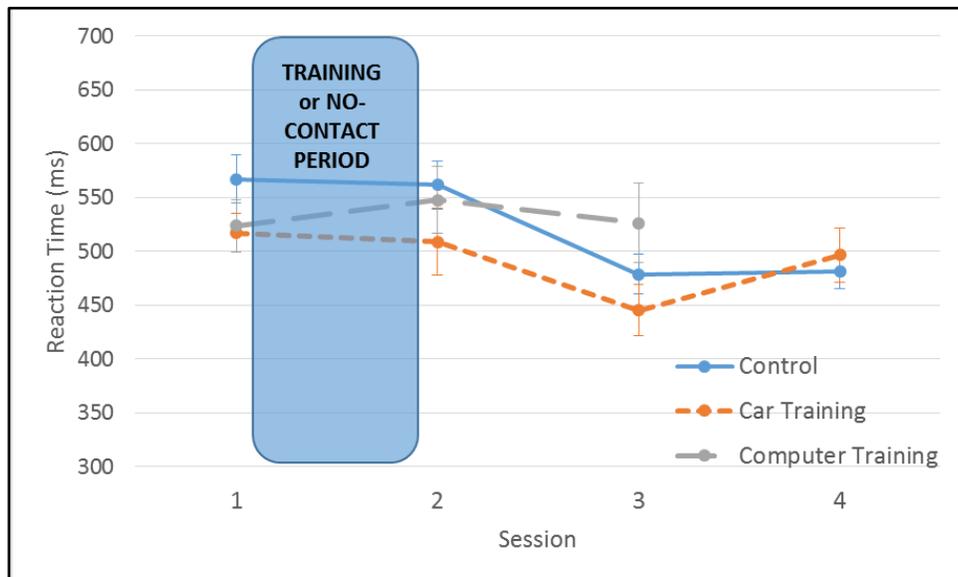


Figure 49. Chart. RT for the left vehicle-centric detection task.

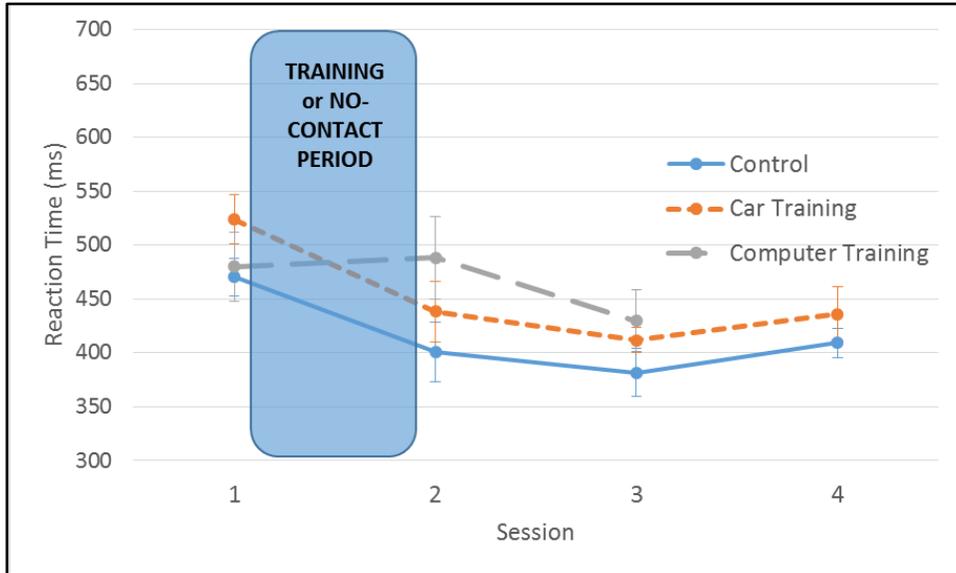


Figure 50. Chart. RT for the center vehicle-centric detection task.

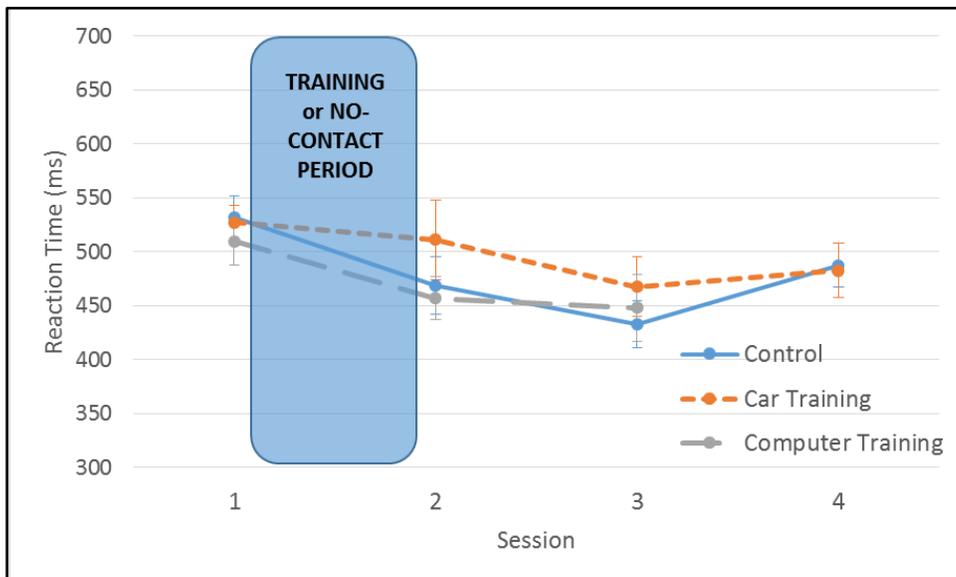


Figure 51. Chart. RT for the right vehicle-centric detection task.

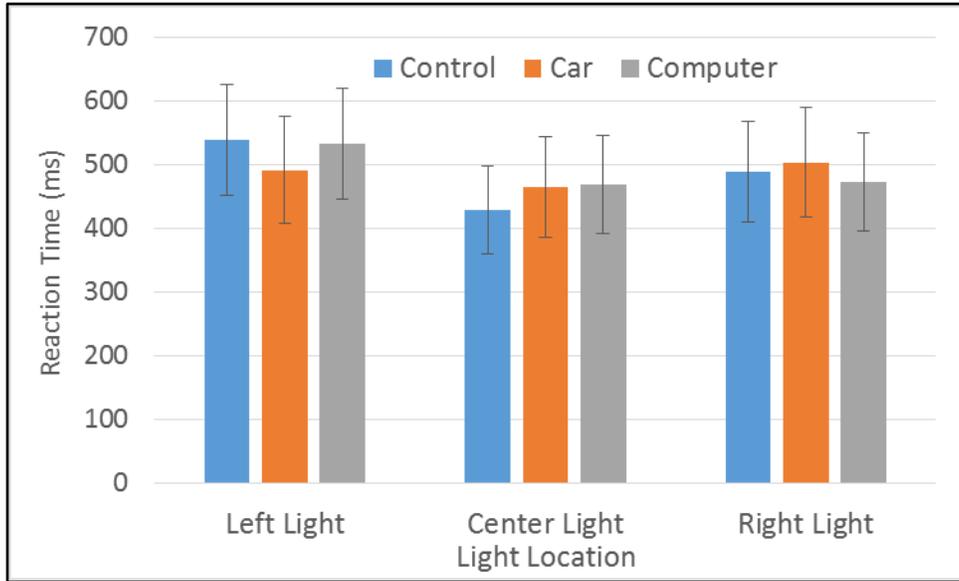


Figure 52. Chart. Reaction time by light location.

The hit rates (HRs), the correct responses/total illuminations, for the vehicle-centric lights are presented below. Figure 53 presents combined hit rate across the three lights, while Figure 54, Figure 55, and Figure 56 present hit rate data for the left, center, and right lights, respectively. Because the hit rate was close to 100% for all conditions, representing a ceiling effect, statistics were not run for this metric. However, there did appear to be a practice effect as performance tended to improve between the first and second sessions. No notable differences were seen among groups, either split across light locations or for the combination of all lights.

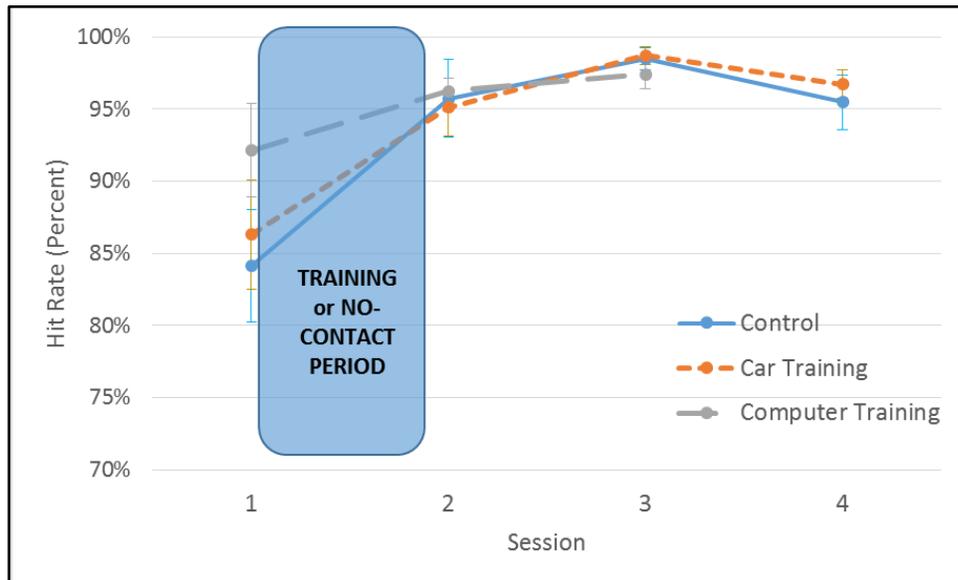


Figure 53. Chart. HR for the vehicle-centric detection task combined.

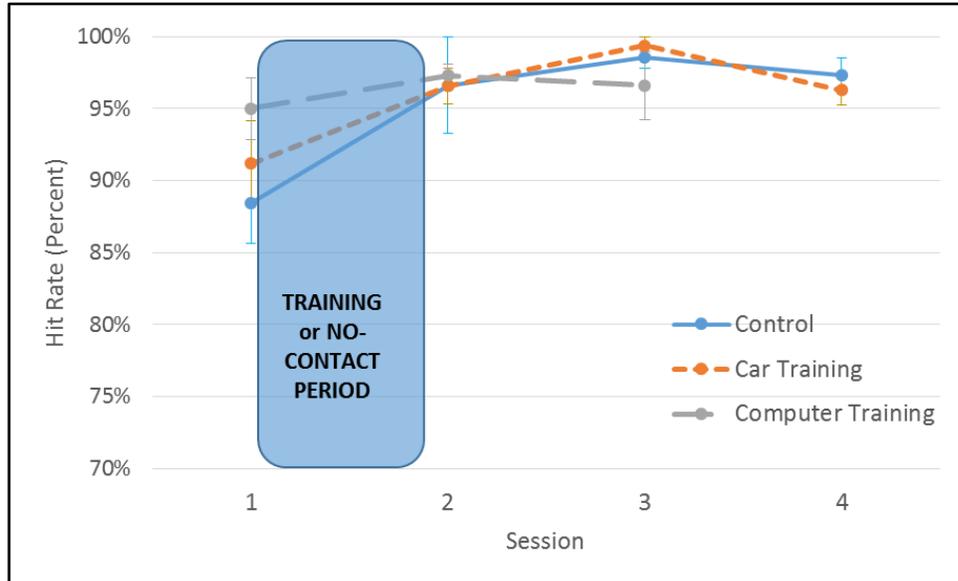


Figure 54. Chart. HR for the left vehicle-centric detection task.

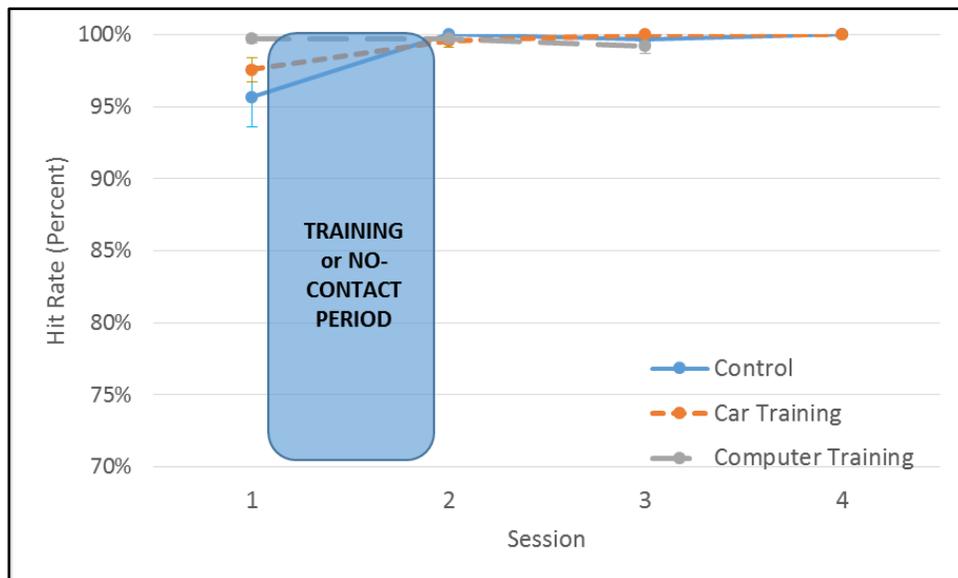


Figure 55. Chart. HR for the center vehicle-centric detection task.

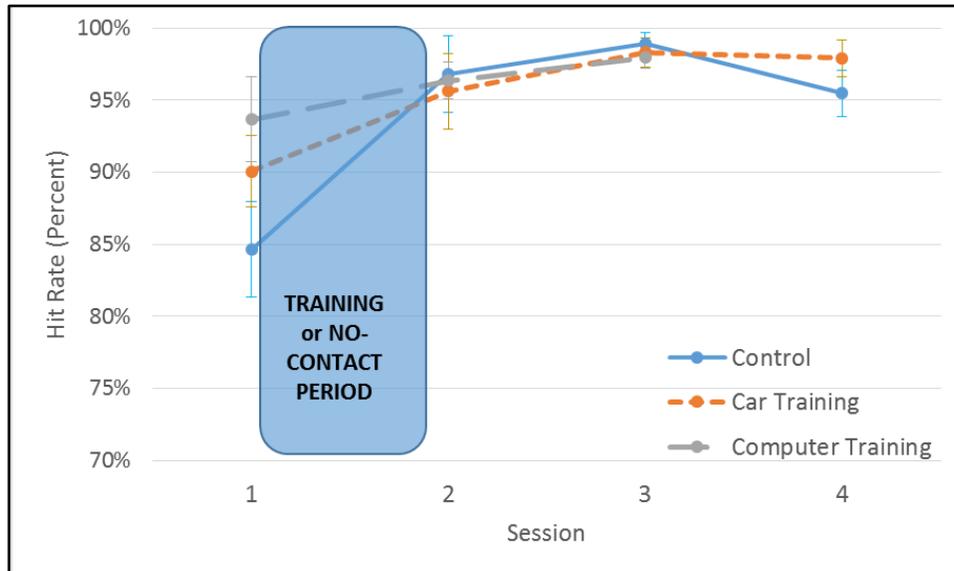


Figure 56. Chart. HR for the right vehicle-centric detection task.

Driver-Centric Peripheral Detection Task

Participants were asked to drive on the closed-road course and use a finger switch to respond as quickly as possible to three randomly illuminating lights mounted on a headband. This constituted a *driver-centric* PDT, as the lights' position in space remained in a constant spatial location relative to the driver's field of view no matter how the participant's head moved. The following graphs illustrate response times and hit rates for each of the three lights. One omnibus ANOVA was conducted to determine the effects of Gender, Session, and Light Location (Left, Center, or Right) on response time, and another ANOVA was conducted on the same variables for hit rate.

Figure 57 shows mean reaction times and standard deviations in milliseconds for all Groups across all sessions, combined across lights. Figure 58, Figure 59, and Figure 60 illustrate mean reaction times and standard errors in milliseconds for all Groups across Sessions, for the Left, Center, and Right light, respectively.

A mixed-design ANOVA found no significant effect of Group, $F(2, 51.3) = 0.48, p > .05$, a marginal effects of Session $F(2, 50.6) = 3.16, p = .05$ and a significant effect of Light Location $F(2, 44.4) = 16.46, p < .0001$. There were significant interactions for Group*Light Location, $F(4, 52.3) = 5.29, p = .001$; Session*Light Location $F(4, 45.5) = 2.59, p = .048$; and a three-way interaction of Group*Session*Light Location, $F(8, 62.2) = 5.36, p < .0001$. There was no significant interaction between Group*Session, $F(4, 59.2) = 1.36, p = 2.59$. An ANOVA testing the independence of Control and Car Training mean reaction times for Session 4 alone revealed no significant effects of Group, $F(1, 49) = 0.84, p > .05$; Light Location, $F(2, 49) = 1.55, p > .05$; or interaction between Group*Light Location, $F(1, 49) = 0.97, p > .05$. There appeared to be a general trend for the Car Training group to improve (decrease reaction time) relative to the other two groups, but this was not supported by a significant Group*Session interaction. The significant main effect and interactions of Light Location can be seen in Figure 61; although the

data are largely similar across light locations, the Control group had the shortest reaction time for the left light. Given the variability in data across the following graphs, and the lack of clear data trends, the Group*Session*Light Location interaction was not further analyzed.

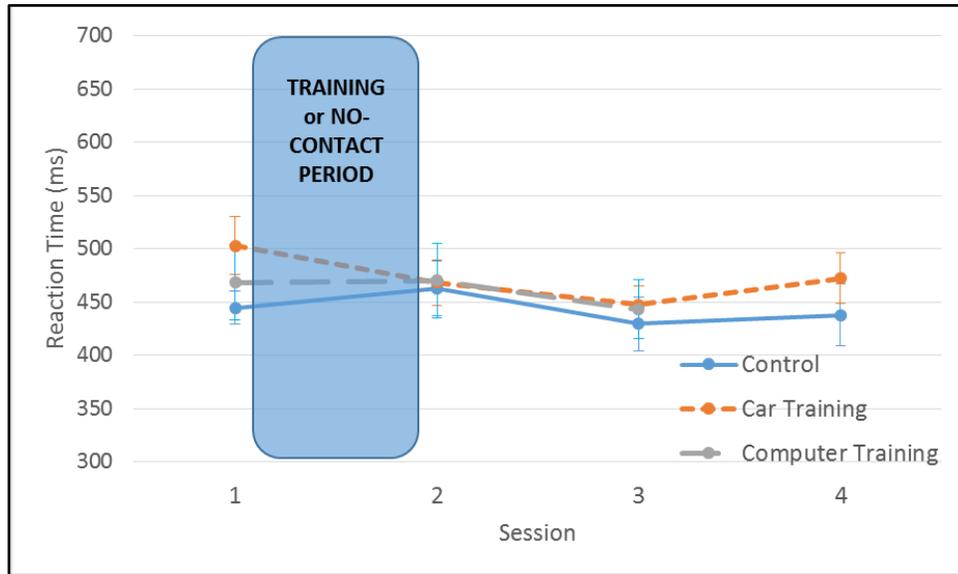


Figure 57. Chart. RT for the driver-centric PDT combined.

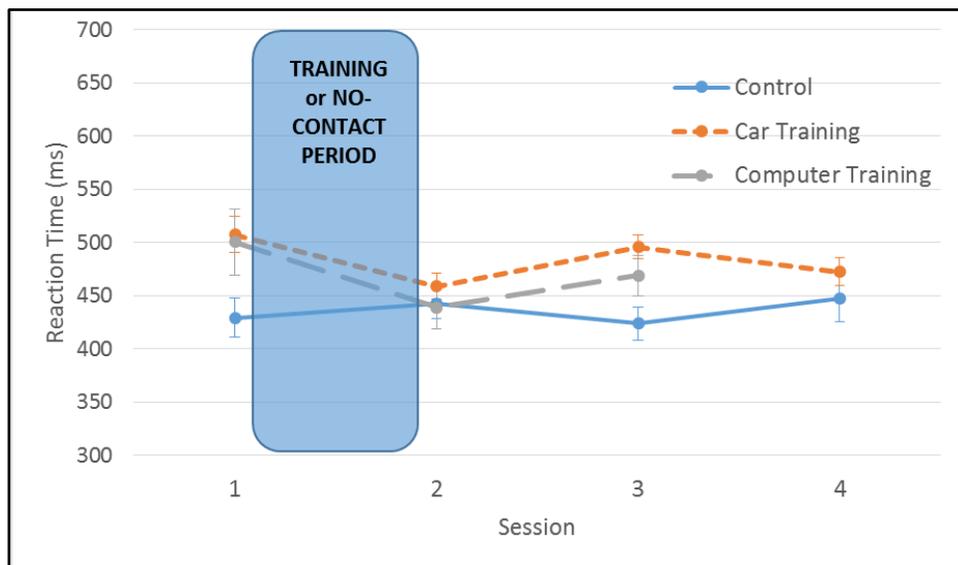


Figure 58. Chart. RT for left driver-centric PDT.

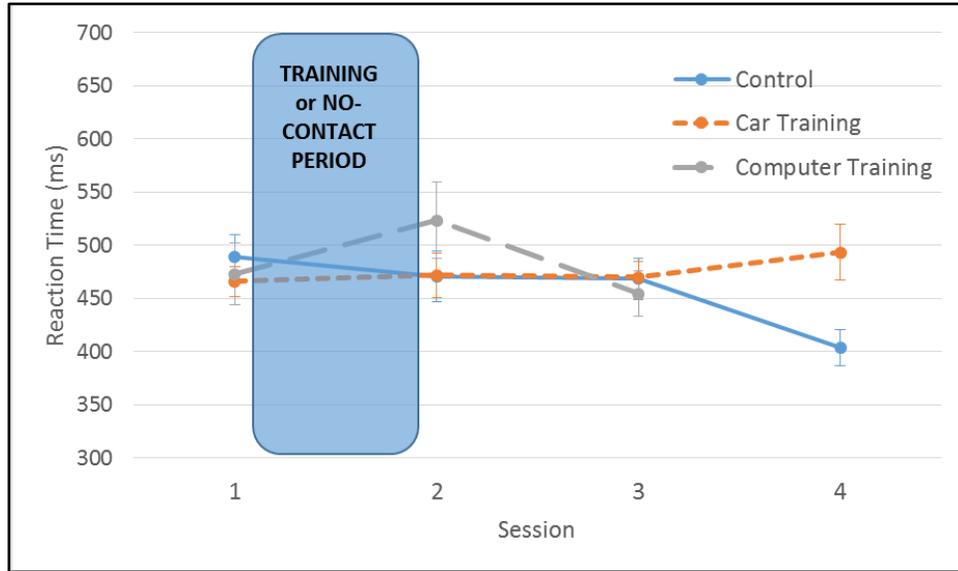


Figure 59. Chart. RT for the center driver-centric PDT.

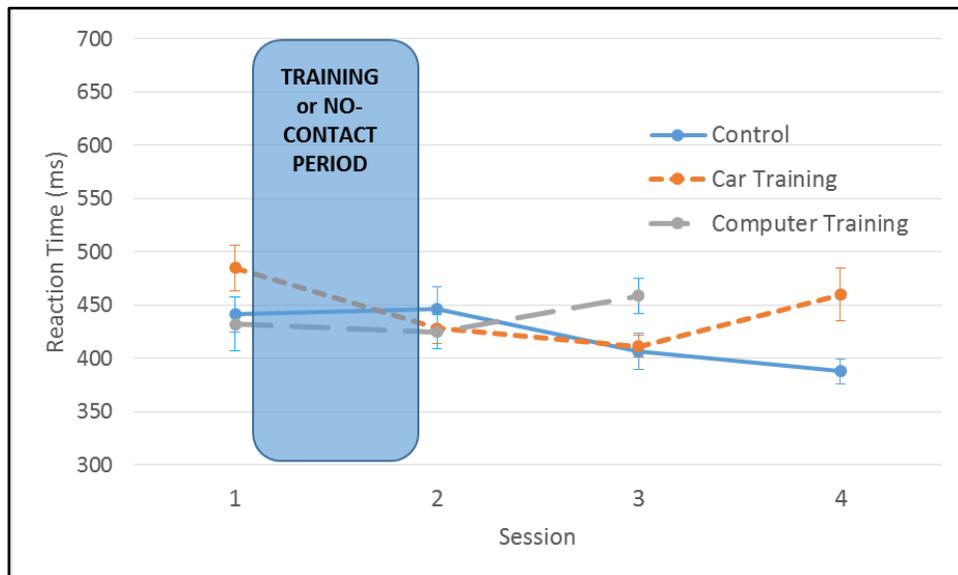


Figure 60. Chart. RT for the right driver-centric PDT.

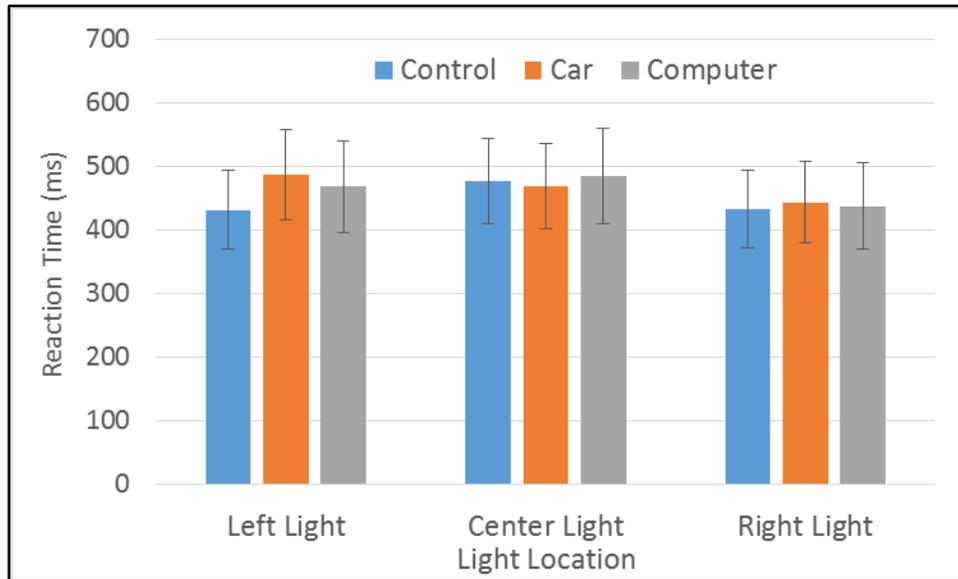


Figure 61. Chart. Reaction time by light location for driver-centric PDT.

The hit rate (correct responses/total illuminations) for the driver-centric PDT is presented below. Figure 62 presents combined hit rate across the three lights, while Figure 63, Figure 64, and Figure 65 present hit rate data for the left, center, and right lights, respectively. Because the hit rate was close to 100% for all conditions, representing a ceiling effect, statistical analyses were not run for this metric. Unlike the vehicle-centric detection task, there did not appear to be an increase in performance across sessions, particularly for the left and right lights, which were near 100% for all sessions. The middle light did have a somewhat lower hit rate, indicating that it may have been harder to detect; however, it still had well over a 90% hit rate for nearly all groups and conditions.

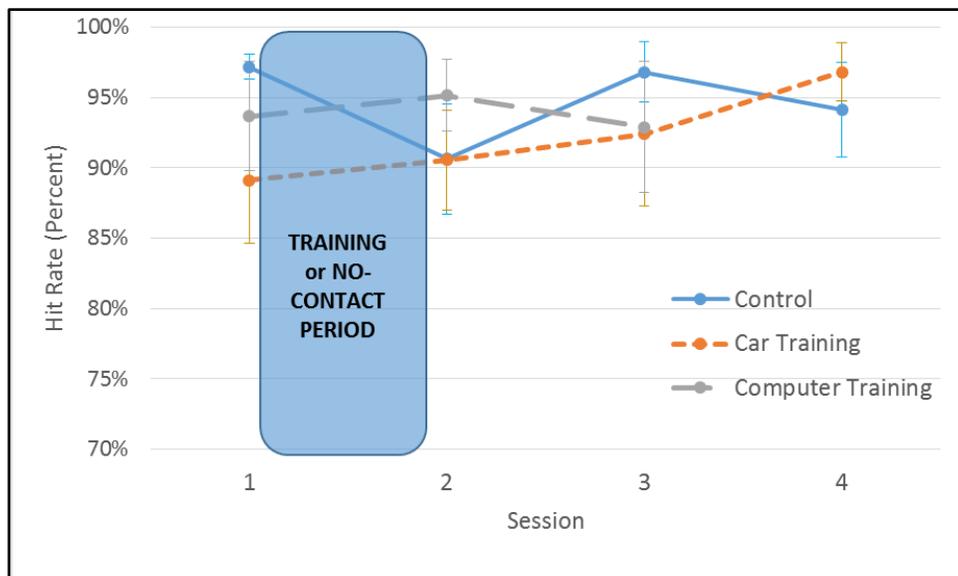


Figure 62. Chart. HR for the driver-centric PDT.

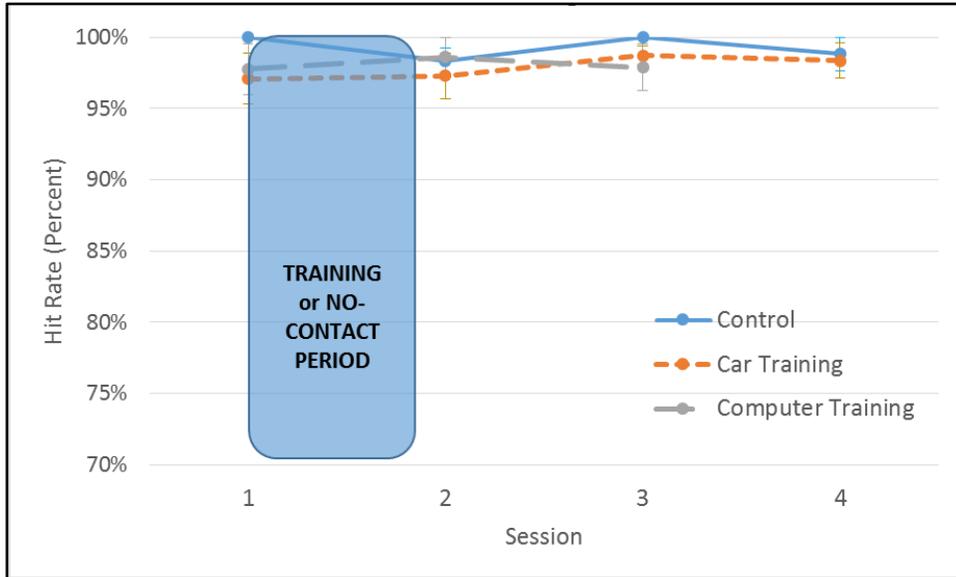


Figure 63. Chart. HR for the left driver-centric PDT.



Figure 64. Chart. HR for the center driver-centric PDT.

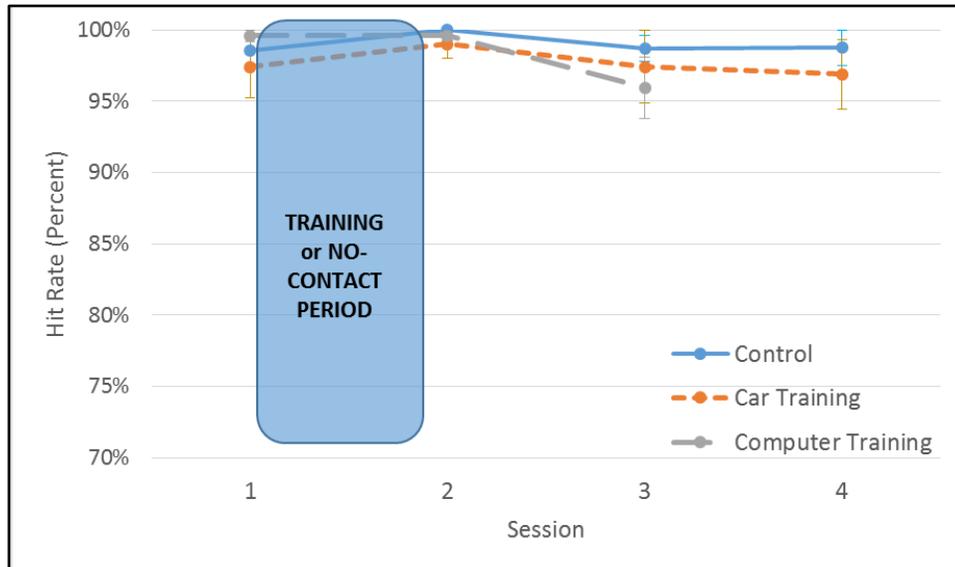


Figure 65. Chart. HR for the right driver-centric PDT.

DIFFERENTIAL EFFECTS OF TRAINING BASED ON INDIVIDUAL DIFFERENCES

All of the analyses reported above have evaluated the benefits of different forms of brain training on undifferentiated groups of individuals. However, it may be the case that this type of training differentially benefits individuals with greater or lower individual differences along dimensions of an ability important for driving.

As a preliminary investigation of this idea, we developed several predictor metrics by creating standardized combinations of initial laboratory-based assessment scores, then using the results of these to group participants into high- and low-ability groups within each of the following dimensions: physical, visual, and cognitive. All z -scores were calculated within groups. This was done to eliminate any influence from unequal sample sizes between the groups. After z -scores were calculated for the predictor variables, low-scoring and high-scoring groups were created within each training group. Values greater than zero standard deviations were deemed “High Scorers” and those lower than zero standard deviations were “Low Scorers.” Various dependent metrics were then plotted based on these groups. Table 11 delineates details of how the training groups were divided into high- and low-ability groups for each dimension.

Table 11. Construction of predictor variables.

Dimension	Metrics	Intermediate Calculations	Creation of Predictive Factors
Physical	Neck and Torso flexibility – left and right rotations	Z-scores were calculated for each flexibility measure individually.	All four z-scores were averaged together to create a total physical z-score.
Visual	Daytime Binocular Acuity and Daytime Contrast Sensitivity	Z-scores were calculated separately for acuity, and then individually for each of 5 contrast sensitivity spatial frequencies.	All five contrast sensitivity spatial frequency z-scores were averaged together then averaged with binocular acuity z-score for a total visual z-score.
Cognitive	UFOV subtests: selective attention and divided attention DHI subtests: VSB and VMI	Z-scores were calculated separately for each subtest in both UFOV and DHI.	UFOV subtests were averaged together and averaged with VSB and VMI to create a total cognitive z-score.

In a few of these cases, it appears that participants who scored in the low category on initial metrics may have obtained differential benefit from training; three examples are presented below, and the entire set of 63 graphs is included in Appendix B.

Figure 66 illustrates the differential effects of the DriveSharp computer training on the vehicle-centric PDT before and after training for participants who were high- and low-scorers on physical flexibility metrics. In this case, reaction time improved after training for participants who scored below average on flexibility; however, participants who had above-average flexibility maintained a constant level of performance on the PDT. It is theoretically possible that brain training provides a compensatory improvement in functional visual field for people with limited flexibility, although that hypothesis would require further investigative research.

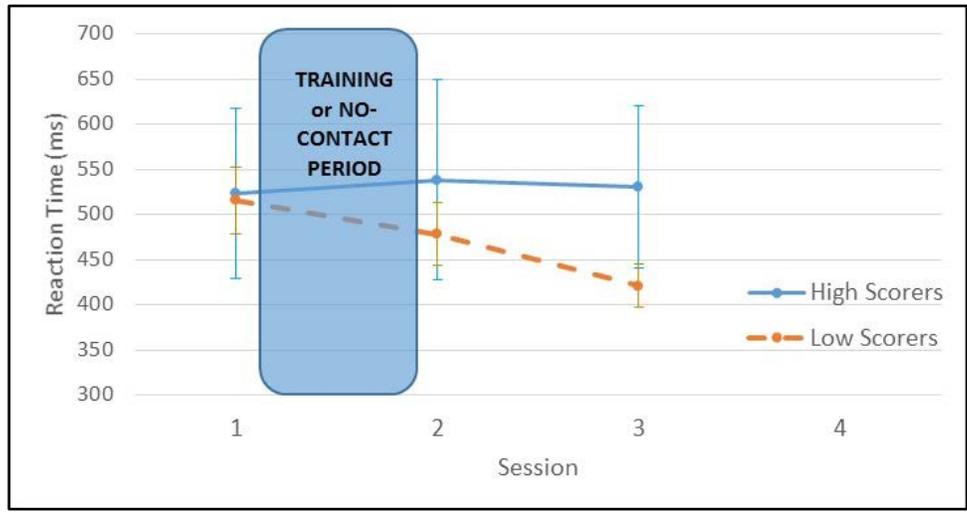


Figure 66. Chart. Average reaction time for the vehicle-centric detection task for the computer training group by z-score on physical metrics.

Similarly, Figure 67 illustrates a minor but consistent improvement in reaction time for the vehicle-centric detection task after Car Training for low scorers on cognitive tests, but not for high scorers. Again, this might indicate the possibility of compensatory improvement that could be investigated in future research.

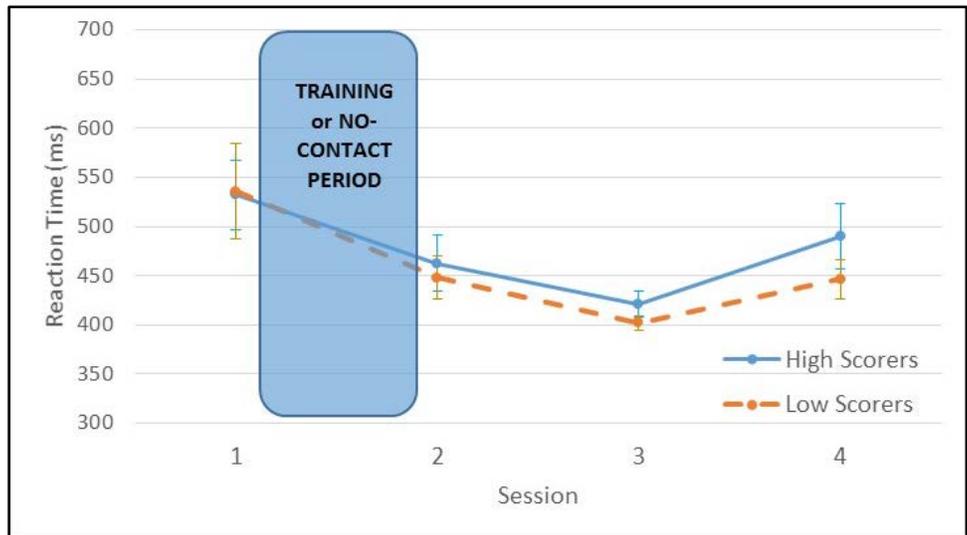


Figure 67. Chart. Average reaction time for the vehicle-centric detection task for the car training group by z-score on cognitive metrics.

Finally, Figure 68 illustrates what may be an interesting post-car-training increase in entropy during road segment driving for low scorers, but not high scorers, on physical metrics. Yet again, this could represent a form of compensation, as after training, low scorers improved their glance distribution relative to that of high scorers; however, this did not seem to persist across the following months. Findings such as this could inform the duration and expected refresh intervals of training.

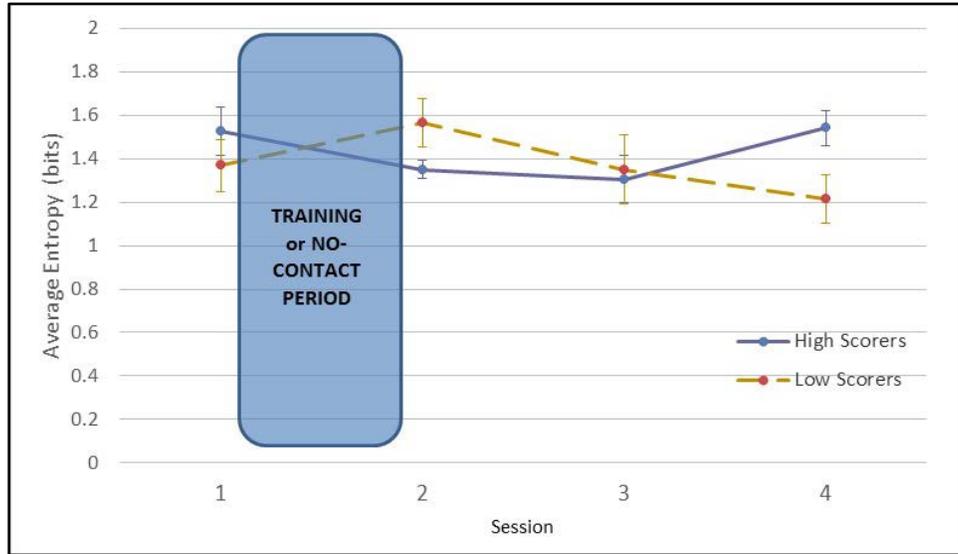


Figure 68. Chart. Average entropy for the car training group for straight road segments grouped by z-score on physical metrics.

CHAPTER 4. RESULTS SUMMARY

DRIVER BEHAVIOR ON PUBLIC ROADS

Three segments of roadway and three intersections were selected to investigate driver behavior on public roadways. These represented a variety of driving environments in order to assess how various aspects of behavior may be affected by situation and training group across experimental sessions. The roadway segments were all 10 s in duration, and included rural, neighborhood, and highway environments. The intersections were all left-hand turns and included one unprotected turn, one signal-protected turn, and one sign-protected turn. An attempt was made to run driving sessions during off-peak times of the day to avoid excessive variability in traffic flow.

Standard Deviation of Speed

Standard deviation of speed was calculated using either the vehicle's controller area network (CAN) or GPS when the network speed was unavailable. Standard deviation of speed in the rural road segment was consistently low across groups and sessions, and no significant differences were found, although the Car Training group was marginally more consistent in speed overall than the other two groups. This segment of roadway was straight and generally had light traffic, so it is possible that it did not pose enough of a challenge to elicit performance differences among groups. For the highway segment, there was more variability in speed, but no clear pattern among groups or across sessions. It is possible that this is due to the increased traffic encountered on this segment relative to the other segments, which varied across time and participants. For the neighborhood section, trials where participants had to slow or stop for pedestrians or stopped vehicles were excluded from analysis. Like the rural segment, the car training group exhibited a nonsignificant trend to have lower deviation of speed than the control, although this did not change across sessions. In addition, there was a trend for all groups to increase deviation of speed between Sessions 2 and 3, although the reason for this is unclear.

Standard Deviation of Lane Position

Standard deviation of lane position was calculated in centimeters using machine vision, which calculated the vehicle's position relative to the lane lines. Lane position was only calculated for rural and highway road segments, since the neighborhood section of roadway did not have lane markings. As was found for speed variability, the rural segment resulted in little variability in lane position; this was potentially due to the relatively low speed (35 mph) and light traffic. Although trials with lane changes on the highway were excluded from analysis, much more variability in lane position was seen on that segment than the rural segment. This may be due to the speed at which the participant was traveling and the surrounding traffic. There were again no clear trends across groups. The Control group was relatively stable, while the Computer Training group showed stability from Session 1 to Session 2, and a nonsignificant increase for Session 3. The Car Training group exhibited the most variability, with the highest of all groups for Session 2, but the lowest for Session 3.

Glance Behavior: Intersections

The glance entropy at intersections was calculated using frame-by-frame glance analysis. A particularly interesting result was seen for the unprotected intersection, where the Car Training

group exhibited an increase of over 0.3 bits of entropy after training, and maintained a mean increase in information gathered relative to the Control group, which stayed relatively consistent across test sessions. Bao & Boyle (2009) found when using the entropy metric that older drivers demonstrated lower entropy at an intersection compared with middle-aged drivers. They concluded that the lower entropy levels seen in seniors represented a less broad and thus less safe scan pattern (i.e., a greater opportunity for salient cues to be missed). While the differences observed in the current study were not statistically significant, the relatively low variance suggests that future research could examine glance behavior across a greater number of participants or a higher number of unprotected intersections to achieve the statistical power to possibly identify a reliable benefit for Car Training in terms of enhanced glance strategy. No significant differences among groups or across sessions were found for protected turns; this may not be entirely surprising if the drivers relied on the protected nature of the intersections for safe traversal.

Glance Behavior: Road Segments

For the rural driving segment, all groups maintained a high level of information gathering across all sessions, with no significant differences detected. Like the speed and lane position metrics, it is conceivable that this represents an ideal scenario that did not pose enough of a challenge to differentiate among groups. For the neighborhood segment, the Car Training group had consistently higher entropy than the Control group, which was marginally significant. However, as there was no interaction with Session, this appears to be a function of the group composition itself. The highway segment exhibited considerable variability among groups; there was a marginal interaction between Group and Session, which (combined with the significant Session 4 *t*-test result) suggests that the Car Training group maintained a high level of entropy across the last two sessions, while the Control group's performance declined. However, as the Car Training group performed approximately equally across all sessions, and this finding is restricted to one of the three driving segments, this result does not appear to be of great scientific interest.

DRIVER VISUAL PERFORMANCE ON CLOSED COURSE

Roadside Object Detection

Participants were asked to identify a total of five roadside objects per experimental session that indicated that there may be children nearby. When participants correctly reported the name of the object, identification distance and detection hit rate were measured. These objects were chosen to all be of approximately equal sizes and salience. There was a definite practice effect, as both the Control and Car Training groups increased their recognition distance across the first three sessions; however, there was only a marginal effect of Group, with the Control group scoring higher at every Session than the Car Training group, and there was no interaction between Group and Session that would indicate that training had a beneficial effect on detection distance. Similarly, while the hit rate performance did not appear to suffer from the ceiling effect present in the peripheral detection tasks, there were no significant differences among groups or across sessions; in all cases, average detection was over 80%. Note that, as there were only five objects, 80% is equivalent to seeing four out of five targets.

Vehicle-Centric Detection Task

After the object detection laps of the closed road course, participants were asked to respond as quickly as possible with a finger switch to a set of three randomly illuminating hood-mounted LED lights. Reaction time results indicated that there was a learning effect over time, but that there was not much improvement among either Car or Computer Training groups after training; in fact, the Control group had a marginally larger improvement in reaction time between Session 1 and Session 2. This consistency, combined with the high hit rate across groups and sessions, suggests that these measures may not be sensitive to any improvement in visual performance that training may provide.

Driver-Centric Peripheral Detection Task

Finally, participants were asked to drive while responding to a PDT mounted on a headband; this represented a driver-centric task, as the illuminating lights stayed constant in spatial location no matter how the driver moved his/her head. As there was no significant main effect of Group, only a marginal effect of Session, and no significant interaction between Group and Session, this task may have provided a ceiling effect of nominal performance prior to training. This assertion is supported by the hit rate data, which were extremely high for all groups, sessions, and light locations, particularly for the left and right lights. Future testing with this device could benefit from a recalibration of light location, which could make the left and right lights more difficult to detect.

Training Effects by Individual Differences

Several interesting effects were identified when dependent measures were broken out across high- and low-scoring participants on different combinations of physical, cognitive, and visual predictor measures. Small, potentially meaningful, improvements were noted for both Car and Computer Training across several metrics (object detection distance and glance behavior) for low scorers on both cognitive and physical metrics. These were not consistent across time, and could suggest interesting topics for future research, including whether particular types of targeted training can differentially benefit drivers with varying existing abilities, and to what extent training refreshers can maintain improved performance for drivers who start out at a disadvantage.

CHAPTER 5. DISCUSSION

OVERVIEW

This study was undertaken to determine whether or not either of two different cognitive training protocols would have a measureable positive impact on key performance metrics underlying seniors' ability to drive safely by helping to improve and/or maintain performance. One training protocol was a commercially available computer-based approach which specifically targeted key visual-cognitive abilities believed to be related to driving safety. The other was an implicit learning paradigm which strove to enhance drivers' ability to scan for, detect, and respond to central as well as peripheral stimuli potentially related to driving safety hazards. Metrics were collected on a closed test track as well as while driving on real roads. They included "hazard" and stimuli detection on the test track and vehicle control, as well as glance behaviors on public roads. In general, we found little in the way of results to support the hypothesis that either training method had any positive effect on seniors' ability to drive better or more safely.

One potentially meaningful exception was that the implicit training paradigm did produce results in the expected direction for glance dispersion in a particularly challenging task: completing an unprotected left turn across path. In this scenario, the data for the implicit training group were essentially identical to that of the control group prior to training, but there was notably greater glance dispersion for the training group at every post-training session relative to the control group (see Figure 40 above). This is potentially important in that it has been previously documented that seniors tend to demonstrate a narrower or more-focused glance pattern relative to younger drivers, thus possibly missing key stimuli (Bao & Boyle, 2009; Romoser and Fisher, 2009; Romoser, Pollatsek, Fisher & Williams, 2013). If an implicit in-vehicle training paradigm can help seniors develop broader and more successful glance patterns, this may be an important countermeasure. However, there are two important caveats to consider. First, it is very important to note that this finding failed to reach statistical significance. That is, even though the average results were in the predicted direction, the variability in the data was simply too high to reach statistical significance with the number of participants tested. Further, few if any of the individual participants' data followed the general pattern noted above. So, even if more data were collected in a subsequent study, it is not obvious that this pattern would even be duplicated, much less found to be statistically significant. Second, if glance patterns truly were being improved with the supposed benefit of being able to better detect and respond to stimuli, this was not borne out in any of the related performance-oriented metrics collected during test track trials.

REASONS FOR GENERAL LACK OF FINDINGS

Thus, the overall lack of positive findings showing the benefits of this type of training was disappointing given the very positive results noted above in the ACTIVE Trial (Ball, Edwards, Ross, & McGwin, Jr., 2010) and others (Cassavaugh & Kramer, 2009). Not only did the ACTIVE Trial find positive results in terms of overall crash rate reduction for seniors who performed some relatively brief forms of cognitive training, but some of the benefits were reported to persist for several years post-training in terms of driving exposure and reduced frequency of cessation (Edwards et al., 2009; Edwards, Delahunt, and Mahncke, 2009). One of the major goals for this research effort was to see if we could identify more performance- or behavior-oriented training-based improvements in the driving environment (i.e., on the micro

scale) which would help to explain the crash rate reductions seen in the ACTIVE Trial (i.e., the macro scale).

There are a variety of possible reasons why we failed to detect any similar benefits in the current study. The first is that this type of relatively brief and somewhat generic cognitive training (i.e., not directly related to the driving task itself) simply is not effective at improving driving behaviors or safety-related outcomes even in the short term, much less the long term. Noack, Lövdén, Schmiedeka, and Lindenbergera (2009) arrived at much the same conclusion after performing a review of the related literature, indicating that even though cognitive training can have measurably positive results for seniors, there is little evidence to demonstrate the type of durable *transfer* effects which it would be necessary to see in light of this report's central topic.

Still, the lack of positive findings in the current study does not equate to determining that this type of training is ineffective; instead, it may indicate that other aspects or limitations of the research protocol were responsible for the lack of findings. These could be related to the particular nature of the cognitive abilities targeted by the training protocols (and any differences in the current study compared with those successfully employed in the ACTIVE Trial). However, the most successful form of training in the ACTIVE Trial was speed of processing, and the computer-based training in the current study also focused on this visual-cognitive ability. Also, the training durations—overall time as well as actual practice time—were comparable across the two studies.

An additional methodological possibility is that the current study lacked experimental control to identify differences among on-road behavior metrics, particularly glance entropy/information-gathering. As this portion of the study was conducted on public roads, the surrounding roadway environment was different for each trial, including variability in the amount of oncoming traffic and/or roadside users present (this variability was necessarily the case even though time of day was controlled in an attempt to keep traffic reasonably consistent). Future analyses of the current data could use traffic level, which was noted, as a covariate, and future studies could make further attempts to control the amount of traffic that the participant encounters, whether by use of confederate vehicles in an on-road environment or use of a more controlled method such as a test track or driving simulator.

Another possibility is that any single approach alone may be ineffective, whereas a multidimensional approach combining the right factors may have a strong positive effect. For example, Ngandu et al. (2015) recruited over 1,000 cognitively at-risk seniors 60–77 years of age. They provided a multidimensional treatment protocol consisting of diet, exercise, and cognitive training. After two years, there were demonstrated benefits in terms of a variety of factors, including executive function, processing speed, and memory. Still, it is impossible to assess the transfer effects of such a protocol based on the data reported.

Another factor to consider is the participant pool. The ACTIVE Trial, due to its nature, was fortunate to have considerably more participants than the study described here—a distinct advantage both in terms of simply being more directly representative as well as in terms of being able to detect statistically significant findings. Another factor to consider with the participant pool is that of individual differences. It may be that either of the training programs delivered would be successful on a different or more targeted population. Several of the descriptive post

hoc data mining activities (documented in Figure 66–Figure 68) suggested that it was the low scorers on some of the pre-study physical and cognitive sets of assessments who may differentially benefit from this sort of training. In support of this notion, Edwards et al. (2009) specifically found that senior drivers with speed-of-process difficulties benefited from the speed-of-processing training in terms of the driving metrics reported. It is also possible that other individual differences could play an important role in determining training outcome success (e.g., gender, physical fitness and flexibility, other specific cognitive abilities related to attention or executive function, etc.).

The metrics chosen must also be considered. In the ACTIVE Trial the only driving-related metric was at-fault crash risk over time, which could easily be argued as being the single most—perhaps only—important macro-scale driving-related metric. As noted above, the current study was focused more on finding micro-scale metrics, mostly related to scanning behavior and success, with other metrics related to vehicular control. It is possible that a different set of metrics may have shown differences where the current set failed, though it is not easy to imagine what those metrics might entail. Finding the right level for various tasks would be an important consideration as we seemed to experience ceiling effects for several of the variables. Another possibility entirely is that either or both of the training approaches were successful in terms of improving at-fault crash rates over time, but this success will not be revealed in the micro-scale metrics at all, but only in the macro-scale metric over time.

FUTURE RESEARCH

While the existing literature suggests that cognitive training may prove beneficial for enhancing senior driver safety, it must also be noted that there have been mixed results, and the current study in particular failed to demonstrate significant improvement on known surrogates of driving safety. Therefore, future research into this topic is warranted, but the parameters must be chosen very carefully if the researcher hopes to demonstrate positive results. The parameters that must carefully be considered include at least the following:

- Participants
 - Total number
 - Composition (e.g., at-risk seniors)
 - Age groups
- Training Protocols
 - Which specific dimension(s) should be targeted
 - Cognitive
 - Physical
 - Health and nutrition
 - Duration
 - Overall
 - Per session
 - Number of sessions
 - Implicit vs. Explicit Mode
 - Booster training
- Control Group
 - No contact

- Alternate contact
- Transfer tasks and metrics (i.e., does the training have a measurable impact on driving mobility and safety for seniors?)

As the most interesting findings of this study were related to glance distribution at unprotected left turns, this presents a compelling topic for future research. While the results found here did not reach statistical significance, they did suggest that the Car Training approach may contribute to enhanced scan patterns in the situations which create the highest risk for senior drivers. As noted by Staplin et al. (2012), left turns are especially risky for senior drivers, and improvements in the ability of drivers to obtain adequate information about their surroundings and oncoming vehicles could lead to a meaningful improvement in driver safety. Future research could target this type of scenario by using an experimental design such as was presented here, but with increased statistical power provided by having more participants travel through more types of unprotected intersections. Alternatively, additional control could be imposed within a similar methodology or by using a more controllable (yet restrictive) methodology.

In addition, several interesting trends were seen when participants were divided into high- and low-performance categories based on initial performance on various physical and cognitive performance metrics. These findings may point the way for future research on targeted training and ideal refresher training for drivers who are in lower-scoring groups on particular metrics.

The Car Training protocol developed by Toyota engineers did show some indication that it may enhance seniors' scan patterns, though this was not proven to a statistically significant degree in the current study. Implicit learning is that which takes place in the absence of feedback on the learned activity and with the learner largely unaware of the learning goals (Reber, 1993). This is the learning paradigm offered by the Car Training approach developed by Toyota engineers, and as such, some day it may be well suited for implementation on a production vehicle. One opportunity for future research would be to collaborate with Toyota staff on the most promising ways to further refine and enhance this type of training protocol based in part on the findings discussed above.

GENERAL CONCLUSION

This study tested driver performance across a wide variety of metrics, including object detection and recognition, vehicle-centric and driver-centric peripheral detection performance, vehicle control, including speed and lane position maintenance, and glance behavior, before brain training and at several intervals after training (or a no-contact period). Results indicated little in the way of significant effects of training. In many cases, there was a significant learning effect, which suggests that in future studies additional practice could be given prior to training in order to establish true baseline performance. The most interesting effects of the Car Training group were found for glance entropy, where several results suggested that Car Training may have contributed to enhanced glance strategy. While these did not rise to the level of significance, the trends are consistent with a theoretical interpretation of visual-cognitive training improving driver scan patterns, particularly in the most challenging and risky of situations.

The computer training group showed very little in the way of interesting results. This is surprising as it was developed to train abilities similar to those which were found to produce

significant and long-term improvements in driving safety with similar training (Ball, Edwards, Ross, and McGwin, 2010). It is possible that the transition from research tool to off-the-shelf product resulted in some modification of the critical factors of the speed-of-processing training that produced a significant decrease in at-fault crashes.

APPENDIX A. QUESTIONNAIRE ITEMS

AMTS

Please ask the participant all of the following questions. As per the standard, a score of 7 or better is needed for participation.

1. How old are you?
2. What time is it (to the nearest hour)?
3. Give the participant the following address for recall at the end of test: 42 West Street. This should be repeated by the participant to ensure it has been heard correctly.
4. What year is it?
5. What is your address?
6. What jobs do these people do (show pictures)?
7. What is your date of birth?
8. What year did the United States enter World War II?
9. What is the name of the current President?
10. Count backwards from 20 to 1.

Demographics Questionnaire

What is your age?

Gender:

Male Female

What is your height?

feet:

inches:

What is your weight?

Pounds:

What is your highest level of education?

Didn't complete high school

High school graduate

Some college

2 yr college degree/trade school

4 yr college degree

Masters degree

Professional degree

Doctorate degree

Are you employed or retired?

Employed Retired

What field is/was your primary occupation in?

Artist/Musician
Business
Education
Engineering
Farming/Agriculture
Homemaker
Mechanic/Repair
Medical
Laborer
Law
Researcher
Technician
Other:

What group do you identify yourself with?

Latino/Latina
African American
Caucasian
Middle Eastern
Pacific Islander
Asian
Other:

How many years have you been driving?

Years:

Have you taken any supplemental driver-training courses or driving-related assessments in the past 10 years?

Yes No

If Yes:

What was the name of the training course or assessments?

Where was it held?

When did you complete this course or assessment?

What type of driving do you usually do? (Please indicate all that apply)

Around town driving
Commuting on freeways
Commuting on other main roads
Short distance travel (50-200 mile round trip)
Middle distance travel (201-500 mile round trip)
Long distance travel (>500 mile round trip)

About how many miles did you drive in the past year?

Miles:

Have you had any of the following in the past year? If so, please describe:

Speeding Ticket:

Car Crash:

Other Moving Violation:

Survey of Technology Use

Generally speaking, how comfortable do you feel using modern technology such as cell phones, computers, GPS devices, etc.?

1 Not at all

2

3 Somewhat

4

5 Very Much So

Do you own a cell phone?

Yes

No

IF YOU OWN A CELL PHONE, is your phone a smartphone, like an iPhone or Android?

Yes

No

I Don't Know

IF YOU OWN A CELL PHONE, how often do you use your cell phone?

1 Rarely

2

3 A Few Times A Week

4

5 Every Day

Do you own a computer?

Yes

No

IF YOU OWN A COMPUTER, is your computer a laptop or a desktop?

Laptop

Desktop

I Have Both

I Don't Know

IF YOU OWN A COMPUTER, how often do you use your computer?

- 1 Rarely
- 2
- 3 A Few Times A Week
- 4
- 5 Every Day

IF YOU OWN A COMPUTER, what types of things do you use your computer for?

- Writing Documents
- Email
- Surfing the Internet
- Shopping
- Digital Pictures (Uploading from camera, editing, etc.)
- Downloading/Listening to Music
- Other:

Do you own a GPS navigation device?

- Yes
- No

IF YOU OWN A GPS DEVICE, is your GPS built into your car?

- Yes
- No
- I Don't Know

IF YOU OWN A GPS DEVICE, how often do you use your GPS navigation device?

- 1 Rarely
- 2
- 3 A Few Times A Week
- 4
- 5 Every Day

Which other technology products, if any, do you use regularly?

- Kindle (or other electronic book)
- iPod (or other digital music player)
- iPad (or other tablet computer)
- Home Theater System
- Digital Camera
- CD Player
- Other:

Vehicle Questionnaire

Please describe the vehicle you currently drive most often:

Year:

Make:

Model:

Features of Vehicle

Does your vehicle have any of the following? (please check all that apply)

Head-Up Display (projects information such as speed onto the windshield)

DVD player

Driver Information Center (displays text messages pertaining to vehicle state and maintenance, fuel-related information, etc.)

OnStar (GM vehicles)

SYNC (Ford vehicles)

Touch screen

Navigation system

Voice recognition

Adaptive Cruise Control

Forward Collision Alert

Forward Park Assist

Lane Departure Warning

Rear Video Display

Rear Park Assist

Cell phone integrated Bluetooth

None of the above

Other safety devices, list here:

Compare your mental sharpness now with how you were in your 40s or 50s. Would you say that you are...

1 A lot less mentally sharp now

2

3

4 Somewhat less mentally sharp now

5

6

7 Just as mentally sharp now

Health Assessment Questionnaire

To the Participant: Please note that your responses to the following questions will in no way affect your ability to participate in the study. Your honest answers are appreciated.

Height:

Weight:

Do you have a history of any of the following?

Stroke

Yes No

Brain tumor

Yes No

Head injury

Yes No

Epileptic seizures

Yes No

Respiratory disorders

Yes No

Motion sickness

Yes No

Inner ear problems

Yes No

Dizziness, vertigo, or other balance problems

Yes No

Diabetes

Yes No

Migraine, tension headaches

Yes No

Depression

Yes No

Anxiety

Yes No

Other psychiatric disorders

Yes No

Arthritis

Yes No

Auto-immune disorders

Yes No

High Blood Pressure

Yes No

Heart arrhythmias

Yes No

Chronic Fatigue Syndrome

Yes No

Chronic Stress

Yes No

Glaucoma

Yes No

Other eye problems, please list:

Other health problems, please list:

If yes to any of the above, please explain:

Do you currently wear prescription glasses?

Yes

No

If yes, what type?

Normal

Bifocals

Trifocals

Continuous

Other:

Have you ever had eye surgery?

Yes

No

If yes, please explain (include date of surgery, if lens replacement, what kind?)

Are you currently taking any medications on a regular basis?

Yes

No

If yes, please list them:

WHO (Five) Well-Being Index (1998 version)

Indicate for each of the five statements which is the closest to how you have been feeling over the last two weeks. Notice that high numbers mean better well-being.

Over the last two weeks I have felt cheerful and in good spirits

- 5 All of the time
- 4 Most of the time
- 3 More than half of the time
- 2 Less than half of the time
- 1 Some of the time
- 0 At no time

Over the last two weeks I have felt calm and relaxed

- 5 All of the time
- 4 Most of the time
- 3 More than half of the time
- 2 Less than half of the time
- 1 Some of the time
- 0 At no time

Over the last two weeks I have felt active and vigorous

- 5 All of the time
- 4 Most of the time
- 3 More than half of the time
- 2 Less than half of the time
- 1 Some of the time
- 0 At no time

Over the last two weeks I woke up feeling fresh and rested

- 5 All of the time
- 4 Most of the time
- 3 More than half of the time
- 2 Less than half of the time
- 1 Some of the time
- 0 At no time

Over the last two weeks my daily life has been filled with things that interest me

- 5 All of the time
- 4 Most of the time
- 3 More than half of the time
- 2 Less than half of the time
- 1 Some of the time
- 0 At no time

Major (ICD-10) Depression Inventory

The following questions ask about how you have been feeling over the last two weeks.

How much of the time have you felt low in spirits or sad?

- All of the time
- Most of the time
- Slightly more than half of the time
- Slightly less than half of the time
- Some of the time
- At no time

How much of the time have you lost interest in your daily activities?

- All of the time
- Most of the time
- Slightly more than half of the time
- Slightly less than half of the time
- Some of the time
- At no time

How much of the time have you felt lacking in energy and strength?

- All of the time
- Most of the time
- Slightly more than half of the time
- Slightly less than half of the time
- Some of the time
- At no time

How much of the time have you felt less self-confidence?

- All of the time
- Most of the time
- Slightly more than half of the time
- Slightly less than half of the time
- Some of the time
- At no time

How much of the time have you had a bad conscience or feelings of guilt?

- All of the time
- Most of the time
- Slightly more than half of the time
- Slightly less than half of the time
- Some of the time
- At no time

How much of the time have you felt that life wasn't worth living?

- All of the time
- Most of the time
- Slightly more than half of the time
- Slightly less than half of the time
- Some of the time
- At no time

How much of the time have you had difficulty in concentrating, e.g. when reading the newspaper or watching TV

- All of the time
- Most of the time
- Slightly more than half of the time
- Slightly less than half of the time
- Some of the time
- At no time

How much of the time have you felt very restless?

- All of the time
- Most of the time
- Slightly more than half of the time
- Slightly less than half of the time
- Some of the time
- At no time

How much of the time have you felt subdued or slowed down?

- All of the time
- Most of the time
- Slightly more than half of the time
- Slightly less than half of the time
- Some of the time
- At no time

How much of the time have you had trouble sleeping at night?

- All of the time
- Most of the time
- Slightly more than half of the time
- Slightly less than half of the time
- Some of the time
- At no time

How much of the time have you suffered from reduced appetite?

- All of the time
- Most of the time
- Slightly more than half of the time
- Slightly less than half of the time
- Some of the time
- At no time

How much of the time have you suffered from increase appetite?

- All of the time
- Most of the time
- Slightly more than half of the time
- Slightly less than half of the time
- Some of the time
- At no time

Activity Questionnaire

How often do you typically socialize or communicate with family members IN PERSON?

- Daily
- A few times a week
- A few times a month
- A few times a year
- Once a year or less
- Never

How often do you typically socialize or communicate with family members BY PHONE?

- Daily
- A few times a week
- A few times a month
- A few times a year
- Once a year or less
- Never

How often do you typically socialize or communicate with family members BY E-MAIL or TEXT MESSAGE?

- Daily
- A few times a week
- A few times a month
- A few times a year
- Once a year or less
- Never

How often do you typically socialize or communicate with family members by LETTER?

Daily

A few times a week

A few times a month

A few times a year

Once a year or less

Never

How often do you typically socialize or communicate with friends, colleagues, acquaintances, fellow group or club members, etc. IN PERSON?

Daily

A few times a week

A few times a month

A few times a year

Once a year or less

Never

How often do you typically socialize or communicate with friends, colleagues, acquaintances, fellow group or club members, etc. BY PHONE?

Daily

A few times a week

A few times a month

A few times a year

Once a year or less

Never

How often do you typically socialize or communicate with friends, colleagues, acquaintances, fellow group or club members, etc. BY E-MAIL or TEXT MESSAGE?

Daily

A few times a week

A few times a month

A few times a year

Once a year or less

Never

How often do you typically socialize or communicate with friends, colleagues, acquaintances, fellow group or club members, etc. BY LETTER?

Daily

A few times a week

A few times a month

A few times a year

Once a year or less

Never

How often do you attend religious services or other related activities?

Daily

A few times a week

A few times a month

A few times a year

Once a year or less

Never

How often do you attend social functions such as dinner parties, craft groups, social clubs, etc.?

Daily

A few times a week

A few times a month

A few times a year

Once a year or less

Never

How often do you engage in mentally stimulating activities such as reading, doing crosswords or other puzzles, viewing challenging movies or TV shows, engaging in discussion groups, games like chess, checkers, or bridge, etc.?

Daily

A few times a week

A few times a month

A few times a year

Once a year or less

Never

How often do you engage in physical activity such as walking or hiking, exercise, hunting or fishing, swimming, organized sports like tennis or golf, etc.?

Daily

A few times a week

A few times a month

A few times a year

Once a year or less

Never

APPENDIX B. STANDARDIZED PREDICTOR GRAPHS

ON-ROAD METRICS

Physical Dimension

Lane Variability

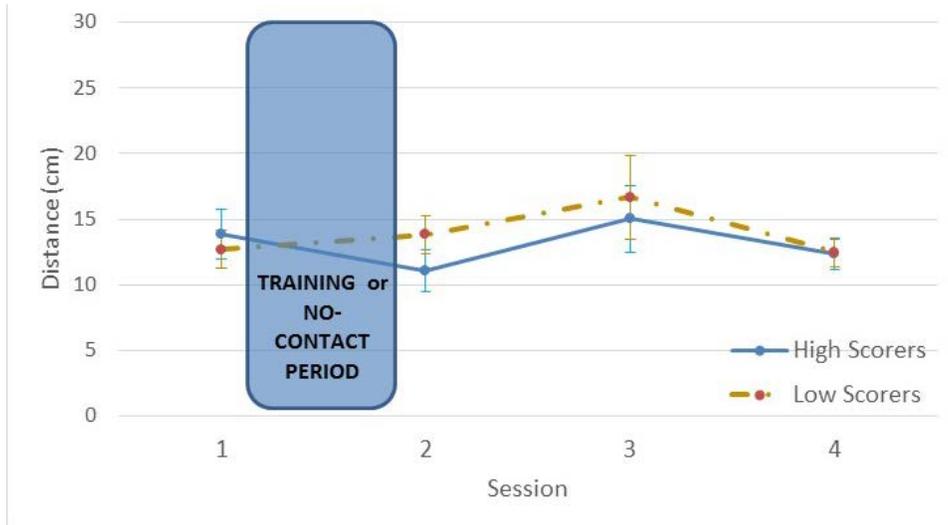


Figure 69. Chart. Average lane variability for the control group by z-score on physical metrics.



Figure 70. Chart. Average lane variability for the car training group by z-score on physical metrics.

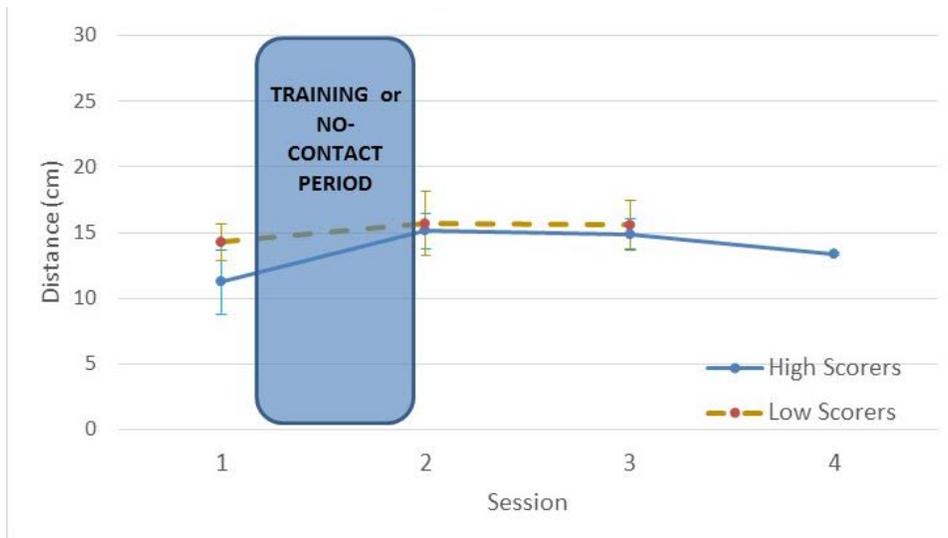


Figure 71. Chart. Average lane variability for the computer training group by z-score on physical metrics.

Speed Variability

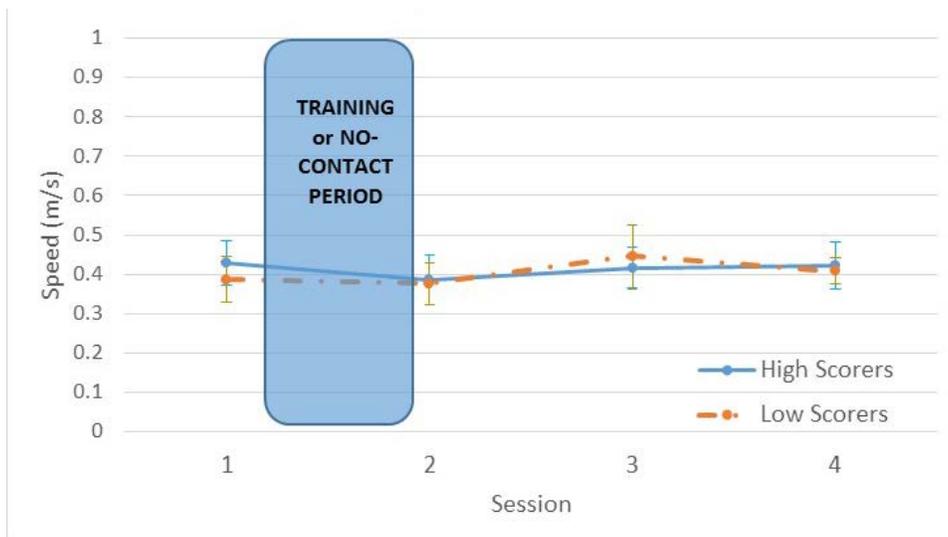


Figure 72. Chart. Average speed variability for the control group by z-score on physical metrics.

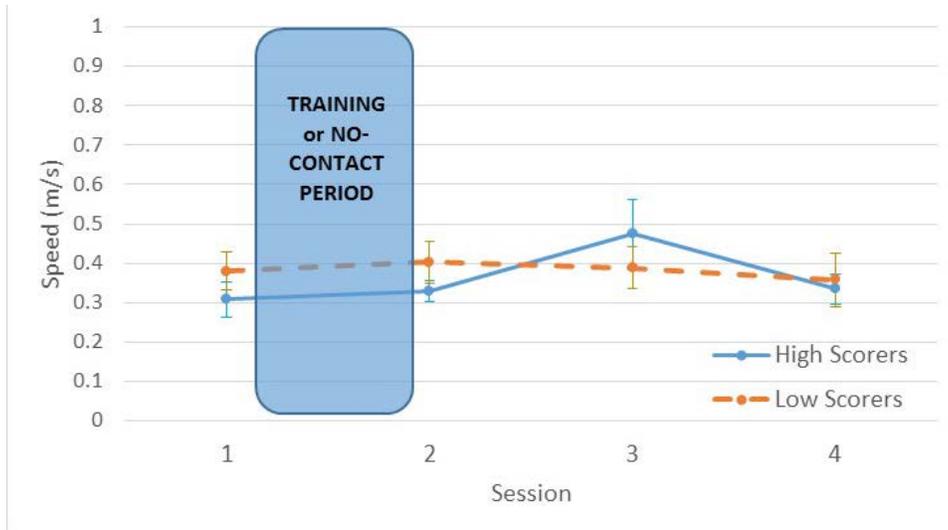


Figure 73. Chart. Average speed variability for the car training group by z-score on physical metrics.

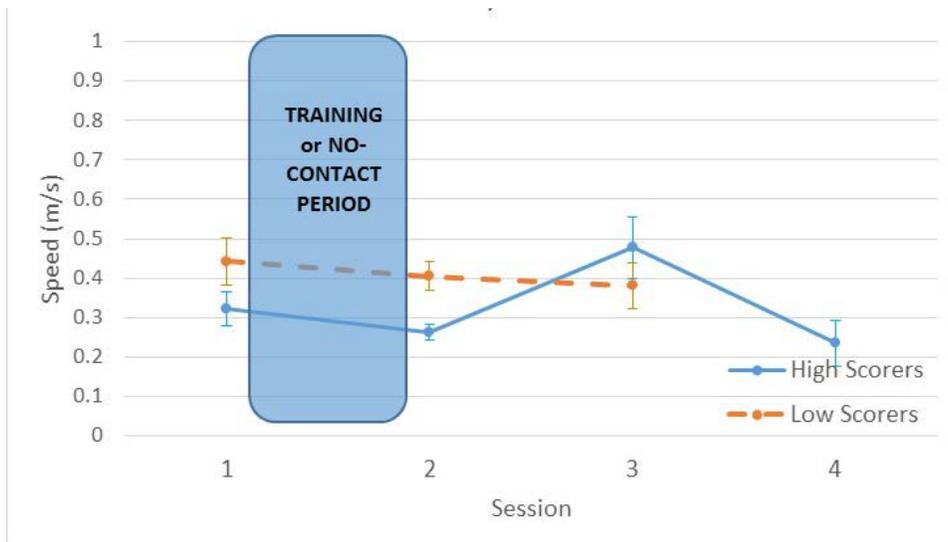


Figure 74. Chart. Average speed variability for the computer training group by z-score on physical metrics.

Entropy

Straight Road Segments:

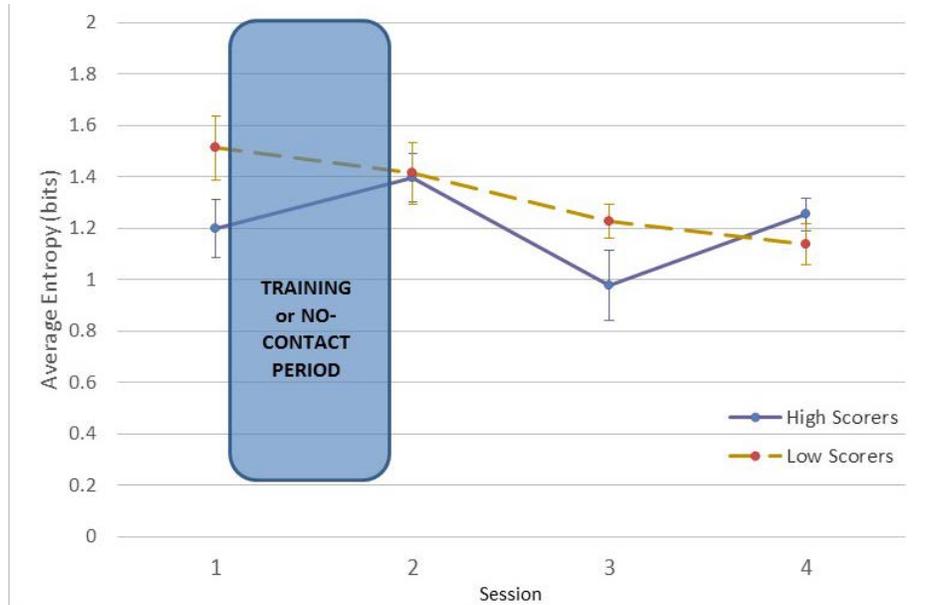


Figure 75. Chart. Average entropy for the control group for straight road segments grouped by z-score on physical metrics.

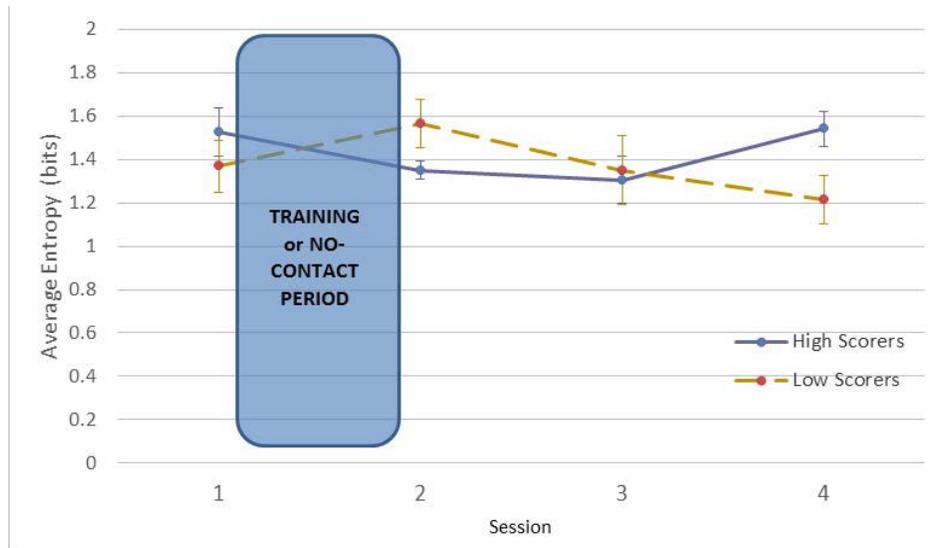


Figure 76. Chart. Average entropy for the car training group for straight road segments grouped by z-score on physical metrics.

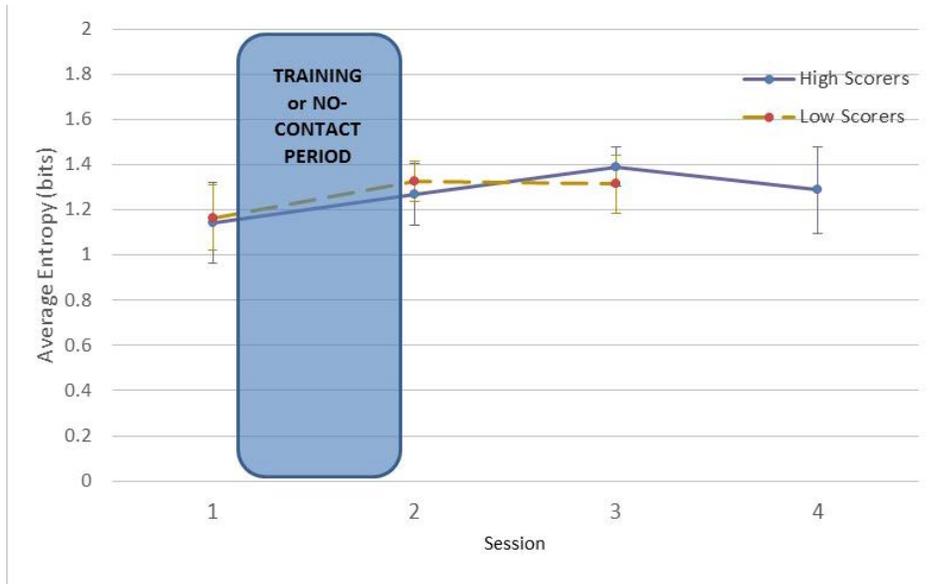


Figure 77. Chart. Average entropy for the computer training group for straight road segments grouped by z-score on physical metrics.

Intersection Segments:

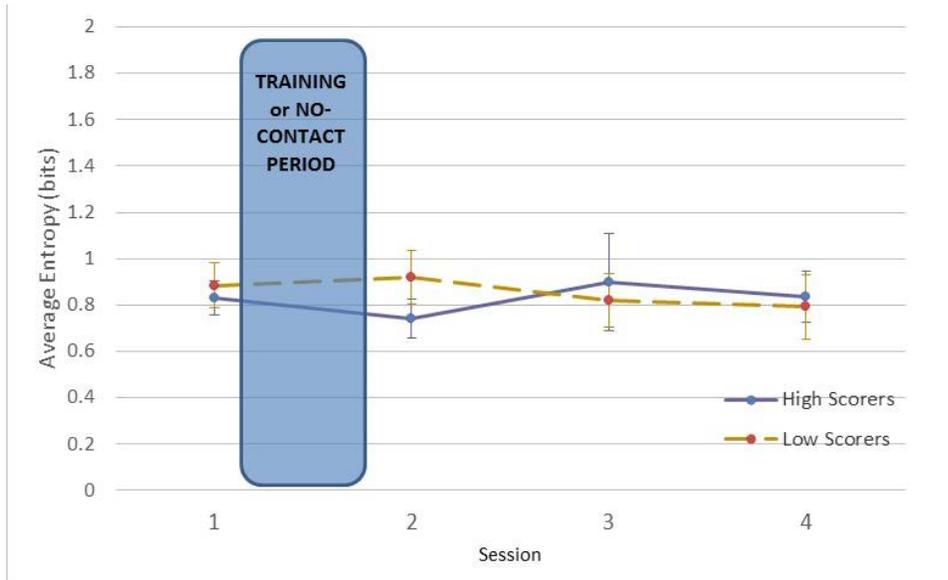


Figure 78. Chart. Average entropy for the control group for intersections grouped by z-score on physical metrics.

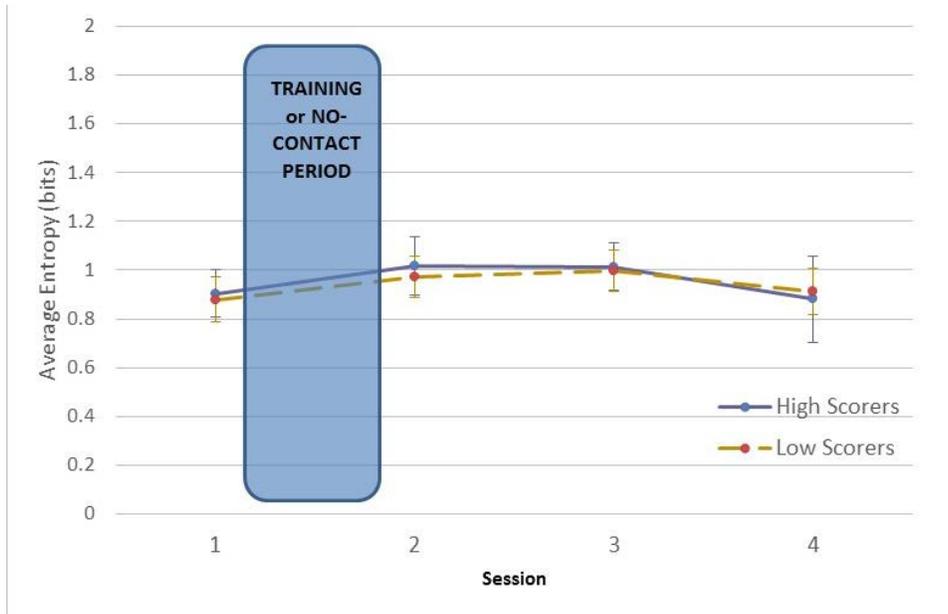


Figure 79. Chart. Average entropy for the car training group for intersections grouped by z-scores on physical metrics.

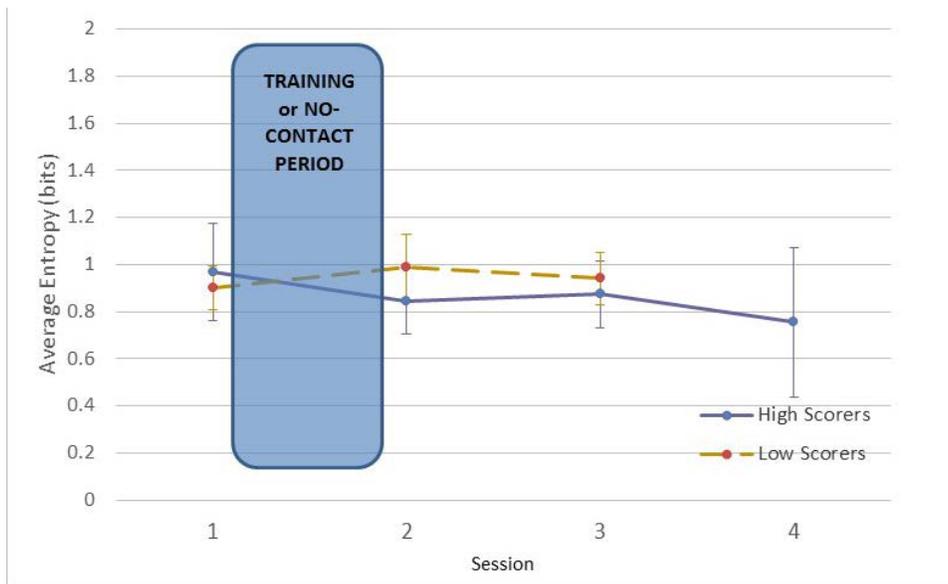


Figure 80. Chart. Average entropy for the computer training group for intersections grouped by z-scores on physical metrics.

Visual Dimension

Lane Variability

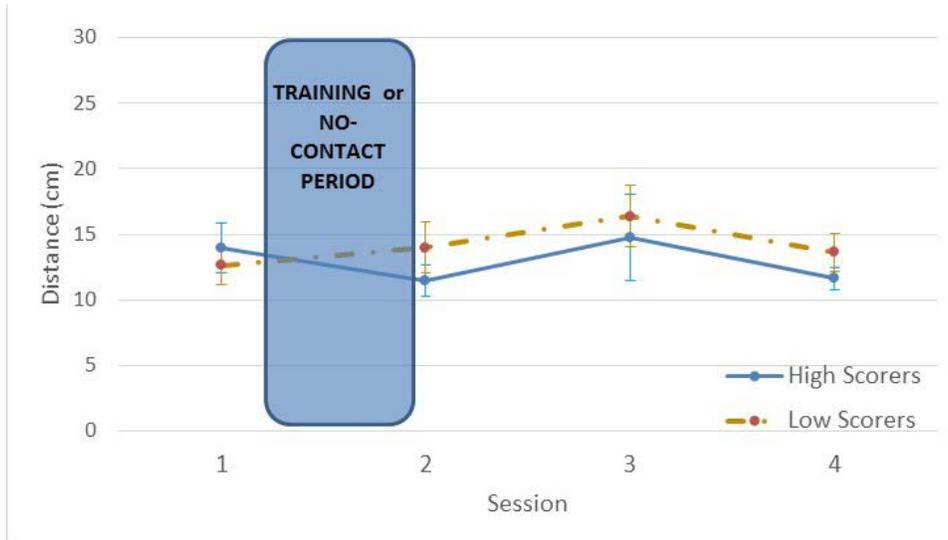


Figure 81. Chart. Average lane variability for the control group by z-score on visual metrics.



Figure 82. Chart. Average lane variability for the car training group by z-score on visual metrics.

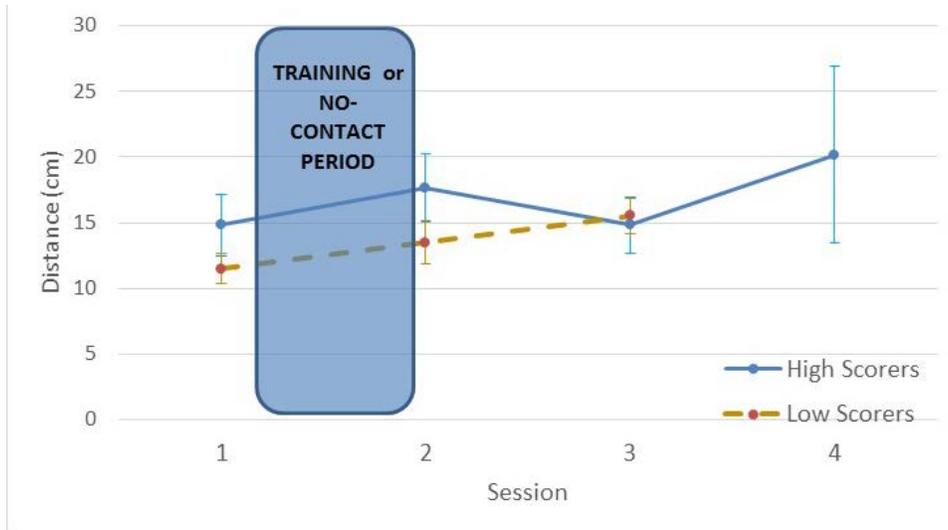


Figure 83. Chart. Average lane variability for the computer training group by z-score on visual metrics.

Speed Variability

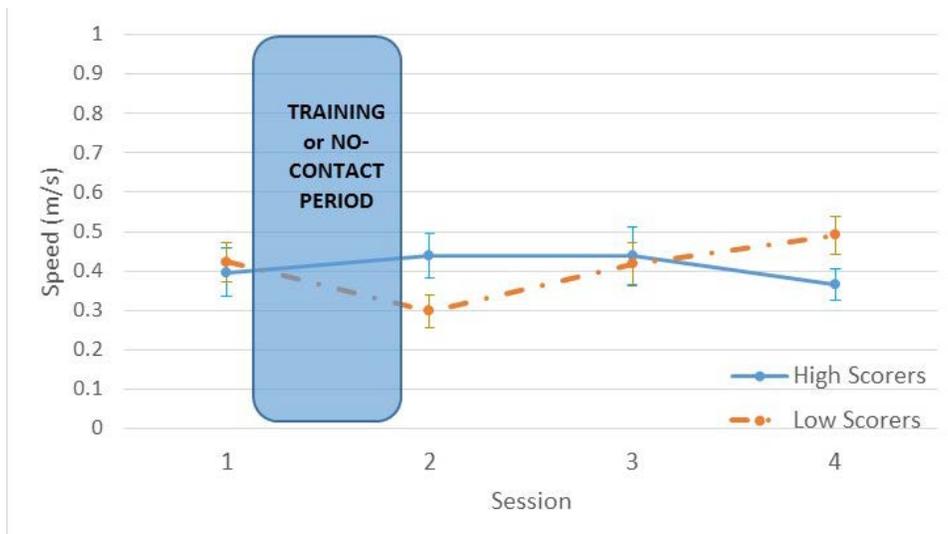


Figure 84. Chart. Average speed variability for the control group by z-score on visual metrics.

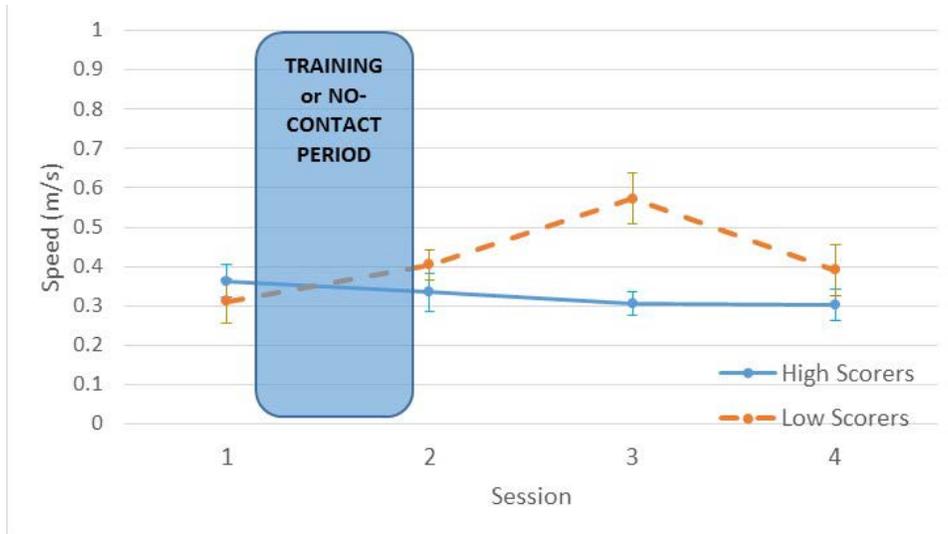


Figure 85. Chart. Average speed variability for the car training group by z-score on visual metrics.

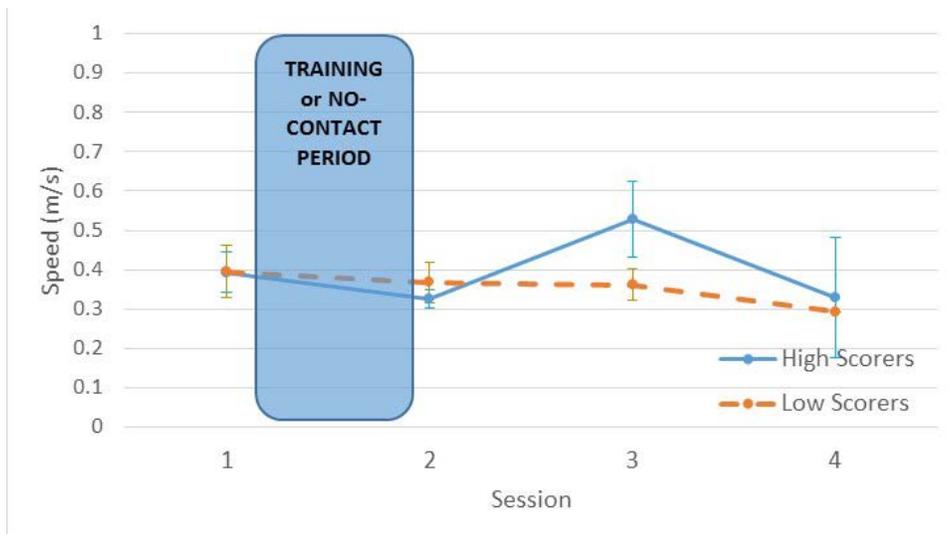


Figure 86. Chart. Average speed variability for the computer training group by z-score on visual metrics.

Entropy

Straight Road Segments:

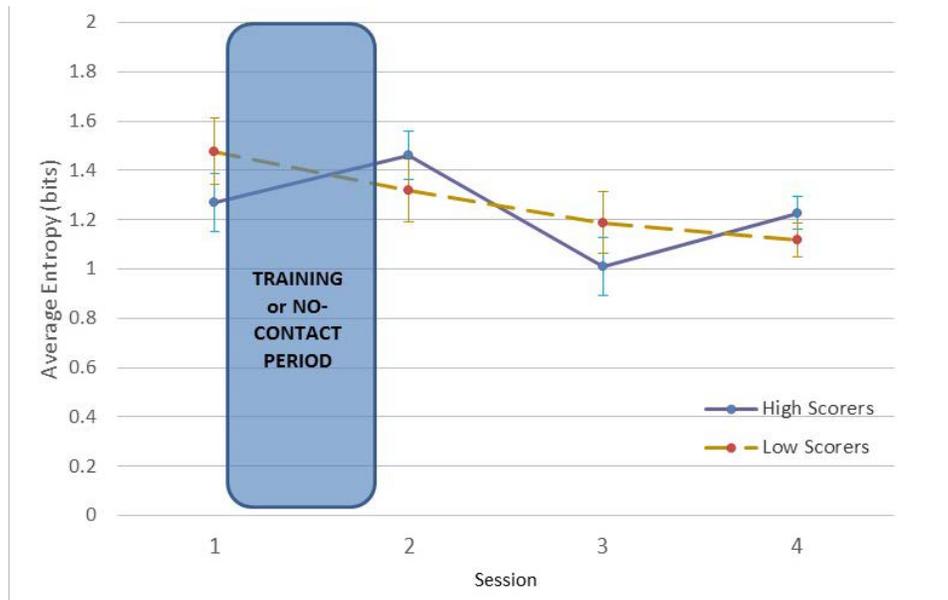


Figure 87. Chart. Average entropy for the control group on straight road segments grouped by z-score on visual metrics.

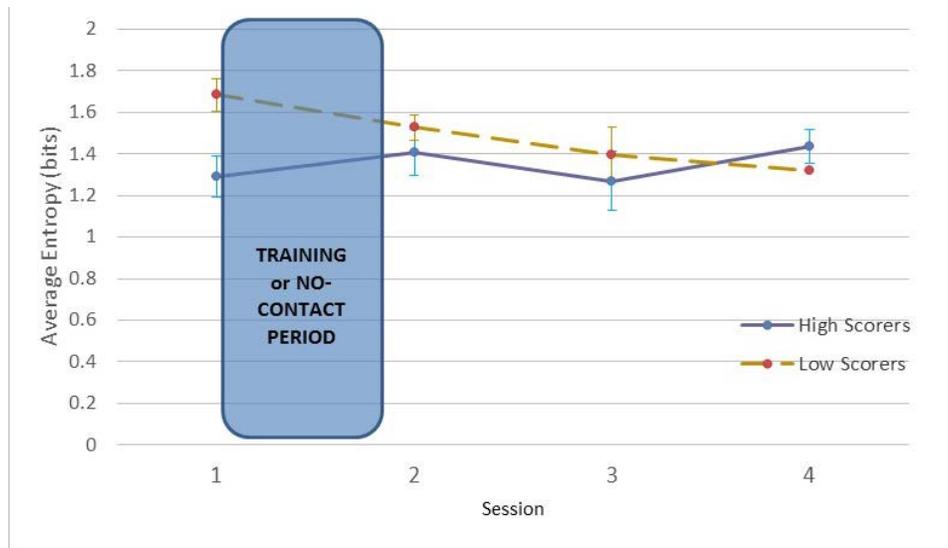


Figure 88. Chart. Average entropy for the car training group for straight road segments grouped by z-score on visual metrics.

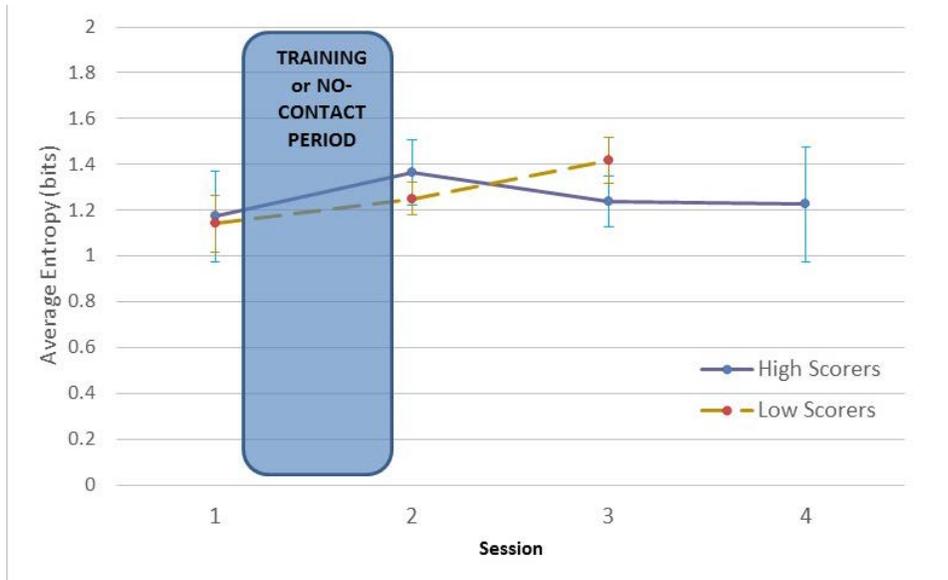


Figure 89. Chart. Average entropy for the computer training group for straight road segments grouped by z-score on visual metrics.

Intersection Segments:

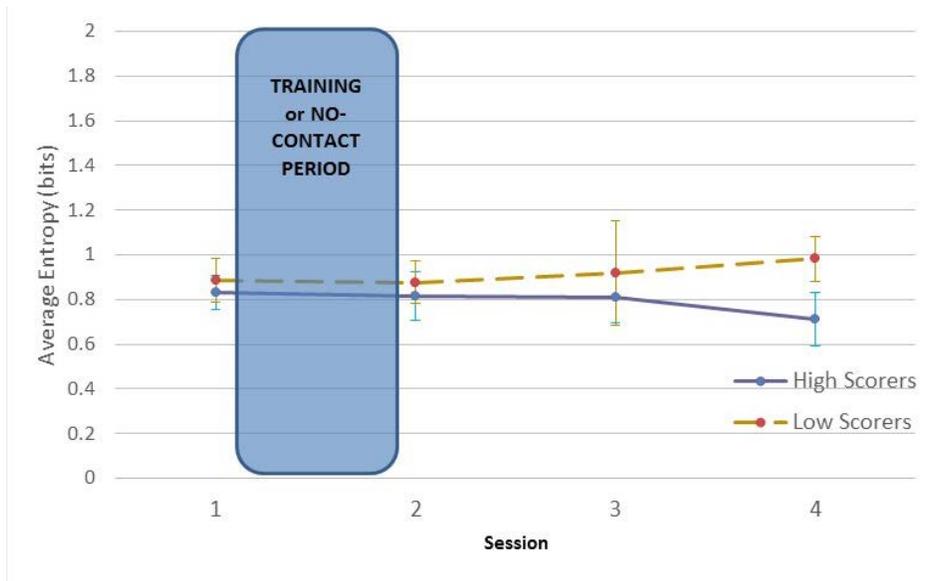


Figure 90. Chart. Average entropy for the control group for intersections grouped by z-score on visual metrics.

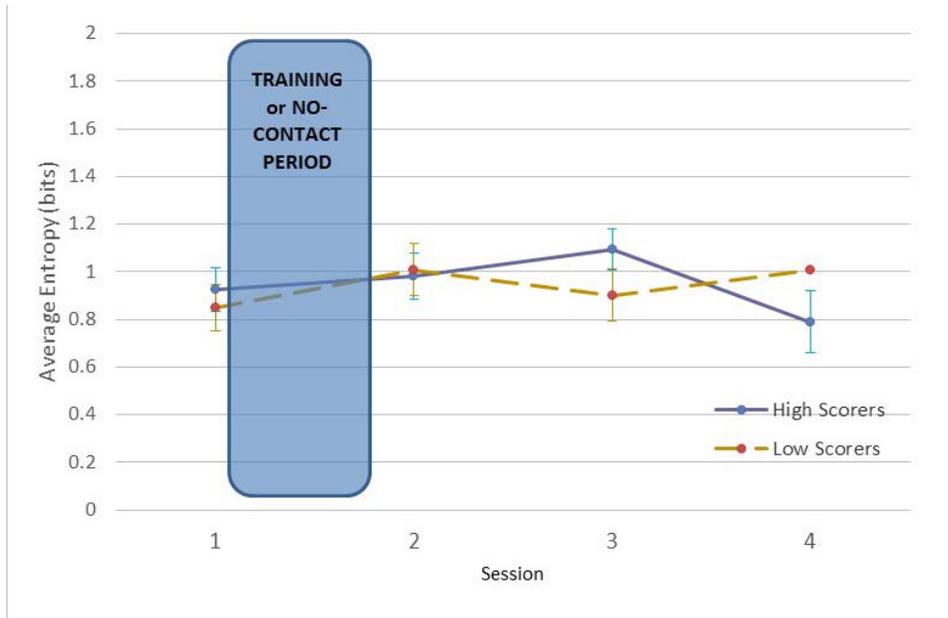


Figure 91. Chart. Average entropy for the car training group for intersections grouped by z-score on visual metrics.

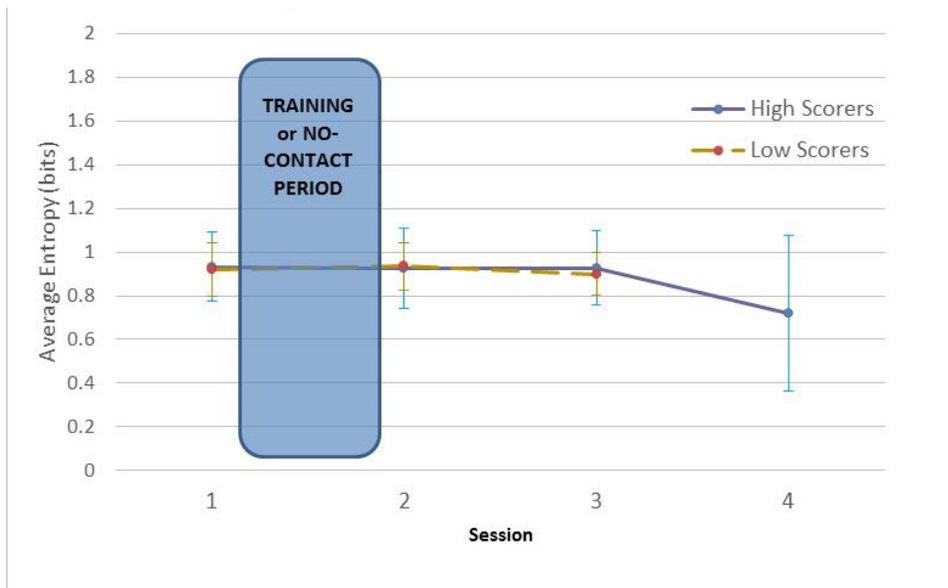


Figure 92. Chart. Average entropy for the computer training group for intersections grouped by z-score on visual metrics.

Cognitive Dimension

Lane Variability

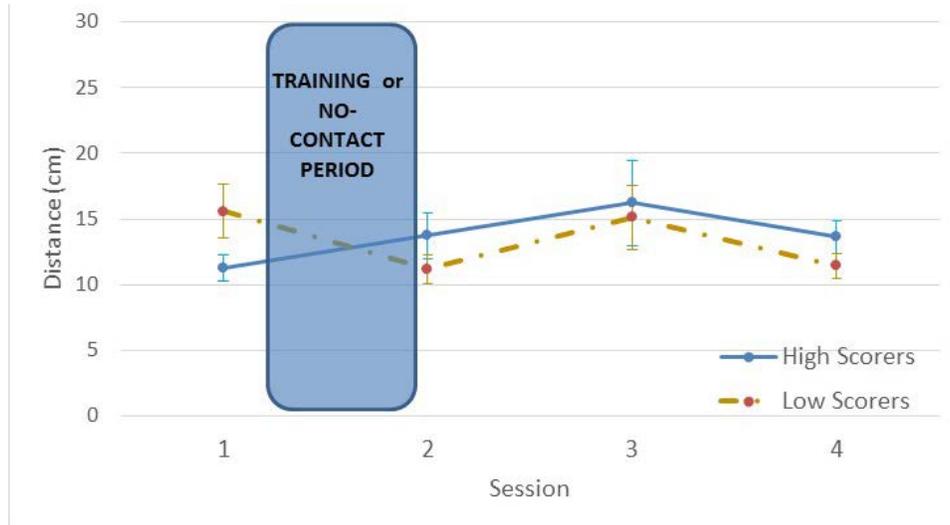


Figure 93. Chart. Average lane variability for the control group by z-score on cognitive metrics.

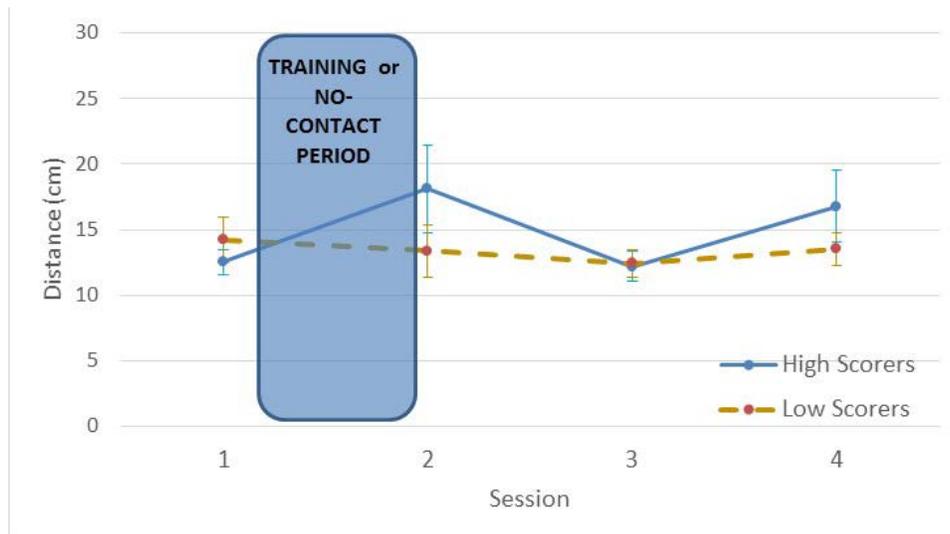


Figure 94. Chart. Average lane variability for the car training group by z-score on cognitive metrics.

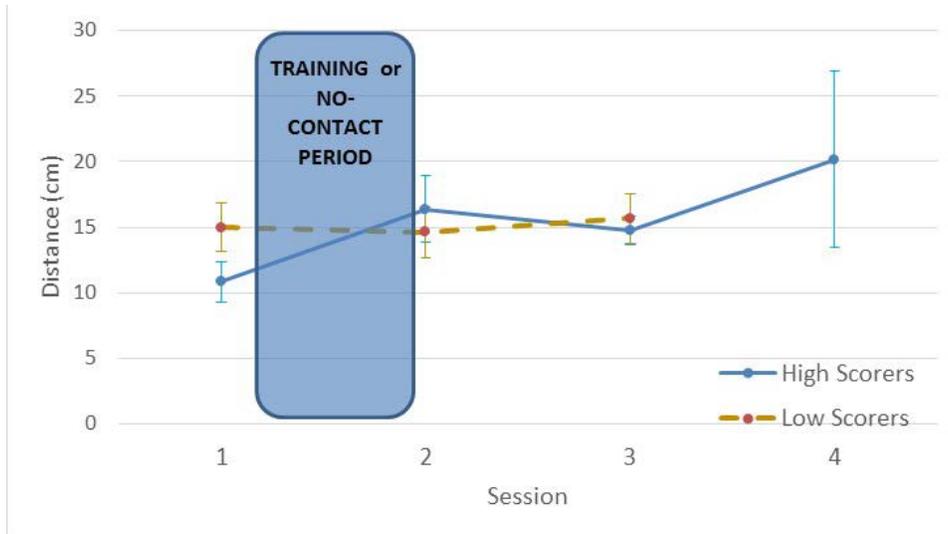


Figure 95. Chart. Average lane variability for the computer training group by z-score on cognitive metrics.

Speed Variability

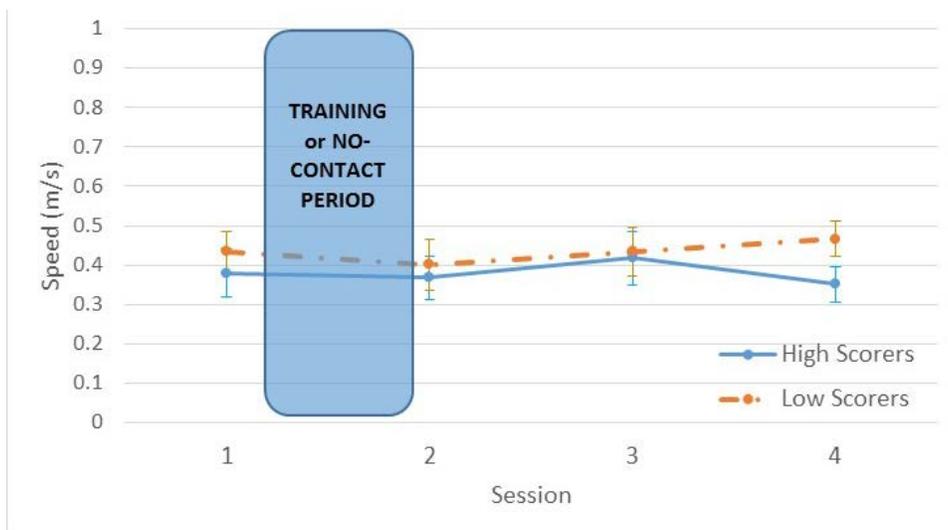


Figure 96. Chart. Average speed variability for the control group by z-score on cognitive metrics.



Figure 97. Chart. Average speed variability for the car training group by z-score on cognitive metrics.

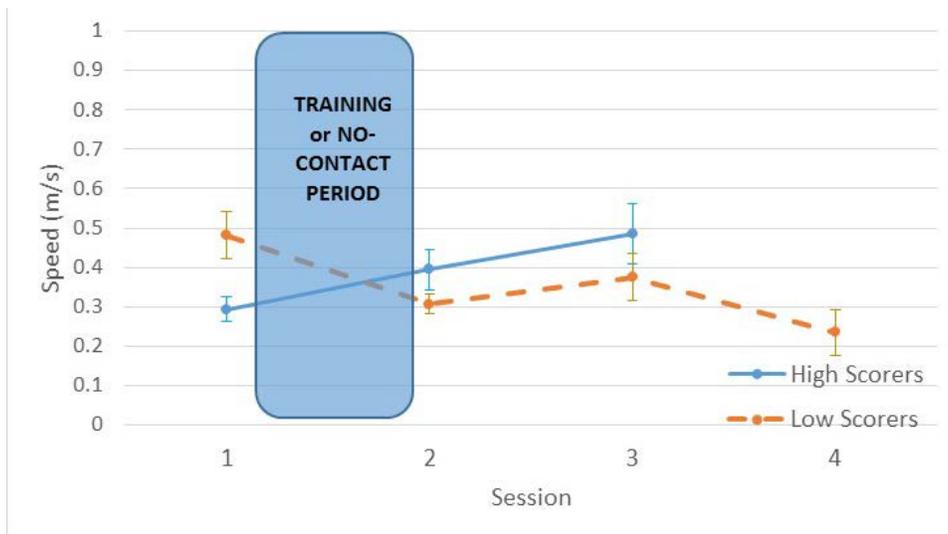


Figure 98. Chart. Average speed variability for the computer training group by z-score on cognitive metrics.

Entropy

Straight Road Segments:

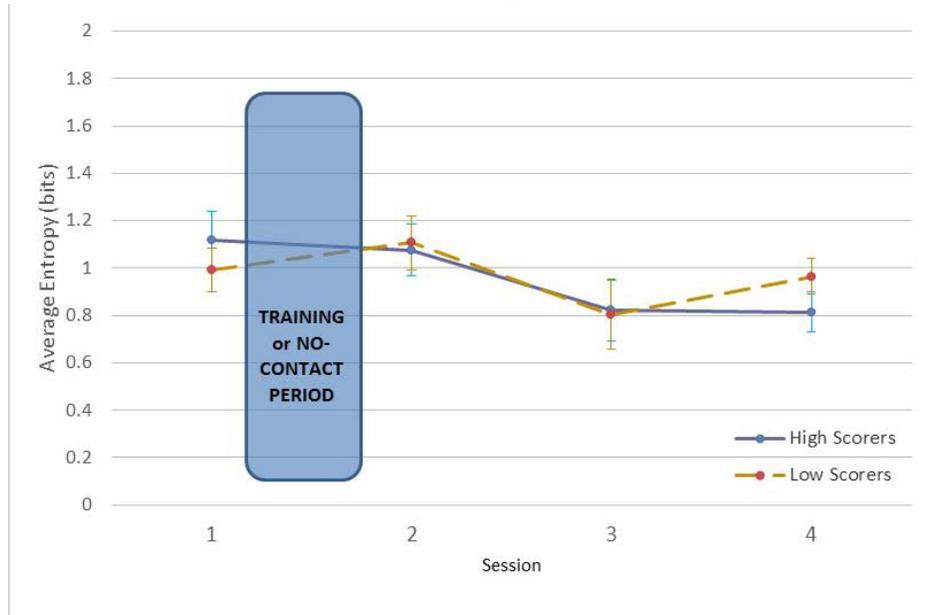


Figure 99. Chart. Average entropy for the control group for straight road segments grouped by z-score on cognitive metrics.

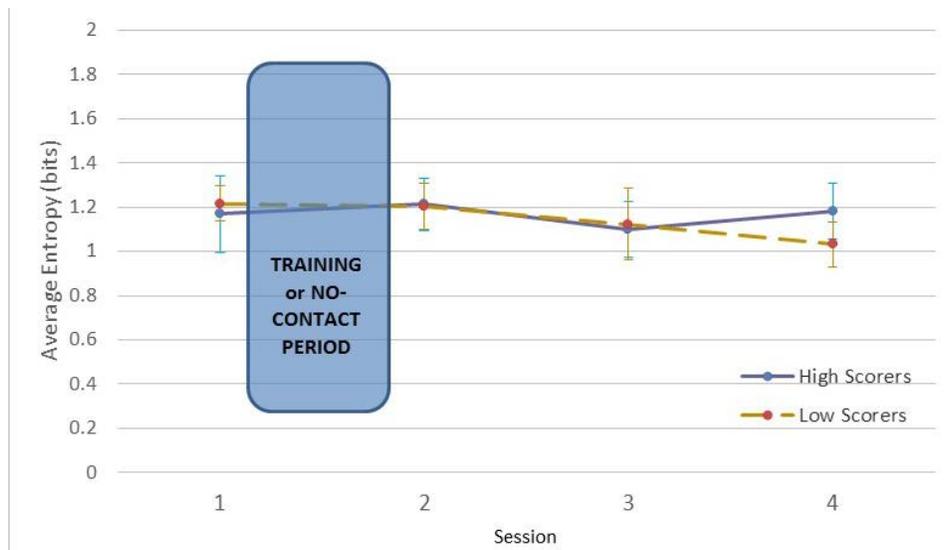


Figure 100. Chart. Average entropy for the car training group for straight road segments grouped by z-score on cognitive metrics.

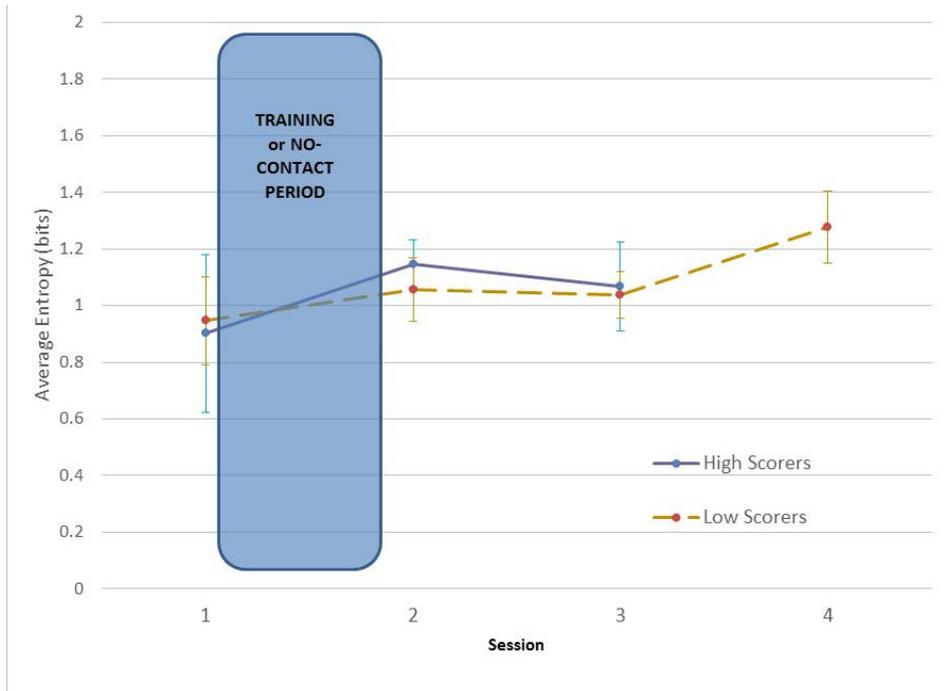


Figure 101. Chart. Average entropy for the computer training group for straight road segments grouped by z-score on cognitive metrics.

Intersections:

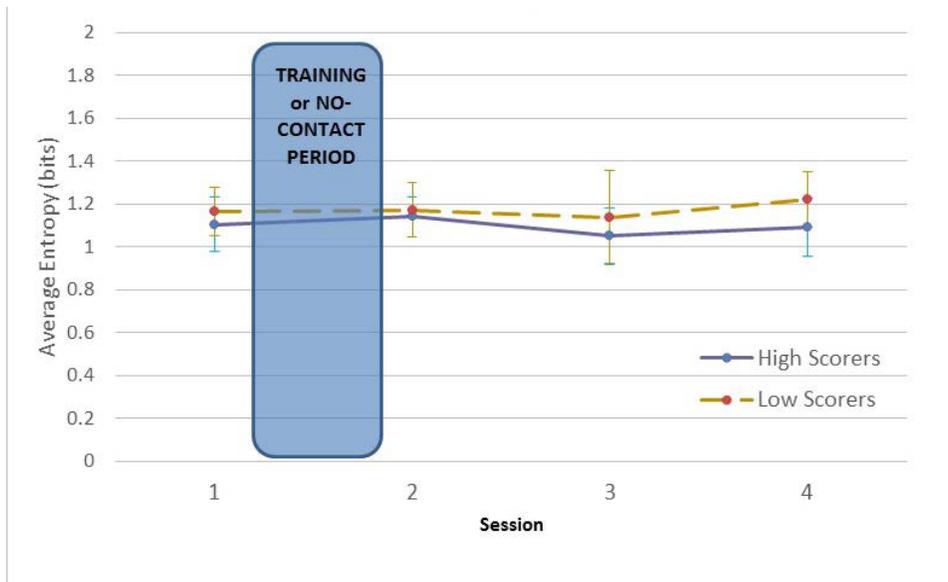


Figure 102. Chart. Average entropy for the control group for intersections grouped by z-score on cognitive metrics.

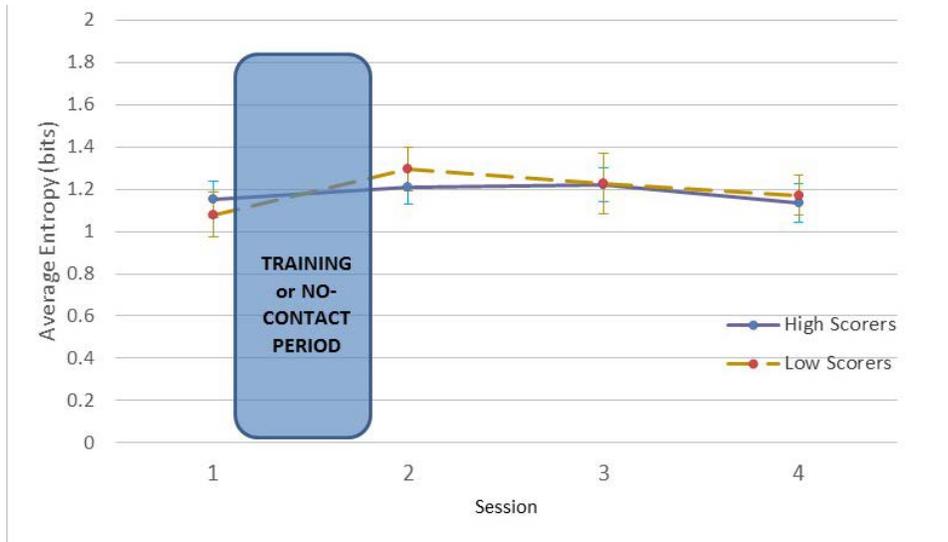


Figure 103. Chart. Average entropy for the car training group for intersections grouped by z-score on cognitive metrics.

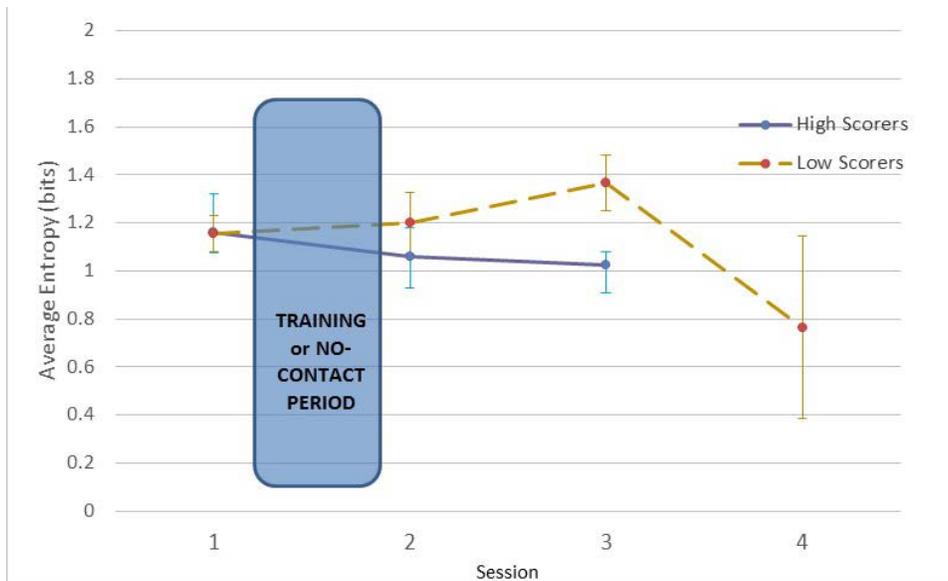


Figure 104. Chart. Average entropy for the computer training group for intersections grouped by z-score on cognitive metrics.

SMART ROAD METRICS

Physical Dimension

Vehicle-Centric Detection Task

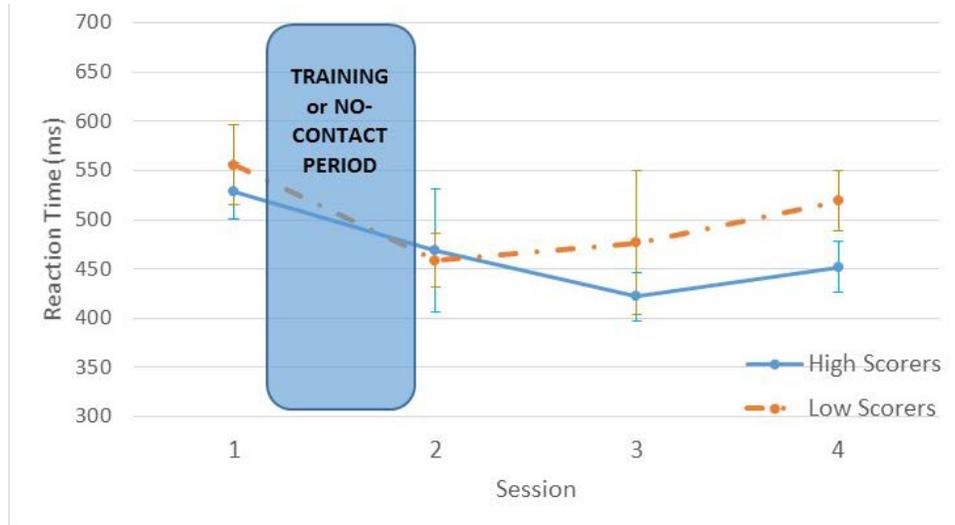


Figure 105. Chart. Average reaction time for the vehicle-centric detection task for the control group by z-score on physical metrics.

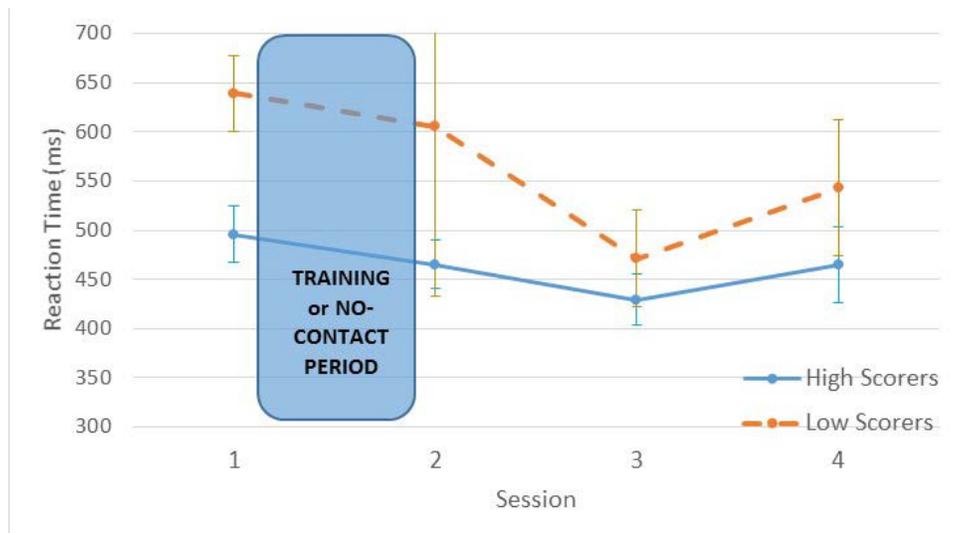


Figure 106. Chart. Average reaction time for the vehicle-centric detection task for the car training group by z-score on physical metrics.

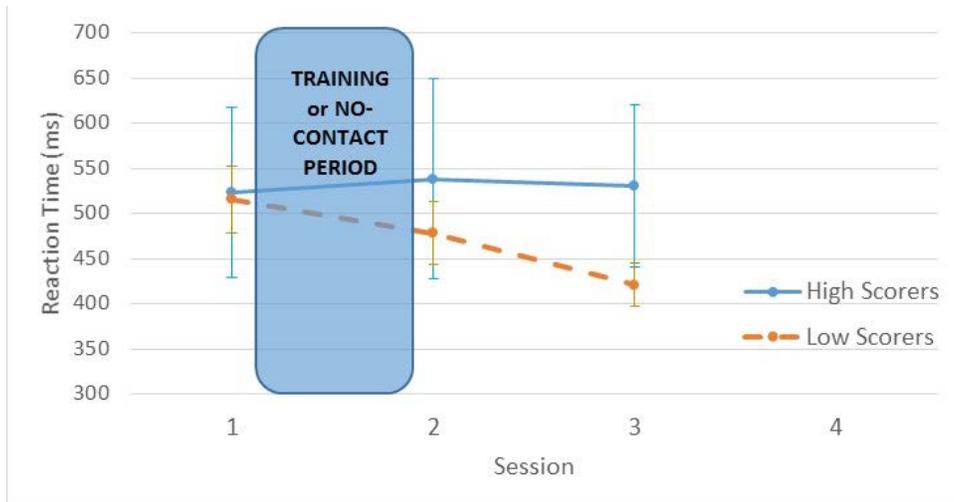


Figure 107. Chart. Average reaction time for the vehicle-centric detection task for the computer training group by z-score on physical metrics.

Driver-Centric Peripheral Detection Task

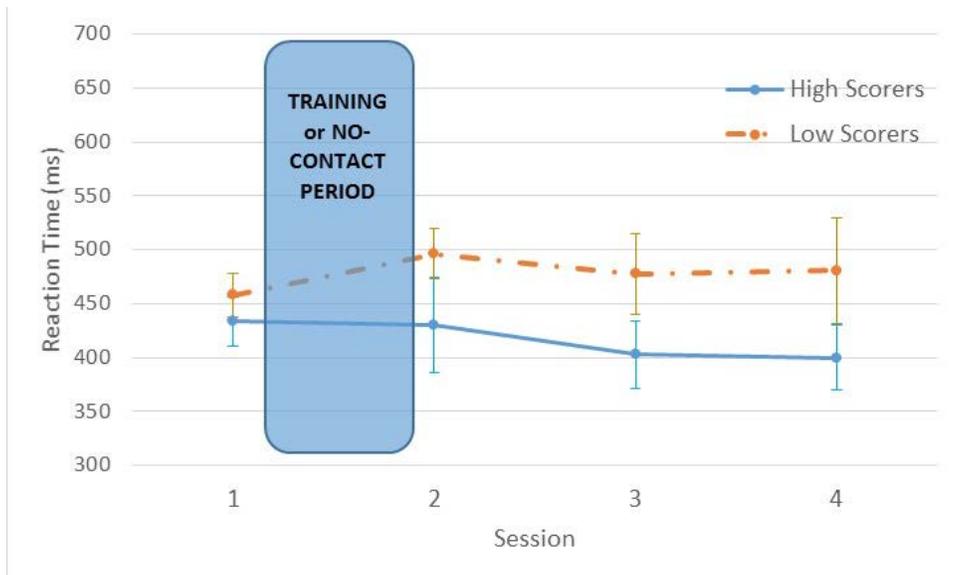


Figure 108. Chart. Average reaction time for the driver-centric peripheral detection task for the control group by z-score on physical metrics.



Figure 109. Chart. Average reaction time for the driver-centric peripheral detection task for the car training group by z-score on physical metrics.

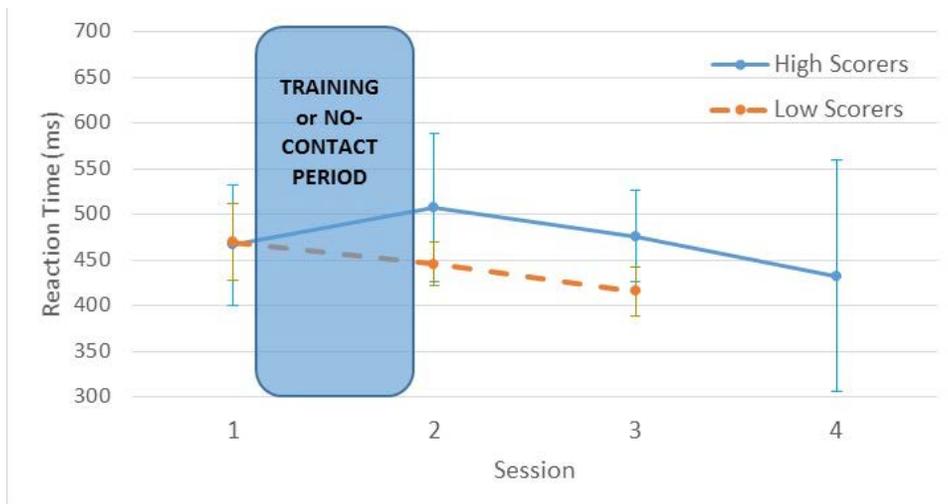


Figure 110. Chart. Average reaction time for the driver-centric peripheral detection task for the computer training group by z-score on physical metrics.

Object Recognition Distance

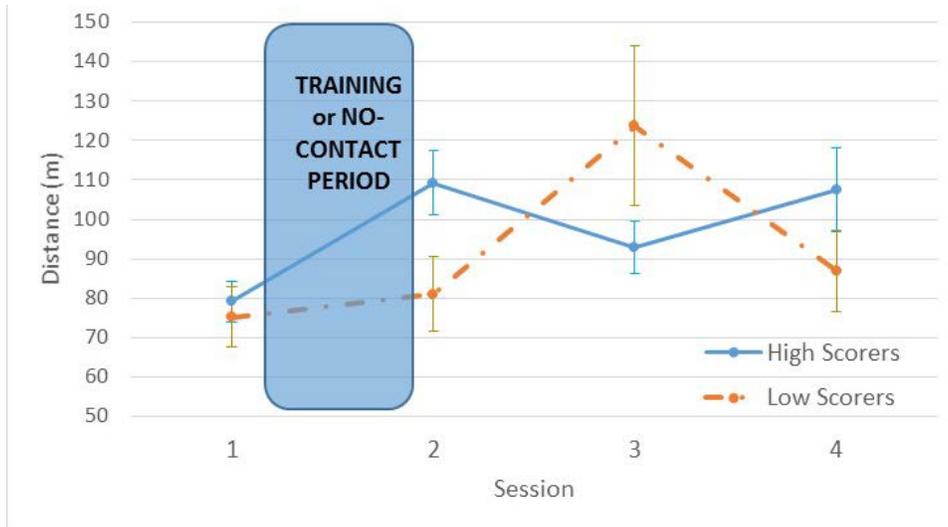


Figure 111. Chart. Average object recognition distance for the control group by z-score on physical metrics.

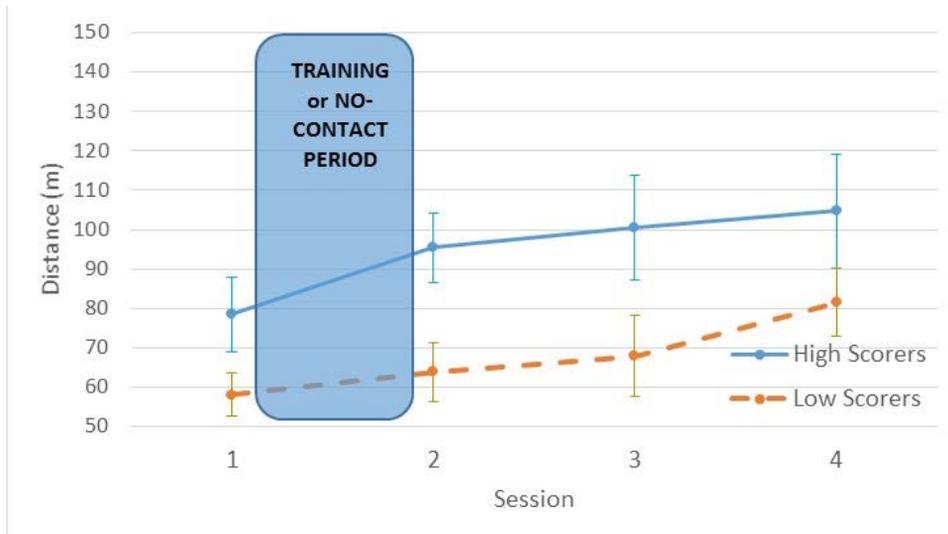


Figure 112. Chart. Average object recognition distance for the car training group by z-score on physical metrics.

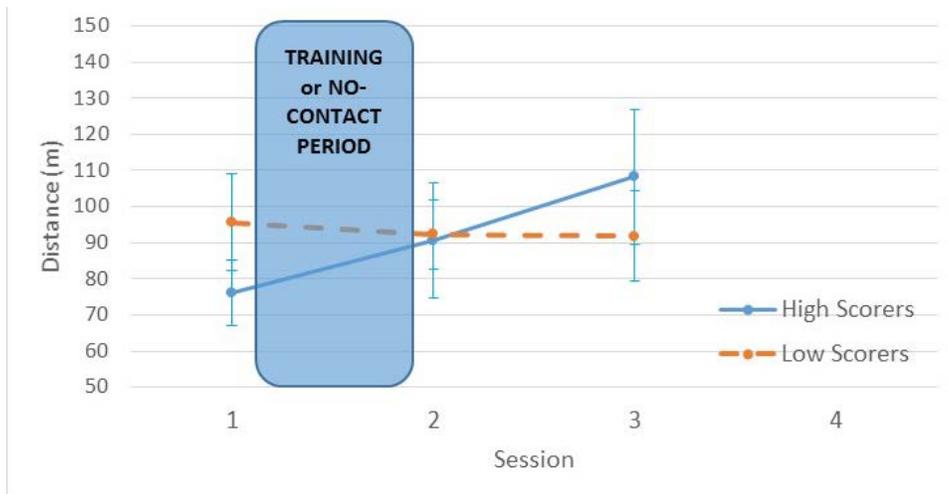


Figure 113. Chart. Average object recognition distance for the computer training group by z-score on physical metrics.

Visual Dimension

Vehicle-Centric Detection Task

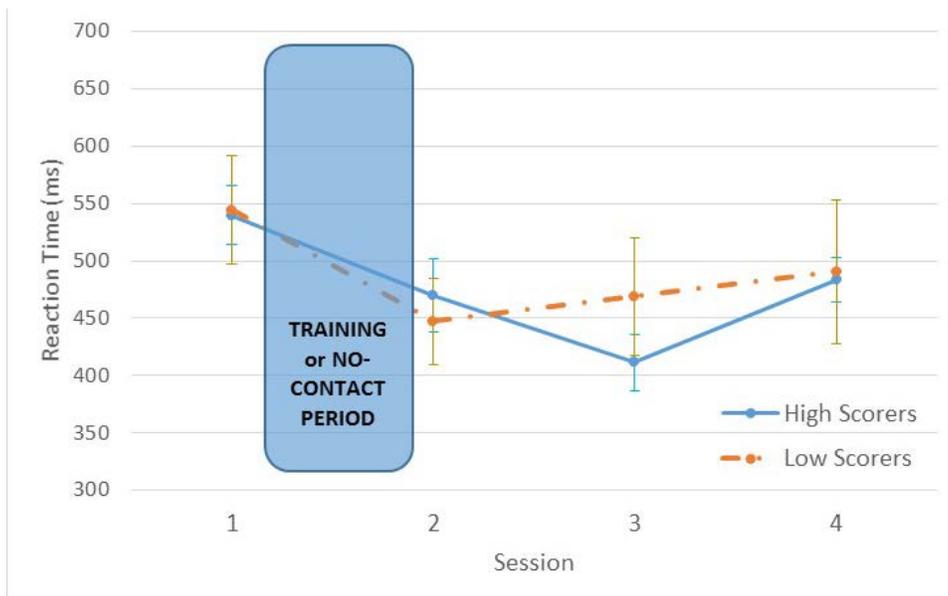


Figure 114. Chart. Average reaction time for the vehicle-centric detection task for the control group by z-score on visual metrics.

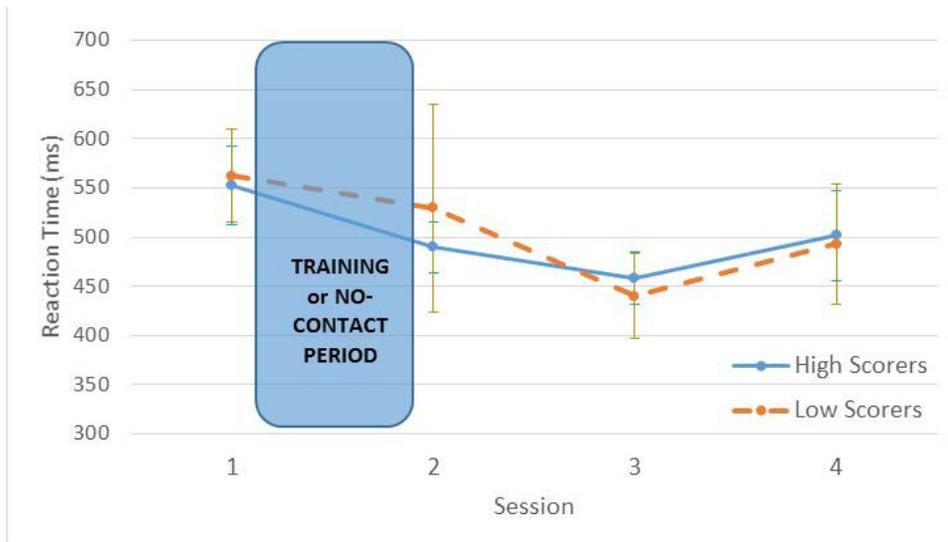


Figure 115. Chart. Average reaction time for the vehicle-centric detection task for the car training group by z-score on visual metrics.



Figure 116. Chart. Average reaction time for the vehicle-centric detection task for the computer.

Driver-Centric Peripheral Detection Task

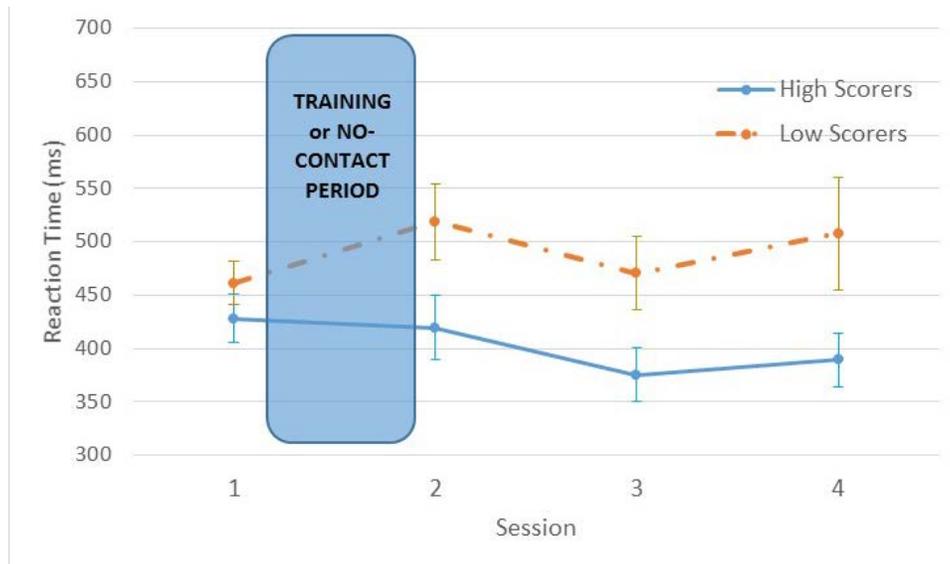


Figure 117. Chart. Average reaction time for the driver-centric peripheral detection task for the control group by z-score on visual metrics.

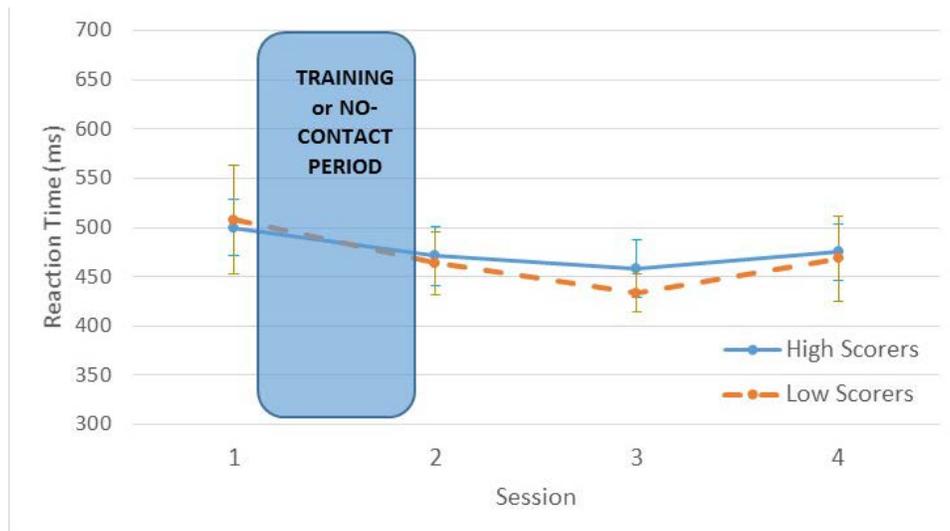


Figure 118. Chart. Average reaction time for the driver-centric peripheral detection task for the car training group by z-score on visual metrics.

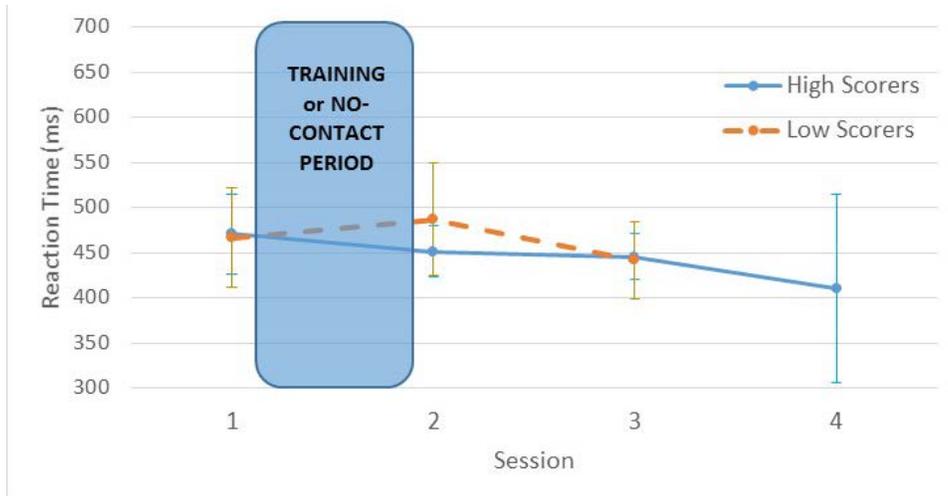


Figure 119. Chart. Average reaction time for the driver-centric peripheral detection task for the computer training group by z-score on visual metrics.

Object Recognition Distance

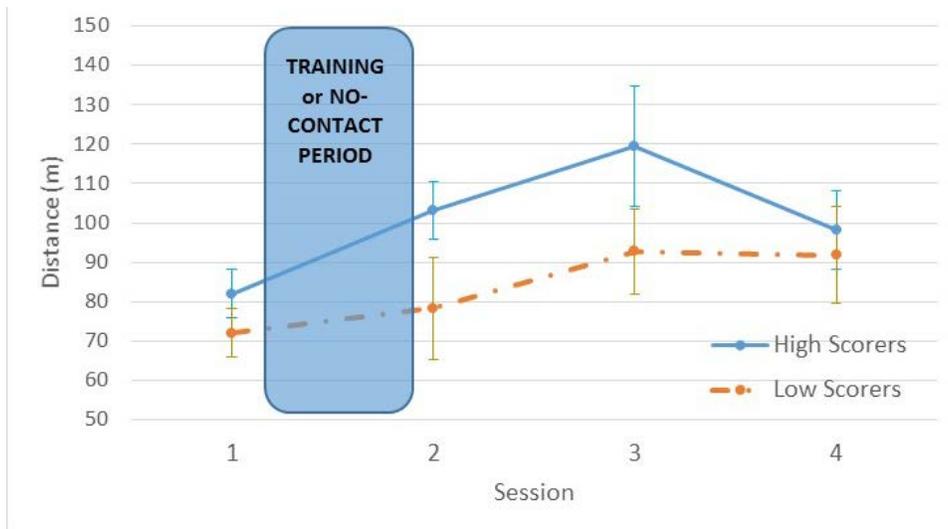


Figure 120. Chart. Average object recognition distance for the control group by z-score on visual metrics.

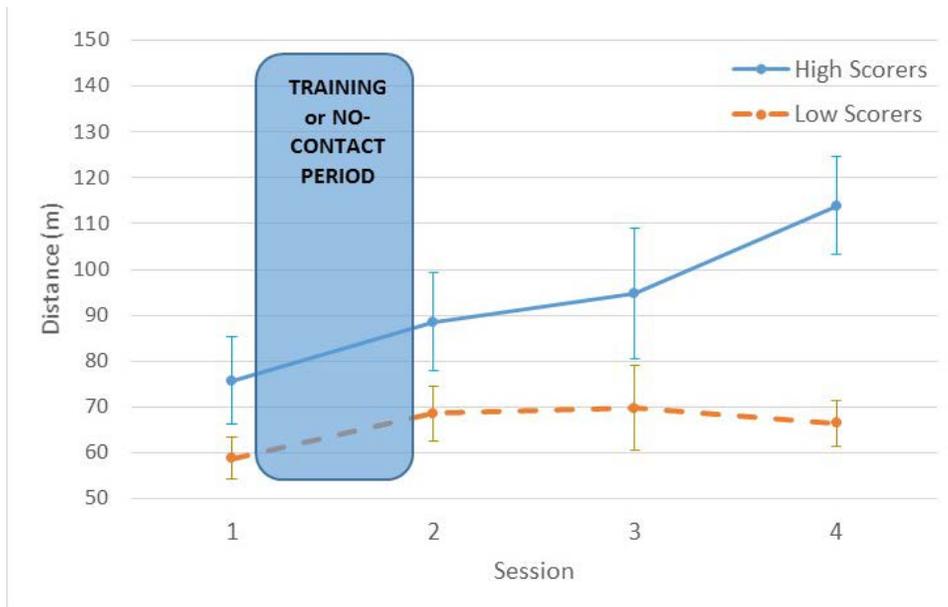


Figure 121. Chart. Average object recognition distance for the car training group by z-score on visual metrics.

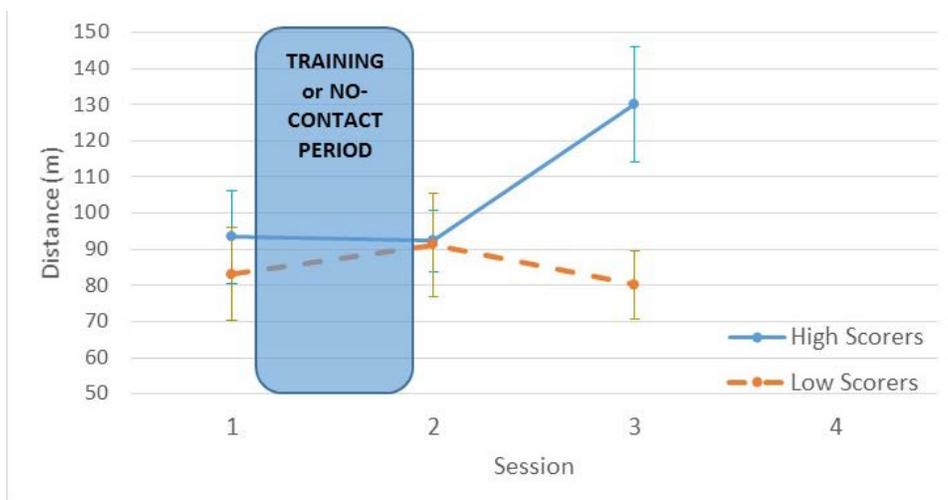


Figure 122. Chart. Average object recognition distance for the computer training group by z-score on visual metrics.

Cognitive Dimension

Vehicle-Centric Detection Task

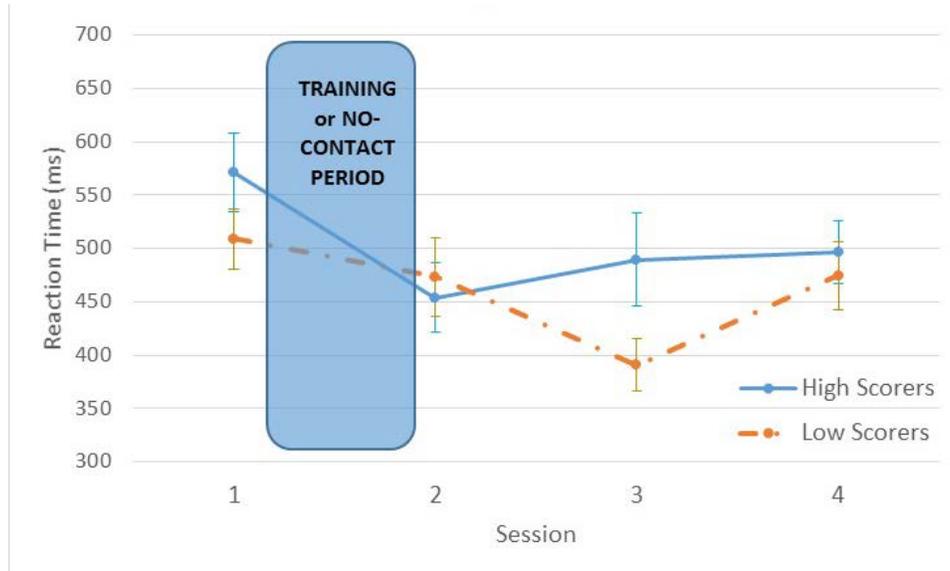


Figure 123. Chart. Average reaction time for the vehicle-centric detection task for the control group by z-score on cognitive metrics.

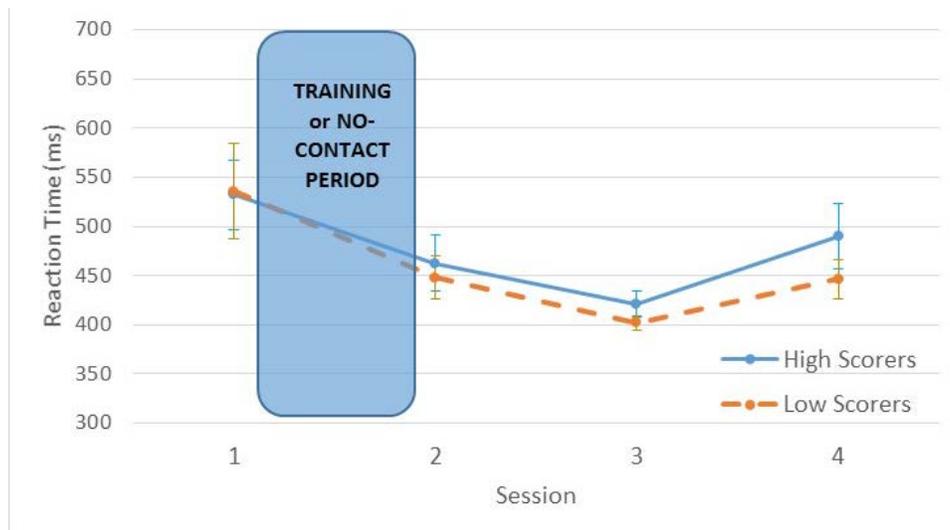


Figure 124. Chart. Average reaction time for the vehicle-centric detection task for the car training group by z-score on cognitive metrics.

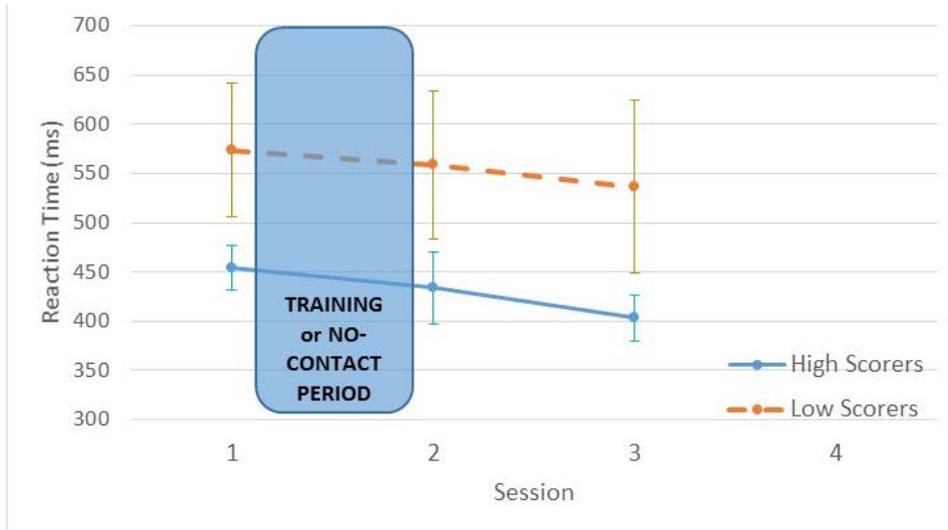


Figure 125. Chart. Average reaction time for the vehicle-centric detection task for the computer training group by z-score on cognitive metrics.

Driver-Centric Peripheral Detection Task

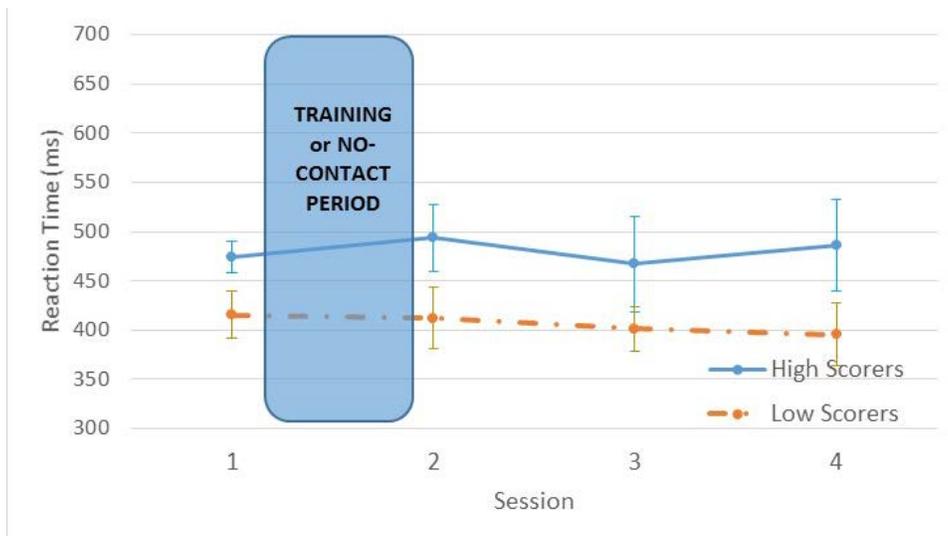


Figure 126. Chart. Average reaction time for the driver-centric peripheral detection task for the control group by z-score on cognitive metrics.

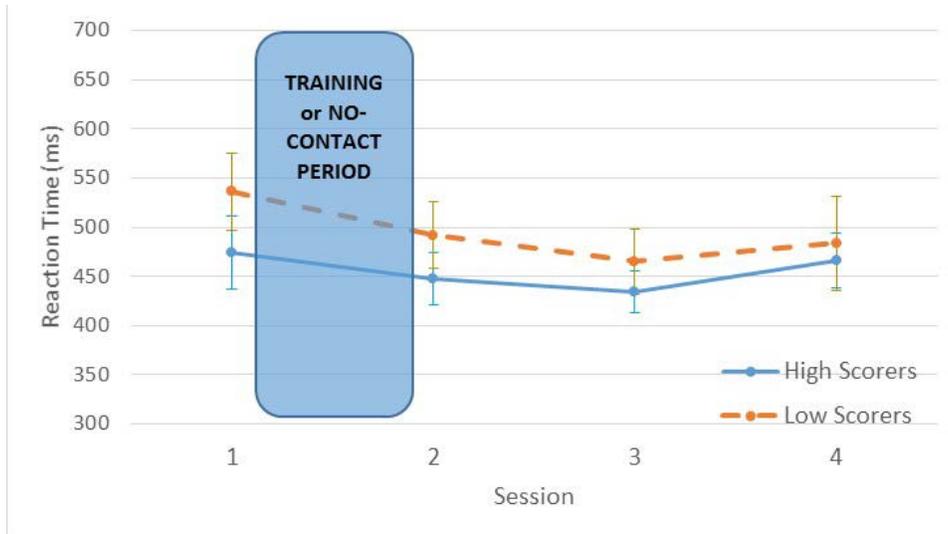


Figure 127. Chart. Average reaction time for the driver-centric peripheral detection task for the car training group by z-score on cognitive metrics.

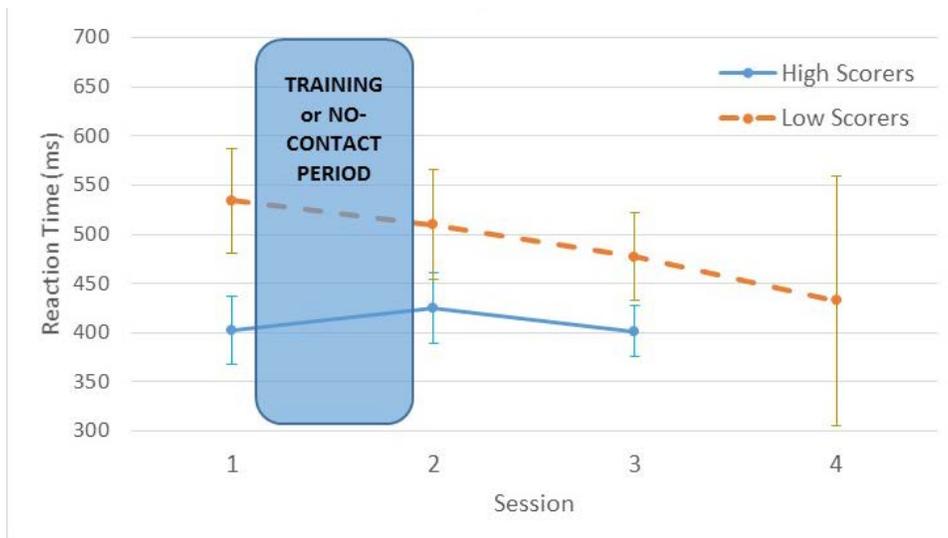


Figure 128. Chart. Average reaction time for the driver-centric peripheral detection task for the computer training group by z-score on cognitive metrics.

Object Recognition Distance

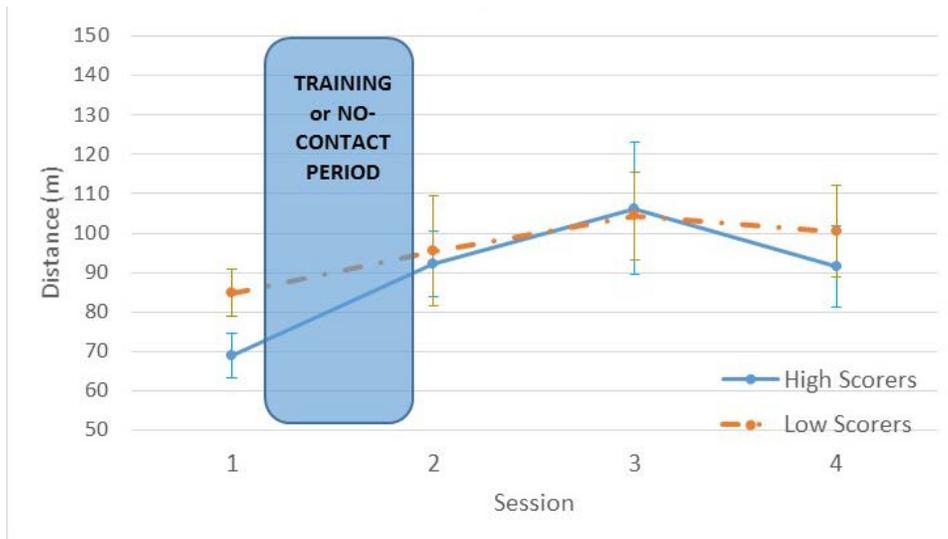


Figure 129. Chart. Average object recognition distance for the control group by z -score on cognitive metrics.

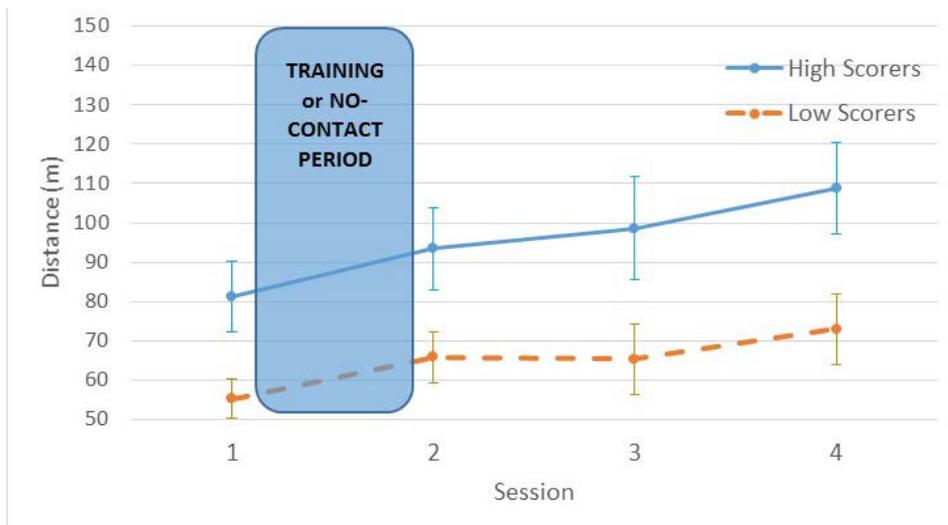


Figure 130. Chart. Average object recognition distance for the car training group by z -score on cognitive metrics.

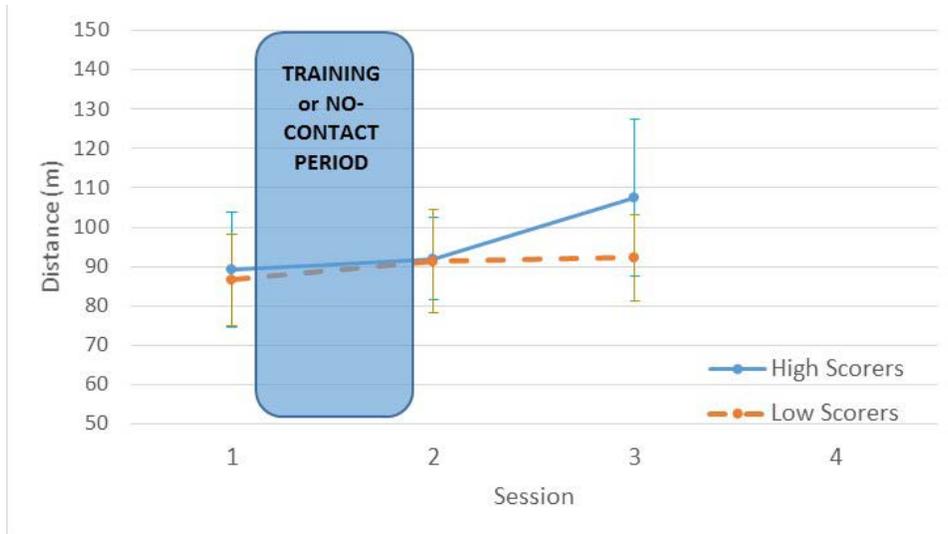


Figure 131. Chart. Average object recognition distance for the computer training group by z-score on cognitive metrics.

REFERENCES

- Ball, K. & Owsley, C. (1993). The useful field of view test: A new technique for evaluating age-related declines in visual function. *Journal of the American Optometric Association*, 64(1), 71-9.
- Ball, K. K., Beard, B. L., Roenker, D. L., Miller, R. L., & Griggs, D. S. (1988). Age and visual search: Expanding the useful field of view. *Journal of the Optical Society of America A*, 5(12), 2210-19.
- Ball, K., Edwards, J. D., Ross, L. A., & McGwin, Jr., G. (2010). Cognitive training decreases motor vehicle collision involvement of older drivers. *Journal of the American Geriatrics Society*, 58: 2107–2113. doi: 10.1111/j.1532-5415.2010.03138.x
- Ball, K., Owsley, C., Stalvey, B., Roenker, D. L., Sloane, M. E., & Graves, M. (1998). Driving avoidance and functional impairment in older drivers. *Accident Analysis & Prevention*, 30(3), 313–22.
- Bao, S. and Boyle, L. N. (2009). Age-related differences in visual scanning at median-divided highway intersections in rural areas. *Accident Analysis & Prevention*, 41(1), 146-52.
- Buitenweg, J. I. V., Murre, J. M. J., & Ridderinkhof, K. R. (2012). Brain training in progress: A review of trainability in healthy seniors. *Frontiers in Human Neuroscience*, 6, 1-11.
- Cassavaugh, N. D. & Kramer, A. F. (2009). Transfer of computer-based training to simulated driving in older adults. *Applied Ergonomics*, 40(5), 943-52.
- Cheung, I. & McCartt, A. T. (2011). Declines in fatal crashes of older drivers: Changes in crash risk and survivability. *Accident Analysis & Prevention*, 43(3), 666–674.
- Cheung, I., McCartt, A. T., & Braitman, K. A. (2008). Exploring the declines in older driver fatal crash involvement. *Annals of Advances in Automotive Medicine*, 52, 255–64.
- Cicchino, J. B. & McCartt, A. T. (2014). Trends in older driver crash involvement rates and survivability in the United States: An update. *Accident Analysis & Prevention*, 72, 44-54.
- Collia, D. V., Sharp, J., & Giesbrecht, L. (2003). The 2001 National Household Travel Survey: A look into the travel patterns of older americans. *Journal of Safety Research*, 34(4), 461-70.
- Draganski, B., Gaser, C., Busch, V., Schuierer, G., Bogdahn, U., & May, A. (2004). Neuroplasticity: Changes in grey matter induced by training. *Nature*, 427, 311-12.
- Edwards, J. D., Delahunt, P. B., and Mahncke, H. W. (2009). Cognitive speed of processing training delays driving cessation. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 64A(12):1262-1267. doi:10.1093/gerona/glp131

- Edwards, J. D., Myers, C., Ross, L. A., Roenker, D. L., Cissell, G. M., McLaughlin, A. M., and Ball, K. K. (2009). The longitudinal impact of cognitive speed of processing training on driving mobility. *The Gerontologist*, 49(4), 485-94.
- IIHS. (2014). Older drivers. Retrieved from <http://www.iihs.org/iihs/topics/t/older-drivers/qanda>
- Jobe, J. B., Smith, D. M., Ball, K., Tennstedt, S. L., Marsiske, M., Willis, S. L., Rebok, G. W., Morris, J. N., Helmers, K. F., Leveck, M. D., Kleinman, K. (2001). ACTIVE: A cognitive intervention trial to promote independence in older adults. *Controlled Clinical Trials*, 22(4), 453-79.
- Mathias, J. L. & Lucas, L. K. (2009). Cognitive predictors of unsafe driving in older drivers: A meta-analysis. *International Psychogeriatrics*, 21(4), 637-53.
- Molnar, L. J. & Eby, D. W. (2008). The relationship between self-regulation and driving-related abilities in older drivers: An exploratory study. *Traffic Injury Prevention*, 9(4), 314-19.
- Ngandu, T., Lehtisalo, J., Solomon, A., Levälähti, E., et al. (2015). A 2 year multidomain intervention of diet, exercise, cognitive training, and vascular risk monitoring versus control to prevent cognitive decline in at-risk elderly people (FINGER): A randomised controlled trial. *The Lancet*, 385(9984), 2255-63.
- Noack, H., Lövdén, M., Schmiedek, F., and Lindenberger, U. (2009). Cognitive plasticity in adulthood and old age: gauging the generality of cognitive intervention effects. *Restorative Neurology and Neuroscience*, 27, 435-53.
- O'Connell, R. G., & Robertson, I. H. (2012). Training the brain: Nonpharmacological approaches to stimulating cognitive plasticity. In M. I. Posner (Ed.), *Cognitive neuroscience of attention*. New York: The Guilford Press.
- Owen, A. M., Hampshire, A., Grahn, J. A., Stenton, R., Dajani, S., Burns, A. S., Howard, R. J., & Ballard, C. G. (2010). Putting brain training to the test. *Nature*, 465, 775-778.
- Owsley, C., Ball, K., Loane, M. E., Roenker, D. L., and Bruni, J. R. (1991). Visual/cognitive correlates of vehicle accidents in older drivers. *Psychology and Aging*, 6(3), 403-15.
- Reber, A. S. (1993). *Implicit learning and tacit learning: An Essay on the cognitive unconscious*. Oxford Psychology Series 19. New York: Oxford University Press.
- Roenker, D. L., Cissell, G. M., Ball, K. K., Wadley, V. G., & Edwards, J. D. (2003). Speed-of-processing and driving simulator training result in improved driving performance. *Human Factors*, 45(2), 218-33.
- Romoser, M.R.E. & Fisher, D.L. (2009). The effect of active versus passive training strategies on improving older drivers' scanning in intersections. *Human Factors*, 51(5), 652-668.
- Romoser, M.R.E., Pollatsek, A., Fisher, D.L., & Williams, C.C. (2013). Comparing the glance patterns of older versus younger experienced drivers: Scanning for hazards while

- approaching and entering the intersection. *Transportation Research Part F: Traffic Psychology and Behaviour*, 16,104-116.
- Ross, L., Vance, D., Ball, K., Cak, L., Ackerman, M., Benz, D., and Ball, D. (2011). Translating laboratory measures to real-world outcomes: Application of the UFOV® test in an insurance company setting. In *Proceedings of the Sixth International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design*.
- Staplin, L., Lococo, K. H., Gish, K. W., Decina, L. E. (2003). *Model Driver Screening and Evaluation Program. Volume 2: Maryland pilot older driver study*. Washington, D.C.: National Highway and Traffic Safety Administration. Retrieved from <http://www.nhtsa.dot.gov/people/injury/olddrive/modeldriver/>
- Staplin, L., Lococo, K. H., Martell, C., and Stutts, J. (2012). *Taxonomy of older driver behaviors and crash risk* (Report No. DOT HS 811 468A). Washington, DC: U.S. Department of Transportation.
- Stutts, J. C., Stewart, J. R., & Martell, C. (1998). Cognitive test performance and crash risk in an older driver population. *Accident Analysis & Prevention*, 30(3), 337-46.
- U.S. Census Bureau. (2012, December). *Table 3. Percent distribution of the projected population by selected age groups and sex for the United States: 2015 to 2060* (NP2012-T3).