

ASSESSMENT OF ATTENTION DEFICITS AND UNSAFE DRIVING AFTER TBI
USING EYE TRACKING AND VIRTUAL REALITY

by

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Dissertation submitted to the Faculty of the
Medical and Clinical Psychology Graduate Program
Uniformed Services University of the Health Sciences
In partial fulfillment of the requirements for the degree of
Doctor of Philosophy 2018

Distribution Statement

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Graduate Education Office (A 1045), 4301 Jones Bridge Road, Bethesda, MD 20814



**APPROVAL OF THE DOCTORAL DISSERTATION IN THE DEPARTMENT OF
MEDICAL AND CLINICAL PSYCHOLOGY**

Title of Dissertation: "Assessment of Attention Deficits and Unsafe Driving After TBI Using Eye Tracking and Virtual Reality"

Name of Candidate: Brian Guise
Doctor of Philosophy Degree
June 13, 2018

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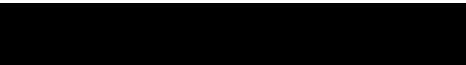
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ABSTRACT

Assessment of Attention Deficits and Unsafe Driving After TBI Using Eye Tracking and Virtual Reality

Brian J. Guise, Ph.D., 2018

Dissertation directed by: Dr. Mark Ettenhofer, Assistant Professor, Department of Medical & Clinical Psychology

Attention is a necessary cognitive domain for safe driving. Research has consistently found that inattention and distraction are the primary causes of motor vehicle accidents. Individuals with traumatic brain injury (TBI) frequently report attention problems, as well as show impaired driving ability across the injury spectrum, from mild to severe. Driving fitness assessment has relied primarily on neuropsychological test performance and on-road driving tests, methods which have limited effectiveness. New assessment tools, such as virtual reality driving simulators (VRDS) and eye-tracking, may be able to replicate the cognitive demands of driving and measure subtler deficits. Using a novel eye tracking assessment tool, the Bethesda Eye and Attention Measure (BEAM), the current study examined 29 individuals with TBI to determine the influence of attention deficits on driving behaviors in a VRDS; data for 20 to 25 participants were available to include in each primary analysis. A second objective of the study was to

examine the predictive validity of both the BEAM and VRDS by examining their relationships with self-reported unsafe driving behaviors on a driving questionnaire over a four-week period. Results did not find significant relationships between attention deficits and driving behaviors (VR and self-report). Study limitations, including small sample size and use of instruments with limited psychometric data, may have impacted the ability to detect these relationships. Examination of effect sizes reveals promising trends for larger-scale studies using these novel methods. Further research is needed to help clarify the relationships between eye tracking, VR driving measures, and real-world driving behaviors.

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CHAPTER 1: Introduction

OVERVIEW

Attention lapses are considered to be the primary cause of motor vehicle accidents (61). This finding is important because attention deficits are commonly reported in a variety of conditions, including neurological insult (e.g., traumatic brain injury [TBI], epilepsy, stroke), psychiatric disorders (e.g., depression and Attention Deficit/Hyperactivity Disorder [ADHD]), pain (both acute and chronic), as a side-effect of some medications, and in normal aging (14). Specifically, among individuals with a history of one or more TBIs, research has shown impaired driving ability across the injury spectrum, from mild to moderate and severe (89, 101).

Despite the impact of attention on driving ability and the prevalence of attention deficits in various conditions, most research has examined only broad characteristics of attention and driving behaviors. Similarly, many studies have focused on correlates of both attention (i.e., distraction) and driving incidents (e.g., number of accidents), but have not provided information on specific unsafe driving behaviors (e.g., speeding or failure to maintain appropriate lane position). Elucidating the relationship between specific attention deficits and unsafe driving behaviors would inform the development of targeted treatment of attention deficits. Also, current methods to assess driving fitness, including on-road driving assessments and neuropsychological evaluations, show some utility in determining driving fitness. However, these methods have limited ecological validity and sensitivity. New clinical tools, such as virtual reality driving simulators (VRDS) and eye tracking, may allow for more refined assessments of how specific attention impairments are related to specific unsafe driving behaviors and may assess driving fitness more accurately. The objectives of the current study were twofold. The first objective was to examine the influence of attention deficits on VRDS driving behaviors using a novel eye tracking assessment tool, the Bethesda Eye and Attention Measure (BEAM;

(33)). The second objective was to examine the predictive validity of both the BEAM and VRDS by examining their relationships with indicators of real-world unsafe driving behaviors.

BACKGROUND

Attention

The brain can only process a limited quantity of information at one time. Therefore, large quantities of environmental stimuli require a system (i.e., the attention system) to identify and organize relevant information for additional processing (69, 115). The attention system is comprised of integrated cognitive networks that enable an individual to filter pertinent information from the environment, hold and manipulate mental responses, and monitor/alter responses (120, 136). These cognitive networks are referred to as the attention networks.

Attention Networks

Cognitive neuroscience and imaging studies support a three network model of attention, that includes alerting, orienting, and executive (37). Neuroimaging studies have provided insight into the functional and anatomical aspects of the attention network (104). All four lobes of the cortex, as well as subcortical structures (e.g., thalamus, tegmentum, and basal ganglia) have been implicated as parts of interconnected networks that comprise the attention system (105). The three networks interact, but are anatomically and functionally distinct (104). See Figure 1 for a schematic of attention networks by brain region.

Alerting

Alerting, commonly referred to as *sustained attention*, is the ability to achieve and maintain readiness in preparation for incoming stimuli (106). Alerting is a foundational network, and is necessary for the performance of higher cortical function (104). The frontal and parietal

regions, particularly in the right hemisphere, are involved in the alerting network (37), whereas the left hemisphere has been associated with the linking of temporal and spatial information of a given stimulus (104).

Orienting

Orienting is the process of selecting specific information from multiple stimuli (37). Orienting attention toward a specific stimulus can be either triggered by the appearance of the stimulus itself, or through voluntary control (e.g., an individual scans the environment for a specific target) (104). The pulvinar of the thalamus, superior colliculi, superior parietal lobe, temporal-parietal junction, superior temporal lobe, and frontal eye fields are all involved in the orienting network (106). Sensory-specific cortex is also involved, depending on the source of the sensory input (i.e., the occipital lobe is activated when attending to visual stimuli) (104).

Executive

Executive attention is the monitoring and resolution of conflicts between different sensory inputs, and involves planning, decision making, working memory, error detection, processing of novel information, shifting attention between stimuli, and inhibitory control (37, 106). Executive attention is the network involved in volitional control, allowing the individual to direct attentional processes to achieve a specific goal. Executive attention is also referred to as selective and alternating attention (106). The anterior cingulate cortex and lateral prefrontal cortex have been implicated as important regions for conflict resolution, error detection, and shifting attention between stimuli, all functions of the executive network (37, 106). These three attention networks allow individuals to successfully interact with the external environment through a variety of behaviors, including driving.

Attention and Driving

Driving is a complex task requiring three hierarchical levels of abilities to be performed safely and effectively to achieve an outcome (e.g., commuting to work)(84). The operational level of driving involves basic cognitive functions, including attention, visual scanning, and motor coordination (84). The tactical level of driving includes skills, decisions, and behaviors performed while driving, such as decreasing speed to maintain distance from a forward vehicle or turning on headlights when raining (6). The strategic level of driving involves planning and decision-making that typically occur before driving to help the individual achieve a particular goal (e.g., choosing a route to avoid traffic)(84). Deficits at the operational level can significantly impact the tactical and strategic levels (e.g., an individual with an arm injury leaves for work earlier than usual to account for reduced driving speed due to difficulty controlling steering wheel)(6).

Within the operational level, attention is a critical cognitive domain as driving requires multiple forms of simultaneous cognitive processing (20). The driver must maintain vigilance (alerting network) and spatially detect (orienting network) a large, continuous volume of stimuli from various senses, including visual, auditory, somatosensory, and vestibular (95). The driver must also inhibit attention to irrelevant or distracting stimuli, and shift attention between different stimuli, while monitoring attentional performance (executive network). Given the necessity of the attention networks in effective driving, attention network deficits can have significant detrimental effects on driving ability.

The inability to sustain attention, due to alerting network deficits, may leave drivers unprepared to detect important stimuli, such as roadway signs or unexpected situations (e.g., forward car quickly braking) (78). Orienting network impairment may prevent a driver from localizing a stimulus within space, despite maintaining vigilance to the environment. Executive

network issues may prevent the driver from filtering out irrelevant details (e.g., radio or passenger conversation) and selectively attending to pertinent information in the environment (78). Executive network impairments may also prevent the driver from shifting attention between pertinent tasks, such as reading traffic signs and dashboard gauges, monitoring location of other vehicles, and checking mirrors (110).

Due to various mechanisms by which attentional difficulties can influence driving behaviors, distractions and inattention while driving are two of the primary causes of accidents (4). An observational study following 100 cars instrumented with sensors and video cameras for one year found that 78% of accidents and 65% of near accidents were attributed to driver inattention, such as glancing away from the road, attentional lapses, using a cell phone, and talking to passengers (60). Attentional failures occur when task demands exceed attentional capacity, and/or when multiple levels of processing are required simultaneously, which can occur frequently during driving due to the complex nature of the task (53). Taken together, inattention/distraction are considered primary causes of accidents.

Most of the research examining the association between attention and driving has focused on distractibility, such as smoking (93) and cell phone use (47, 121) while driving in samples of healthy individuals. Although studies on distraction provide some insight into the importance of attention while driving, they do not explain how deficits in specific attention networks are related to driving fitness. Also, distractibility may not be analogous to the attention deficits seen in clinical conditions. Therefore, it is important to discuss factors that are associated with unsafe driving that may impact attention, including alcohol use, risk taking, age, and fatigue.

Alcohol Use and Driving

Drunk driving is a significant risk factor for motor vehicle accidents. In 2012, more than 10,000 people were killed in alcohol-related accidents (88). Though driving under the influence of alcohol decreased by almost 50 percent over the ten-year period from 1996 to 2007, there are still a large number of individuals driving while intoxicated (2.2 percent)(20). In the largest study ever conducted to examine the influence of substance use on driving ability, more than 9,000 drivers were surveyed in Virginia over a 20-month period (11). Drivers with 0.08 percent breath alcohol concentration were four times more likely to crash than sober drivers, while those at 0.15 percent were twelve times more likely to crash.

Alcohol use has been shown to negatively impact driving ability, even at lower blood alcohol content (BAC) levels. Low levels of BAC (0.02) are associated with decreased cognitive abilities needed for safe driving, including tracking a moving target and divided attention (87). At BAC levels above the legal limit (0.09), performance on a driving simulator was significantly impaired, with participants driving at higher rates of speed and having increased number of collisions (13). Alcohol consumption negatively affects multiple brain areas associated with cognitive-motor processing, including disrupting the frontal-temporal-basal ganglia functional network, which negatively impacts attentional processes (135). Alcohol's effects on driving ability are related to decreasing cognitive processes as well as disinhibition, resulting in increased risk taking.

Risk Taking and Driving

Risk taking is related to unsafe driving behaviors and accidents. Service members returning from deployment engage in a greater number of high-risk driving behaviors, including speeding and aggressive driving, which could be attributed to combat driving practices as well as

a belief of invincibility (58). Attitudes toward traffic safety also influence unsafe driving behaviors. Attitudes toward rule violations and speeding predicted self-reported unsafe driving behaviors at a one-year follow-up, including speeding more than 10mph, tailgating another vehicle, and ignoring traffic signals (56). Attitude regarding risky driving behaviors has been shown to be related state characteristics, such as aggression following specific traffic situations (92), as well as more enduring trait characteristics, including sensation seeking and anger/hostility (23, 114). Conversely, high conscientiousness was related to fewer unsafe behaviors (114). Demographic variables are also associated with risky driving, with men and younger drivers performing more risky driving behaviors (10, 55).

Age and Driving

Age is related to accidents in a U-shaped curve, with teenagers and older adults being at the highest risk of fatal accidents (127, 133). Young drivers are a greater risk to themselves and others until a rapid decline around the age of 25, with continued decline until age 70, when it then increases (127). This risk rapidly increases after the age of 75 (127). Though older drivers are at higher risk of being involved in a fatal accident, the fatalities primarily result in their own deaths (43 per 100,000) compared to others (3 per 100,000) (133). This contrasts with young driver fatalities, which primarily result in the death of others (93 per 100,000) compared to themselves (28 per 100,000). The higher self-death associated with older drivers is attributed to frailty (67).

The relationship between age and driving risks are related to cognitive and attitudinal factors. Older individuals display declines in multiple cognitive domains, including attention, reaction time, executive functions, and visuospatial functions which likely impact driving ability (3). Compared to younger drivers, older drivers showed longer reaction times for simulator

driving scenarios, with the most complex driving situations, such as overtaking a vehicle, producing disproportionate increases in reaction time (14). A similar finding was observed in another simulator study, where attentional demand increased as the driving complexity increased, with older adults showing greater cognitive demand than young and middle age drivers even when controlling for baseline reaction times (119). Thus, older drivers are more susceptible to cognitive decline and require more cognitive effort when negotiating complex driving scenarios. Other factors associated with aging, such as medication use, functional injuries, and medical issues may also contribute to driving deficits (36).

However, older drivers are often more aware of their heightened crash risk and use strategic-level planning to adjust their exposure to threatening travel conditions, such as only driving during the day, staying off of highways, driving shorter distances, and using more familiar routes (67). They also display more positive attitudes towards safe driving interventions, such as speed cameras, and negative attitudes towards unsafe driving behaviors, such as speeding and cellphone use (85). The relationship between cognitive decline and safe driving attitude/practices may help explain why older drivers are at a higher risk for being involved in accidents but are a lower risk of other-driver fatalities.

For younger drivers, cognitive issues may also have a role in their increased risk for accidents. Novice drivers have more effortful, slow, controlled processing compared to experienced drivers that use more automatic processing (124). Experienced drivers have a quicker response to hazards (130) and are better able to scan their field of vision (129). Younger drivers are also more likely to endorse risky behaviors on questionnaires, and engage in unsafe driving behaviors, including speeding, disregarding traffic signals, tailgating, and cellphone use (10). They also have lower risk perception, which has been shown to be related to risky driving

behaviors and accidents (55). Thus, while older drivers display cognitive deficiencies, they often adjust their driving behaviors to compensate. Younger drivers, on the other hand, display both cognitive inefficiencies and increased risk-taking behaviors, resulting in being at a higher risk for being involved in accidents and accidents that result in fatalities which could be related to behaviors such as speeding and disregarding traffic signals.

Fatigue and Driving

The effects of fatigue on driving are significant. Numerous studies of factors that cause fatigue, including work shift, medication, sleep disorders, and general sleep deprivation, have shown that fatigue contributes to unsafe driving behaviors and accidents (see (94)). Fatigue accounts for 22 to 24 percent of crashes and near-crashes, and drowsy drivers are four to six times more likely to be involved in a crash or near-crash (60). One study examining the effects of sleep deprivation on a driving simulator found increased lane position variability, as well as vehicle heading difference (i.e., how much to right or left vehicle is facing relative to lane) (86), indicating that drowsy drivers may be more likely to move within, and also out of, a lane. The study also found cognitive deficits, including increased reaction time and lapses in attention, as well as decreased oculomotor activity (86).

Each of the factors discussed above negatively impact cognitive processes, including attention. This finding is important because complaints of cognitive issues, fatigue, and impulsivity/risk taking are commonly reported following TBI (28, 57, 63). Therefore, assessing individuals with TBI may be particularly useful because TBIs are prevalent and are associated with attention deficits.

Traumatic Brain Injury

TBI is the leading cause of death and disability in children and adults below the age of 44, with over ten million people worldwide experiencing a TBI serious enough to require hospitalization or cause death (68). TBI is defined as "...an alteration in brain function, or other evidence of brain pathology, caused by an external force" (p. 1638, 81). TBI is classified as either closed injury, in which the skull remains intact, or penetrating injury, in which the skull and dura are crushed or penetrated by an object. There are two distinct types of injuries in TBI that cause the resulting sequelae: primary injury and secondary injury (76). Primary injury results directly from the trauma forces at the moment of injury and may include: contusions and lacerations typically observed at the site of impact (i.e., coup) and the area opposite the impact (i.e., contrecoup) (76), diffuse axonal injury that results in shearing of axons and white matter tracks from movement of the brain within the skull (45), and hematomas and hemorrhaging that result from blood vessels tearing on impact (76).

Secondary injury is delayed brain damage due to the physiological processes that can occur after primary injury (73). Secondary injuries result from the interaction of changes in cerebral blood flow and metabolism, changes in neurochemical concentrations, and inflammatory processes that occur following primary injury (132). These changes can result in decreased cerebral oxygenation (i.e., ischemia), excessive stimulation by the neurotransmitter glutamate (i.e., excitotoxicity), and intracellular concentration changes that result in water entering the cells, causing them to expand (i.e., edema) (29, 132). Each of these changes can result in nerve cell damage or death (i.e., infarction) (29, 76, 132). The type and severity of pathophysiology following TBI is related to the characteristics of the trauma forces.

Measuring Traumatic Brain Injury Severity

TBI severity is defined by the acute injury characteristics, including: impaired consciousness, as measured by the Glasgow Coma Scale (GCS; 123), length of posttraumatic amnesia (PTA), and duration of loss of consciousness (LOC) or alteration of consciousness (AOC). The GCS measures level of consciousness based on three response dimensions: eye opening (1 to 4), verbal response (1 to 5), and best motor response (1 to 6), with higher scores reflecting higher levels of functioning. GCS score has been shown to predict outcome following TBI (28). LOC duration is also a good predictor of functional and neuropsychological outcome in moderate-severe injuries, but not in mild TBI (72). There is limited research regarding the ability of AOC in predicting outcome as it was added to the Veteran's Affairs (VA) Guidelines for TBI Classification in 2009 to account for altered consciousness that does not meet the threshold for either LOC or PTA (90). PTA is a period of disorientation and confusion after injury where memory for current events is not continuous (28); it is one of the best predictors of outcome after TBI, with longer durations correlating with worse outcome (25, 31).

TBI is divided into injury levels of mild, moderate, and severe based on the injury characteristics. GCS scores ranging from 3 to 8, 9 to 12, and 13 to 15 are classified as severe, moderate, and mild, respectively (126). LOC duration of less than 30 minutes is classified as mild injury and greater than 30 minutes as moderate-severe injury (15). PTA of less than 24 hours is classified as mild injury and greater than 24 hours as moderate-severe injury (15, 90). When any of the injury characteristics exceed the threshold for mild TBI, or there are abnormal findings on structural imaging, the injury is classified as moderate-severe (90). See table 1 for injury classification criteria.

Table 1. TBI Injury Classification Criteria

Criteria	Mild	Moderate	Severe
Glasgow Coma Scale	13-15	9-12	< 9
Loss of Consciousness	0 – 30 min	> 30 min & < 24 hrs	> 24 hrs
Alteration of Consciousness	< 24 hrs	> 24 hrs	> 24 hrs
Post-traumatic Amnesia	< 24 hrs	> 1 day & < 7 days	> 7 days
Structural Imaging	Normal	Normal or abnormal	Normal or abnormal

Heterogeneity of TBI

Due to the various injury characteristics which comprise severity classification (e.g., GCS, PTA, LOC, AOC), as well as the numerous potential mechanisms of injury (e.g., blunt force, rotational force, and/or blast force), injury sites, and resulting pathophysiological processes that can occur (i.e., primary and secondary injury factors), TBI can display a range of symptoms, cognitive deficits, and functional outcomes that make determining prognosis difficult (2). Another factor impacting prognosis is that TBI severity is based on the acute injury characteristics, and as such, are not representative of long-term cognitive and functional impairments. Other factors, such as age and premorbid functioning, are also factors that influence outcomes and may be more important in predicting outcomes (2, 15, 128).

Natural History of Cognitive Recovery Following TBI

Mild TBI may produce axonal damage that results in predominantly short-term symptoms and little permanent damage, while more severe TBIs can produce damage resulting in widespread cell death and persistent symptoms (44, 57). The pathophysiology resulting from TBI underlies the neuropsychological deficits observed after injury (57). A meta-analysis of 39 primarily cross-sectional studies examined recovery following both mild and moderate-severe

TBI (112). Results showed that deficits were seen in mild TBI in the first week ($d = -0.41$) but were negligible after one month ($d = -0.08$) and completely resolved by three months ($d = 0.04$). A systematic review of over one-hundred primarily cross-sectional studies from 2001 to 2012 examining the recovery of cognitive functioning after mild TBI (15) found similar results. Results showed that deficits were seen in the first week post-injury, but mostly resolved by one-month post-injury. By three months post-injury, approximately 10% displayed deficits.

In contrast, moderate-severe TBI had a very large effect ($d = -0.97$) on neuropsychological test performance less than six months post-injury and a moderate effect ($d = -0.60$) 6 - 24 months post-injury (112). Studies with longer follow-up periods have found cognitive deficits up to ten years post-injury (79). These data suggest a dose-response relationship between injury severity and neuropsychological impairment, with moderate-severe TBI resulting in greater impairment for a longer duration. These impairments have a significant impact on the attention system.

Effects of TBI on Attention

Brain areas that are commonly damaged by trauma, including the frontal and anterior temporal lobes, are also involved in attention (78). TBI patients with lesions to the frontal and parietal regions, especially in the right hemisphere, may have difficulty maintaining alertness (104). Lesions to the basal forebrain, parietal lobe, superior and inferior colliculi and pulvinar interfere with orienting attention (98). Lesions in the temporal-parietal junction and superior temporal lobe also disrupt the ability to disengage from a particular stimulus, preventing the effective shifting of attention (104). Damage to the anterior cingulate cortex is associated with deficits in voluntary behavior and control of attentional processes, both tasks of the executive network (104).

Following TBI, recovery of attention function is similar to the recovery other cognitive processes. Attention impairment is most severe in the acute injury period (118). Recovery occurs quickly in the early post-acute injury phase, beginning with basic attention functions and followed by higher-level attention components, such as working memory and divided attention (112). Attention deficits resulting from moderate-severe TBI show the most improvement during the first year post-injury and plateau during the second year, though more severe injuries continue to show recovery of complex attention components, such as selective attention (112). Some patients have continued recovery and impairment of complex attention ten years post-injury (79). Individuals who sustain a mild TBI and experience attention deficits show the most extreme impairment in the first week, with most complex attention deficits resolved by one month (27, 65) and typically complete resolution by three months (9). These deficits can have significant functional implications, including impaired driving.

Effects of TBI on Driving

TBI often leads to deficits in sensory, motor, cognitive, and behavioral functioning that can make driving difficult (62). However, the research examining the effects of mild TBI on driving is sparse. Preece et al (101) examined the reaction times of 42 individuals who had sustained a mild TBI within 24 hours post-injury on a computerized hazard perception test, in which participants were asked to identify potential traffic hazards as early as possible on real-world driving videos seen from the driver's perspective. The participants with mild TBI were significantly slower to respond to hazards than controls with mild orthopedic injuries. One study that compared the driving simulator performance of individuals with mild TBI who were within 48 hours of being asymptomatic (days post injury: $M = 15.9$, $SD = 9$) with healthy matched controls found that the groups did not significantly differ on the number of unsafe driving

behaviors, including crashes and number of tickets (111). However, the mild TBI group did produce significantly more lane excursions and lane position variability (111). These findings are important because they provide insight into the potential impact of mild TBI on driving ability, even in the post-acute phase when an individual may be unaware of subtle deficits.

For individuals with moderate-severe TBI, the impact of cognitive deficits on safe driving ability is typically more significant than for those with mild TBI. Approximately only half of individuals with moderate-severe TBI resume driving (77, 89, 95). Of those who resumed driving, over one third (35.5%) had at least one accident (95). There is also a positive correlation between the number of years post-TBI and the number of accidents, suggesting that unsafe driving associated with TBI persists over time (95). There is a 2.3-fold greater risk of accident in severe TBI patients than the general population (42). While these studies have found an increased risk of accidents, other studies produced conflicting findings.

A study comparing 47 individuals with moderate-severe TBI and 22 healthy controls did not find that TBI severity was related to increased accident risk (21). However, accident risk was related to neuropsychological test performance, indicating that those with cognitive deficits were more likely to be involved in an accident. Another study also did not find significant differences in driving performance between individuals with TBI and healthy controls (113). However, the study did find that individuals with TBI were 1.5 times more likely to be involved in an accident and had more documented traffic violations (10.4% vs 0%) but did not meet statistical significance (113). These findings were also likely impacted by the sample characteristics. The injury severities of the TBI group were not known, and only individuals who completed a driving evaluation were included in the study (113). Another potential explanation for the conflicting findings between TBI severity and driving performance is the

heterogeneity of TBI, where some individuals with more severe injuries may not display significant cognitive deficits which would impact driving ability. Also, similar to the previous discussion of age and driving, individuals may apply strategic-level planning (e.g., avoiding driving on the interstate) and/or tactical-level adjustments (e.g., driving slower due to slowed information processing speed) due to awareness of cognitive deficits. The potential for individuals to resume driving while still experiencing cognitive deficits can have significant implications for daily life.

Driving Impairment and Functional Independence

Driving is an integral activity of everyday life for many individuals and can have a significant impact on functional independence and psychological well-being (22). Forfeiture of a driver's license has been associated with depression, low self-confidence, and poor quality of life (54). Inability to drive can prevent individuals from attending social/recreational activities, leading to social isolation (12). Additionally, driving ability is a significant predictor of employment after TBI (74). Individuals who resume driving one year after injury were approximately eight times more likely to be employed than those dependent upon others for transportation (64). The inability to drive may preclude functional independence, often leading injured individuals to return to driving when they are still experiencing impairment (74).

Approximately 50% of moderate-severe TBI patients return to driving, with the rates for mild TBI likely being much higher (101). Of those who resume driving, most (approximately 65%) do not receive an evaluation or medical examination (125). Given that driving can significantly influence functional independence, combined with the latent nature of some TBI sequelae, TBI patients may return to driving while still experiencing cognitive deficits which

may negatively impact driving ability (78). Therefore, it is important to assess for potential changes in driving ability following brain insult.

Driving Ability Assessment

Current methods for evaluating driving capacity include driving questionnaires, neuropsychological tests, on-road driving evaluations, and more recently, virtual reality driving simulators.

Self-Report Driving Questionnaires

Questionnaires serve as a practical means to gather information on a variety of driving behaviors, and may be the only means to assess some behaviors which may otherwise be cost-prohibitive or nearly impossible to collect using other methods (e.g., risk-taking attitudes) (48, 66). A meta-analysis of 70 studies examining health individuals using the Driver Behavior Questionnaire (107), a popular self-report survey, found a significant relationship ($r = .40$) between self-reported driving behaviors and accidents when correcting for measurement error (26). While these findings are encouraging, there are multiple concerns with self-report data. First, the majority of the current research focuses on retrospective and cross-sectional data for self-reported driving behaviors (56), with individuals completing a questionnaire at one time-point addressing previous driving behaviors. Second, the reliability of self-report driving questionnaires may be negatively impacted by biases that affect all self-report surveys, such as social desirability (26, 66). Self-report questionnaires have shown some utility in predicting unsafe driving behaviors in a longitudinal setting (48, 56), and social desirability bias in self-reported driving behaviors has shown to be relatively small (66). One significant possible bias when using self-report questionnaires to collect retrospective data is consistency motif, which is the tendency for individuals to complete questionnaires in a congruent manner (26). When

participants complete questionnaires related to driving behaviors and real-world accidents/violations at one time point, the relationship may reflect the bias to answer the items in a consistent manner and not an actual association (26).

Self-Report Driving Questionnaires and TBI

A significant limitation of driving survey research is that there are few studies that evaluate the relationships between driving survey report and driving performance in individuals with TBI. One study evaluating the driving performances of 216 individuals with TBI (77% moderate-severe, [TSI mean = 5.2, SD = 4.8]) using the Barriers to Driving Questionnaire (102) found that risk of adverse driving incidents (i.e., accidents and/or citations) were lower for individuals with better neuropsychological test performance (OR = 1.73)(7). The study also found that self-rating of driving fitness was related to adverse incidents in individuals with poorer neuropsychological test performance, with driving incident risk decreasing as self-reported ability ratings decreased (OR = 0.37), indicating that better self-awareness of cognitive deficits influenced driving behaviors. Individuals with TBI who wanted to resume driving (n = 64) reported themselves as currently fit to drive and viewed their current level of cognitive functioning as comparable to those who previously resumed driving (n = 116), despite displaying cognitive deficits similar to individuals with TBI that did not seek to resume driving (n = 70). This group drove more than those who recognized their deficits ($p = .62$), and both driving time ($p = .42$) and cognitive deficits ($p = -.41$) were related to adverse incidents. The authors posited that the discrepancy between actual and perceived driving ability may have been related to difficulty accurately assessing driving fitness due lack of awareness of driving issues caused by cognitive deficits, and/or a reluctance to give up hope about resuming driving (103). Thus, self-reported driving behaviors may not reflect real-world driving behaviors in individuals with TBI.

Therefore, while self-reported driving questionnaires can provide some insight into driving behaviors, assessment of driving ability also requires objective measurements, such as neuropsychological tests.

Neuropsychological Tests

Neuropsychological tests are useful in providing information about cognitive domains necessary for safe driving, including executive functioning, information processing speed, divided attention, and motor speed (24). However, available tests provide limited insight into actual driving (18). Only two tests, the Useful Field of View (5), and part B of the Trail Making Test (TMT-B; (109), have established consistent associations with driving impairment (91). In addition to the heterogeneity of TBI discussed previously, one possible explanation for the limited predictive validity of neuropsychological tests is the complexity of driving. Driving is a dynamic process that requires the integration of physical, cognitive, and behavioral skills under time pressure (20). In contrast, neuropsychological tests primarily assess specific processes within cognitive domains in a structured environment, and predictive validity for driving may be limited.

Neuropsychological tests have previously shown limited ecological validity in determining functional outcome following brain insult (117). This may be due to the historical emphasis of using these tests to detect and localize brain damage (16). The development of advanced imaging techniques, and increased referral services from non-medical sources (e.g., schools, lawyers), has switched the focus of assessment from neuropathology localization to determining functional outcomes (16). Efforts to enhance the ability of neuropsychological assessments to predict functional outcomes have primarily focused on two areas: 1) evaluating the ability of currently used measures to predict outcomes and 2) developing new measures

which may better reflect real-world functioning (117). Another approach is to conduct translational research, utilizing methods and constructs from basic research (i.e., cognitive neuropsychology and neuroscience) in clinical settings to assess their effectiveness. The call for translational research is not specific to neuropsychology, and has been emphasized for many disciplines in psychology (52). Advancements in technology have created the opportunity to use basic research tools, which were previously cost- and/or size-prohibitive, in clinical assessment and may be more fine-tuned to detect subtle deficits that may not be detected by conventional neuropsychological measures.

Eye-Tracking Measures

Eye-tracking is one approach that has shown promise to detect subtle deficits in a variety of conditions, including mild TBI (50, 122, 123). This technology may also help detect driving difficulties. Eye movements are controlled by cerebellar-cortical white matter tracts, which are also involved in cognitive processing (122). Therefore, brain insult that affects eye movements will also likely affect cognition. The ability of five types of eye movements to detect deficits have been examined: pupillary light reflex, vergence, saccades, accommodation, and smooth pursuit, with most of the research focusing on saccades and smooth pursuit (92). Smooth pursuit eye movements involve tracking moving targets by changing the eye gaze in a continuous motion, while saccades involve rapid eye movements, often described as a “jump,” to a new position or target (92). Eye tracking may be more likely to detect subtle impairments than standard neuropsychological measures. For example, our research group has previously shown that eye tracking can detect impairments associated with chronic mild TBI, even among individuals who perform normally on conventional neuropsychological tests (32). There are multiple potential explanations for this high degree of sensitivity. First, eye tracking can

measure small variations in eye movements, as opposed to broader measurements in standard tests (19). Second, eye movements are performed primarily for the purposes of visual input. Therefore, eye tracking provides a more direct measure of attention than other response modalities that perform motor output functions (i.e., manual response) (30).

Eye-Tracking and Driving

Multiple studies have examined the use of eye-tracking while driving in a virtual reality simulator (40, 96, 100). These studies primarily focused on determining if, and when, individuals identified an upcoming hazard. Like the studies discussed above, these studies found that inexperienced drivers were less likely to identify hazards compared to experienced drivers. While these studies provide insight into the possible benefits of utilizing eye-tracking to measure cognitive skills necessary for safe driving, they focused on whether an individual identified a hazard, not the functioning of the attention networks. There are no known studies that use eye-tracking to examine the relationship between attention deficits and driving ability. One study of 38 healthy individuals (mean age = 45.3, range = 18 – 83) using the Attention Network Test (ANT) (37), which is a manual response time task that measures the alerting, orienting, and executive networks, found that overall ANT performance was significantly related to driving simulator performance, accounting for nine percent of the variance above the influence of age (131). Individual attention network tasks were not significantly related to simulator performance, but executive attention performance did produce a small effect ($R^2 = .03$) (131). However, the ANT is not an eye-tracking measure, and the simulator performance was evaluated using an observer-rating format adapted from on-road driving tests. Therefore, the non-significant findings for the individual attention networks may be related to the ANT not being

able to detect subtle attention networks, as well as the observer rating not being able to detect subtle unsafe driving behaviors.

These findings do, however, provide evidence that assessing the attention networks may be useful in predicting driving deficits. Eye-tracking may be able to provide a more sophisticated measurement of attention network functioning. Measurement of eye movements may be useful in predicting driving deficits due to their ability to detect cognitive deficits. Additionally, their purpose is to gain visual information about targets in the environment, which is a skill necessary for effective driving. However, until there is more research examining the utility of these new computerized measures, neuropsychological assessment must be complemented by more direct evaluations of driving behavior.

On-road Driving Assessment

On-road driving assessment has shown promise as a means to assess driving fitness and has been considered the gold standard in detecting impaired driving ability by many healthcare professionals (24). On-road assessment provides an analog to real-world driving situations, because the participant is actually driving a vehicle (78). During the assessment, the participant drives a standard route and an examiner scores the performance on a variety of skills, such as attending to relevant stimuli in the environment, and maintaining appropriate speed and vehicle distance (78). Studies have shown the efficacy of on-road assessment to detect driving impairments in individuals with brain insult. One study examining 38 stroke patients (between 6 and 15 weeks post-stroke) found that on-road driving performance was able to correctly classify 79% of patients who failed a driving screening assessment battery (1). Another study found a significant relationship ($r = 0.38$) between road test performance and previous two-year driving

history of 43 elderly, diabetic, or neurologically impaired participants (41). Despite these findings, there are important limitations to address.

Most on-road assessments are not standardized; therefore, this limits their ability to determine which procedures effectively predict impairment (113). This limitation may be due to a number of factors that can be highly variable and cannot be controlled, such as weather and traffic (125). Moreover, the validity of on-road driving tests has not been adequately established, with few studies evaluating the association between on-road test performance and future accidents and traffic violations (43, 78). As evidenced in the previous section, most validity studies have compared on-road test performance to test batteries or retrospective driving records. Though on-road driving tests may have face validity, they may not have ecological validity (43). In many driving tests, the participants are presented with step-by-step instructions, precluding the assessment of decision-making and information processing seen in every-day driving (78). Also, rigorous on-road assessments would place individuals with TBI in a situation where they may be a danger to themselves or others (125). By comparison, controlled on-road driving tests, where an individual is exposed to a situation where traffic and environmental fluctuations are kept to a minimum, can help protect the participant, but are less ecologically valid. Thus, while studies have shown that on-road driving assessments can detect driving impairments, the lack of standardized assessments and measurement of skills needed in every driving make the validity of on-road assessments questionable. Therefore, accurate assessment of driving fitness may require a standardized, complex driving environment.

Virtual Reality Driving Simulators

In contrast to on-road assessments, virtual reality driving simulators allow the assessment of realistic driving behaviors in a safe environment where factors such as amount of traffic can be controlled (71), and an individual can safely attempt increasingly complex driving scenarios (70). Driving simulators also provide more precise measurements (22). On-road assessment is limited to broad observations (e.g., Did the individual correctly stop at a traffic light?). In contrast, driving simulators can obtain the same observations, but can also measure more detailed information (e.g., How long did it take to react to a stop light?). Refined data allow for determining subtle driving difficulties and can also provide information on how an individual is improving over time.

Despite the benefits of driving simulators, there is little research examining their predictive value for real-world driving performance. Lew et al (70) found that driving simulator performance was better than on-road test performance at predicting driving ability in eleven participants with moderate to severe TBI, as measured by family member rating on driving skills, such as controlling steering and speed, and accidents at ten-month follow-up. The better predictive ability of the driving simulator was attributed to two factors: 1) the simulator was able to measure more subtle aspects of performance (i.e., fluctuations in acceleration and lane tracking) than an observer; and 2) the simulator tested a wider range of driving situations than is safely possible on a road test (70). For example, individuals with post-acute mild TBI did not produce significantly more broad unsafe driving behaviors (e.g., crashes, traffic citations), but did produce significantly more subtle driving behaviors (i.e., lane position deviation) on a driving simulator when compared to healthy controls (111). This same pattern was also observed in individuals with moderate-severe TBI (7). Driving simulators were found to be significantly correlated with self-reported previous unsafe driving behaviors, as well as

discriminate between individuals with ADHD and controls, in a sample of 40 subjects (approximately 20 per group) (108). Driving simulators were also found to be correlated with an on-road driving test ($r = .83$, $p < .001$), as well as the three subtests of the Useful Field of View (UFOV) test ($r = .61$, $.67$, and $.72$, respectively, $p < .001$) in a sample of 38 healthy participants (8). The concurrent validity with an on-road driving test, as well as discriminant validity of VRDS, was also supported in a sample of healthy participants with various levels of driving experience (80). Though these findings are encouraging, more studies are needed to establish the validity of driving simulators, particularly predictive validity.

Summary

Attention is a necessary cognitive domain for successfully completing required daily tasks, including driving. Researchers have consistently found that inattention and distraction are the primary causes of motor vehicle accidents. However, most previous research has focused on broad characteristics of either attention or driving, as opposed to examining the relationship between specific attention deficits and unsafe driving behaviors. This information is important because attention impairments are commonly reported in a variety of conditions, including history of TBI. Individuals with TBI may show impaired driving ability across the injury spectrum, from mild to severe. This finding highlights the need to assess driving fitness in this population.

Driving fitness assessment has relied primarily on neuropsychological test performance and on-road driving tests. These assessment tools may not accurately predict driving ability because they may not be able to replicate the cognitive demands associated with driving. Virtual reality driving simulators (VRDS) may be able to replicate the cognitive demands of driving and measure subtler deficits. However, the use of simulators is relatively new, and the few studies

that have examined their validity, with only one study examining predictive validity. Additionally, newly developed computerized assessment tools used previously in basic research may be more fine-tuned to detect subtle deficits that may not be elicited by the circumscribed focus of many current neuropsychological measures. One new approach, utilizing eye-tracking, has shown promise to detect subtle deficits which may help predict driving difficulties. There is limited research evaluating the relationships between eye-tracking and driving ability, and no known studies that address the relationship between attention network functioning, measured by eye-tracking, and driving ability. Further research including VR driving simulators and eye-tracking measures may be able reveal subtler attention deficits that can negatively influence driving ability.

PURPOSE AND SIGNIFICANCE

To accurately understand how attention deficits influence driving ability, it is necessary to examine the relationships between specific attention deficits and unsafe driving behaviors. Unfortunately, most research has focused on broad characteristics of attention, such as distraction from cell phone use. This distractibility may not be analogous to attention deficits seen in clinical conditions. In studies of individuals with conditions known to commonly cause attention deficits (e.g., TBI), the emphasis has been on examining general driving incidents (e.g., reaction time, number of accidents), which may not necessarily reflect attention deficits. Relatively new assessment tools in clinical research, such as eye tracking and VRDS, may enhance our ability to examine relationships between specific attention deficits and unsafe driving behaviors.

Findings from the current study may elucidate the relationship between specific attentional deficits and unsafe driving behaviors, as well as provide evidence for the use of eye-

tracking as a tool to assess driving ability. This information could inform both the assessment of driving fitness and targeted rehabilitation of attentional deficits in TBI patients. The findings may also bolster the predictive validity of driving simulators. The sophisticated measurements may reveal subtler TBI effects, resulting in better knowledge of how TBI, both mild and moderate-severe, influences driving ability. The combined results could lead to a safer driving environment.

CHAPTER 2: Methods

SPECIFIC AIMS AND HYPOTHESES

The current study examined the influence of attention network deficits on specific driving behaviors using a novel eye tracking assessment tool, the Bethesda Eye and Attention Measure (BEAM; (33), to detect unsafe driving behaviors on a virtual reality driving simulator (VRDS; (81). A second objective of the study was to examine the predictive validity of both the BEAM and VRDS by examining their relationships with self-reported unsafe driving behaviors. Additional exploratory analyses were also conducted to help describe the findings and elucidate possible trends not captured in the primary analyses. These analyses involved examination of TBI severity, level of BEAM impairment, and specific self-reported driving behaviors (e.g., instances of speeding).

Specific Aim 1.

To examine the relationships between attention network deficits and unsafe driving behaviors in individuals with TBI.

Hypothesis 1a.

Poorer attention network performance (alerting, orienting, and executive attention) measured by the BEAM nondirectional cue (NDC), directional cue (DC), and misdirectional cue (MDC) difference scores, respectively, will be related to poorer VRDS performance in the form of significantly worse overall cognitive component scores, measured by the operational driving quotient.

Hypothesis 1b.

Poorer attention network performance (alerting, orienting, and executive attention) measured by the BEAM NDC, DC, and MDC difference scores, respectively, will be related to

poorer VRDS performance in the form of significantly worse overall driving performance scores, measured by the tactical driving quotient.

Hypothesis 1c.

Poorer attention network performance (alerting, orienting, and executive attention) measured by the BEAM DC, NDC, and MDC difference scores, respectively, will predict accidents on the VRDS.

Hypothesis 1d.

Poorer alerting attention, measured by the BEAM NDC difference score, will be related to poorer VRDS performance in the form of significantly more occurrences of tailgating and greater standard deviations for speed (difficulty maintaining speed) and lane position (swerving).

Hypothesis 1e.

Poorer orienting attention, measured by the BEAM DC difference score, will be related to poorer VRDS performance in the form of significantly greater standard deviations for speed (difficulty maintaining speed) and lane position (swerving).

Hypothesis 1f.

Poorer executive attention, measured by the BEAM MDC difference score, will be related to poorer VRDS performance in the form of significantly more occurrences of tailgating and greater standard deviation for speed (difficulty maintaining speed).

Specific Aim 2.

To evaluate the predictive validity of two novel assessment tools (BEAM and VRDS) in predicting unsafe driving behaviors in the real world.

Hypothesis 2a.

There will be an inverse relationship between BEAM performance and indicators of real-world unsafe driving behaviors, such that worse attention network performance (alerting, orienting, and executive attention), measured by the BEAM NDC, DC, and MDC difference scores, respectively, will be related to significantly more occurrences of self-reported, real-world unsafe driving behaviors over a four-week period.

Hypothesis 2b.

There will be a direct relationship between VRDS performance and indicators of real-world unsafe driving behaviors, such that poorer performance on the VRDS operational and tactical driving quotients will be related to significantly more occurrences of self-reported, real-world unsafe driving behaviors over a four-week period.

STUDY DESIGN

This study was derived from a parent study, a randomized controlled trial of a novel behavioral intervention (Neurocognitive Driving Rehabilitation in Virtual Environments [NeuroDRIVE]” for improving both cognitive and driving abilities in individuals with a history of TBI. The parent study had both correlational (Aims 1 and 2) and longitudinal (Aim 3) design components, and examined variables collected at the baseline visit, four weekly internet driving surveys, and a follow-up visit. All variables utilized for this study were collected from the baseline visit and four-week driving surveys, prior to the investigational intervention.

PARTICIPANTS

Participants in the current study are 29 adults with a history of TBI (17 Mild and 12 Moderate-severe) who met the inclusion and exclusion criteria from the larger intervention study. See Tables 2 and 3 for study inclusion and exclusion criteria, respectively.

Table 2. Study Inclusion Criteria

Inclusion Criteria
Currently has a valid driver's license, or had a valid driver's license prior to injury
18 years of age or older
Able to effectively manipulate the steering wheel and the gas/brake pedals without adaptive equipment
Able to read, write, and speak in English
History of traumatic brain injury greater than 12 weeks prior to initiation into the current study
Able to provide informed consent
Neurobehavioral Symptom Inventory score greater than or equal to 16 (For mild TBI group only)

Table 3. Study Exclusion Criteria

Exclusion Criteria
History of serious medical condition other than TBI that could affect cognitive or motor abilities (e.g., multiple sclerosis, encephalitis, cerebrovascular disease)
History of penetrating brain injury
Other medical or psychological instability that could create difficulty fulfilling the study requirements (e.g., untreated mental illness, auditory/visual hallucinations, and narcolepsy)
Risk for injury from an MRI magnet (e.g., pacemakers and other electrical devices, metallic prostheses and other metal in body, and pregnancy)

Recruitment

Participants for the larger intervention study were recruited in the National Capital Area primarily through a National Institutes of Health (NIH) research protocol examining TBI in individuals that present to local community emergency rooms, and the Center for Neuroscience and Regenerative Medicine's Recruitment Core. The current study used data from the baseline visit of the parent study, prior to intervention.

Sample Size by Hypothesis

Twenty-nine participants completed the BEAM and VRDS. Five individuals were not able to complete the tactical driving tasks due to simulator sickness. Also, four BEAM data files were lost due to system malfunction and four individuals did not complete the driving surveys due to not driving during the survey time-frame. Of note, none of the participants were removed from the study but were excluded from individual analyses when data were missing. Therefore, the sample sizes vary across analyses. See Table 4 for a breakdown of sample sizes by hypothesis.

Table 4. Sample Size by Hypothesis

Hypothesis	Sample Size
Hypothesis 1a. BEAM and VRDS operational driving quotient	25
Hypotheses 1b – 1d. BEAM and VRDS tactical driving variables	20
Hypothesis 2a. BEAM and driving survey score	20
Hypothesis 2b. Operational driving quotient and driving survey score	25
Tactical driving quotient and driving survey score	20

PROCEDURES

To determine study eligibility, an initial brief telephone screening was conducted with potential research participants. The telephone screening focused on basic demographic information, TBI history, medical or psychological conditions, and current symptom severity.

Individuals who met eligibility requirements and agreed to participate in the study were then scheduled for an in-person session. The initial portion of the session consisted of obtaining informed consent and completing a structured interview, which was conducted to obtain information about driving history (e.g., number of tickets and years driving), as well as factors that may influence testing, including poor sleep and recent alcohol use. Participants then completed an online driving survey to assess unsafe driving behaviors (e.g., speeding, failing to follow traffic signals) over the past week (see Appendix A). Next, participants completed a visual acuity test using a standard Snellen Eye Chart (Figure 1) followed by the BEAM protocol. Upon completion of the BEAM, participants then completed the VRDS tasks. The VRDS tasks were the last portion of the in-person session. Participants then completed the online driving survey at home for four consecutive weeks.

As noted above, participants were queried regarding substance use in the previous 24 hours to assess for conditions which may influence performance on the BEAM and VRDS (e.g., alcohol, nicotine, caffeine). However, information was not collected regarding more general use of these substances, or whether an individual had a substance use disorder. Some participants may have reported real-world unsafe driving behaviors on the weekly driving surveys that reflect substance use as opposed to attention network deficits. This issue will be discussed further in the limitations section.

Ethical Considerations/Procedures for Driving Simulator Performance

During the driving simulator assessments, some participants performed multiple unsafe driving behaviors, producing scores in the impaired range. This impaired performance may provide insight into real-world driving behaviors for some participants, indicating possible safety issues. At the end of both the assessment and intervention sessions, the administrator discussed

the observed strengths and weaknesses with the participant. For participants that displayed multiple unsafe driving behaviors, the administrators inquired about real-world driving difficulties to help participants become aware of potential difficulties while driving. The participants were also given the option to receive a free taxi ride to their residence if they reported concerns about driving.

Though impaired simulator performance may suggest real-world concerns, this driving simulator has not been validated for this purpose. As mentioned above, there is limited research evaluating the validity of this virtual reality driving simulator. The available validity information focuses on the ability of the simulator to discriminate between healthy controls and individuals with conditions that may negatively impact cognitive functioning (e.g., Parkinson's disease, Alzheimer's Disease, and stroke) (80). Therefore, unsafe driving behaviors observed on the simulator were addressed with the individual participant to increase awareness but was not reported to an authority, such as the Department of Motor Vehicles.

Measures

Neurobehavioral Symptom Inventory

The Neurobehavioral Symptom Inventory (NSI; (17) is a 22-item self-report measure of post-concussive symptoms divided into three subscales: Somatic/Sensory (e.g., dizziness, light sensitivity), Cognitive (e.g., forgetfulness, poor concentration), and Affective (e.g., depression, anxiety). The NSI has demonstrated high internal consistency ($\alpha = .95$), and it has been shown to be sensitive to the effects of TBI (59). The NSI was used in the current study to help determine participant eligibility for those with mild TBI.

T3 Virtual Reality Driving Simulator

The T3 virtual reality driving simulator (81) consists of three projector screens that produce a 180-degree field of vision, and a driving console with realistic steering wheel, gas/brake pedals, and turn signals. See Figure 2 for visual image of the T3 VRDS. The participant sits in the driving console and operates the steering wheel and pedals to navigate the virtual environment projected onto the screen. An examiner operates the virtual environment from a nearby computer. The test protocol consists of two separate sets of tasks: operational and tactical.

The operational tasks, listed in Table 5, consist of twelve highly structured and constrained scenarios to assess different abilities in three domains (i.e., cognitive, vision, and motor). For example, the Hand/Arm Motor task requires an individual to only manipulate the steering wheel to react to potholes in the road, while the computer controls vehicle speed. The scoring of the operational tasks produces individual z-scores for each of the tasks, as well as a composite driving quotient. The operational tasks take approximately 50 minutes to complete.

Table 5. Operational Component Domains and Associated Tasks

Domain	Tasks
Cognitive	Rapid Information Processing Speed Divided Attention Dual Processing Response Inhibition Divided Selective Attention Working Memory
Vision	Visual Acuity Contrast Sensitivity Dynamic Vision Peripheral Vision
Motor	Arm/Hand Coordination Foot/Leg Coordination

The tactical tasks are similar to an on-road driving test, where the driver follows instructions to navigate through a virtual environment. The specific tactical task used in this study consists of four miles of simulated city driving with traffic and voice-command prompts for directions. The task consists of different types of traffic, including: oncoming, same lane, cross, and both signaled and non-signaled sudden stop. Driving performance (i.e., steering, braking, speed control, and judgment) is assessed throughout the task, which is approximately 15 minutes in length. Similar to the operational tasks, the tactical tasks produce individual scores for each of 14 variables as well as a composite driving quotient (See Table 6). The driving quotients are created from the total performance on the operational and tactical tasks and have a mean of 100 and a standard deviation of 15. Driving data was automatically collected via computer, and was transferred to the software development company, MBFARR, for processing and scoring. For the current study, the variables being assessed are the raw scores for inappropriate driving behaviors of difficulty maintaining speed (standard deviation of speed) swerving (standard deviation of lane position), tailgating (number of tailgating instances), and accidents (crashes; yes/no) from the tactical task (specific aim 1), as well as the driving quotients for the operational and tactical tasks (specific aims 1 & 2). Accidents were dichotomized (yes/no) due to only three individuals being involved in more than one accident.

Table 6. Tactical Component Domains and Variables

Domain	Variables
Speed Control	Tailgating (within 15ft of car) Speeding (5-20mph above posted speed) Difficulty Maintaining Speed Reckless Driving Acceleration Smoothness
Steering	Off-road Events Across Midline Swerving Time Off-road
Braking	Rolling Stops Deceleration Smoothness Crashes Bumps
Judgment	Driving Slow (20mph below posted speed) Lane Changes

Psychometric Characteristics

Although limited research has been conducted evaluating the reliability and validity of the T3, the existing literature is promising. Unpublished feasibility studies in our lab and one published study (22), suggest that participants regard the T3 as a realistic analogue to real world driving. A study of senior drivers using the T3 found that individuals who performed poorly on the simulator had four times the number of real-world accidents than those with normal performance, providing some evidence for the predictive validity of the simulator (21). The T3 was also able to discriminate between the normative sample and a clinical group consisting of participants with Parkinson's disease, Alzheimer's Disease, or following stroke (80). The clinical group had significantly worse performance on all of the operational variables, almost half (6 of 14) of the tactical variables, and both the operational and tactical driving quotients (80). The T3 was also shown to be correlated with neuropsychological tests, with poorer overall neuropsychological test performance being significantly associated with the tactical composite

score ($r = .54$) and accidents ($r = .75$) in a preliminary analysis of 15 individuals (34). Regarding reliability, the T3 generally displayed consistency in test-retest reliability, internal consistency, and inter-rater reliability (See Figures 5 and 6). Four-hundred-forty-eight healthy participants in Virginia served as the normative sample for the VRDS. The sample was 27% women with a mean age of 43.52 (SD = 12.82) and 15 years of education (SD = 3.27) (80). The mean number of years with a driver's license was 27 (SD = 19.46).

Bethesda Eye and Attention Measure (BEAM) v.34

This description of the BEAM was derived from a previously-published manuscript (33). The BEAM is a cued visual attention task designed to elicit saccadic and manual responses across a number of test trials for the assessment of multiple components of attention and neuro-motor function. Completion of BEAM, including all instructions and calibration, is typically completed in 15 min or less. During each trial, a target stimulus (an unfilled white circle) appears 7.5° above, below, left, or right of the center of the screen. On each trial, one of six visual cues is presented at the center of the screen to influence the examinee's response to the target. The BEAM task consists of a practice block of 24 trials and four measurement blocks of 48 trials in a fixed, pseudorandom sequence to facilitate comparison of results at the individual participant level. Each block is counterbalanced with respect to cue type and target circle location.

Stimulus presentation and recording of manual motor responses were implemented using the E-prime software suite using a Dell T1500 PC with 2.80-GHz processing speed and a 60-Hz 15" LCD monitor with 1440 × 900-pixel resolution. Manual responses were recorded using a Cedrus RB-530 response pad placed centrally in front of the LCD monitor. Participants were instructed to use the index finger of the dominant hand to press the bottom button of the response

pad when providing a response. Gaze data were acquired at 120 Hz using an Applied Science Laboratories (ASL) D6 High-Speed (HS) Desktop Eye Tracker with video-based head tracking enabled. ASL D6-HS optics were positioned directly below the stimulus monitor, facing the participant.

Participants were seated with their head on a chin support, which is 24 inches from the stimulus display and were instructed to limit head and body movements as much as possible. Gaze vectors were calibrated using a nine-point rectangular calibration screen. After calibration, each participant viewed a two-minute, standardized multimedia tutorial including the following task instructions:

“You are about to take the BEAM. The BEAM consists of a series of trials with objects that appear on the screen. At the beginning of each trial, look at the fixation cross at the center of the screen. A target circle will appear above, below, left, or right of the fixation cross. When the target circle appears, look at it and press the button as fast as you can. On some trials, you may see an arrow or a diamond at the center of the screen. However, if you see a red arrow, do not look at the target circle and do not press the button.”

Participants were then shown example task trials to evaluate their ability to recognize and respond to cues and targets appropriately. Practice trials were initiated once the examiner was confident that the participant understood the instructions and that gaze data were being recorded successfully. The examiners monitored gaze and manual responses to identify errors and provide corrective verbal feedback during completion of the 24 practice trials.

At the beginning of each trial, a white central fixation cross was presented for 1500–2500ms. Next, the central fixation cross was replaced by one of the following: a white diamond (“nondirectional” cue); a white arrow pointing toward the impending target location

(“directional” cue); a white arrow pointing opposite the impending target location (“misdirectional” cue); a red arrow pointing toward the impending target location (“no-go” cue); a blank screen (“gap” cue); or no change (i.e., the fixation cross persisted for “uncued” trials). BEAM v.34 trial design is illustrated in Figure 4. After 200ms of cue presentation, a target stimulus (white circle) was presented 7.5° above, below, to the left, or to the right of the central fixation cross. Manual RT and saccadic RT (defined in this task as the latency to initiate fixation on the target) were collected for each uncued, gap, nondirectional, directional, and misdirectional trial.

Psychometric Characteristics

Split-half reliability for saccadic RT medians ranged from .79 (directional cue) to .89 (misdirectional cue), which are considered in the “good” range (31). Difference scores showed mixed reliability: .81 (alerting), .38 (orienting), and .72 (executive), which are similar to RT difference scores from other attention measures (41). Saccadic RTs were not significantly associated with age, education, or sex. The variables used for this study included the saccadic RT medians for the nondirectional, directional, and misdirectional cues. The nondirectional cues, which provide temporal indication of an upcoming target but not spatial information, reflect the activity of the alerting network. The directional cues indicate an upcoming target and its location, assessing the orienting network. Misdirectional cues require the participant to inhibit the learned response (i.e., looking in the direction indicated by the cue) and reorient to the correct location of the target, a function of the executive network. Difference scores will be used to isolate the distinct networks: alerting (uncued – nondirectional RTs), orienting (nondirectional – directional RTs), and executive (directional – misdirectional RTs). Relationships between primary outcomes and raw RTs were examined as secondary analyses. For the difference scores,

more positive scores indicate better performance. For example, the alerting attention score measures how much RT decreases when presented with a nondirectional cue compared to an uncued trial. Thus, the faster individuals respond to the nondirectional cues, the more positive the alerting attention score would be. The raw BEAM scores reflect reaction time to a cue type, so higher reaction times reflect poorer performance.

While the BEAM measures both manual and saccadic response times, manual response times were not evaluated in the current study for two reasons. First, manual responses reflect different processes than saccadic eye movements and are controlled by different brain regions. Manual responses allow the individual to manipulate the environment and are controlled by the motor areas of the brain (i.e., primary and premotor cortices, and supplementary motor area)(106). Eye movements enable the individual to acquire information from the environment and involve the frontal and supplementary eye fields, and the superior colliculi (104). Thus, manual response times reflect the activity of the motor system and not attention. Second, manual response times are influenced by other factors, such as general intellectual ability and education level (33, 105) In contrast, saccadic response times have not been shown to be influenced by these factors (33). Therefore, this study evaluated only saccadic response times since it is believed to be a purer measure of attentional processes that is not as influenced by confounding factors.

Internet Driving Survey

An online driving survey, created for the parent study, was used to obtain information about specific unsafe driving behaviors (See Appendix A). The survey consists of 15 items, with 14 items assessing the number of unsafe driving behaviors performed over the previous week, including bumping or hitting an object, speeding 10mph over the speed limit, and disregarding

traffic signs or signals. This measure includes questions adapted from the Barriers to Driving Questionnaire (102), which is a 40-item questionnaire assessing barriers to returning to driving across five domains (physical, psychological, cognitive, social, and resource-oriented). Other questions were designed to assess prevalence of concrete driving behaviors, such as number of times the individual disregarded a traffic signal. The variable examined in the current study was the number of unsafe driving behaviors *per hour* reported over the four-week period (total number of unsafe driving behaviors/number of hours driven).

Most of the items specify the frequency of a behavior. However, one item assessing mind wandering requests a qualitative response (e.g., Never, Sometimes, Always). This item was scored on a six-point scale ranging from 0 to 5, representing “Never” to “Always,” respectively. Additionally, two items (hitting an object and being pulled over by law enforcement) reflect unsafe driving behavior outcomes which likely indicate more severe inappropriate driving behaviors. Therefore, these two items were weighted to account for five points per instance (e.g., two instances of hitting an object will account for 10 points towards the total score), opposed to one point per instance for the items assessing unsafe driving behaviors. Individuals who indicated that they did not drive during the previous week were not included in the primary analyses. However, these individuals were examined in separate analyses to determine if their lack of driving may have been related to attention deficits.

Psychometric Characteristics

Reliability analyses conducted for the current study found that the driving survey displayed “good” test-retest reliability across the four weeks, ranging from $r = .695$ to $r = .946$ (all significant, $p < .01$). Split-half reliability was also shown to be good for each week: Cronbach alpha = .804 (survey 1), .867 (survey 2), .864 (survey 3), and .831 (survey 4).

Rationale for Study Variables

The internet driving survey was developed for the parent study as means to assess instances of unsafe driving behaviors performed over the course of four weeks. Frequently used driving questionnaires, such as the Driving Behavior Questionnaire (107), were not utilized due to their focus on factors such as attitudes related to unsafe driving behaviors. Also, the questionnaires are commonly used in research as predictors of unsafe driving behaviors, not as outcome measurements. The self-report unsafe driving behavior survey used as the outcome variable for another simulator study was deemed not appropriate due the focus on long-term retrospective data (one year), as well as content, with the outcome measure being recency of unsafe behaviors (e.g., today, within past month, not in past year) (19). Therefore, this survey was created to assess the number of unsafe driving behaviors performed over the previous week.

The specific unsafe driving behaviors selected for this study were based on real-world driving and simulator research findings. Tailgating was found to be the most common factor (14%) contributing to accidents and near-accidents while the driver was distracted (82). Lane position variability (swerving) was the fourth most common contributing factor (7%) (82) and was also shown to predict self-reported unsafe driving behaviors, both on a driving simulator (108) and in real-world driving (70). Speeding is one of the most prevalent factors involved accidents (75) and may indicate other unsafe driving behaviors, as individuals who speed are more likely to engage in other unsafe behaviors (46). Speeding was also found to predict self-reported unsafe driving behaviors on a simulator (108). However, difficulty maintaining speed was chosen for this study because speed variability may be a better indicator of how attention network performance influences speed (i.e., individual must attend to multiple stimuli such as accelerator pressure, speedometer, and street signs), opposed to instances of speeding which

could be intentional and not reflect an attention deficit. Individuals with TBI have been shown to display significant deficits in speed regulation on a driving simulator, resulting in more speed limit violations and accidents on the simulator (70), and was also associated with poorer real-world driving performance (70).

In regard to the relationships between specific attention network deficits and unsafe behaviors, there are no research findings to support these hypotheses. As mentioned previously, only one study has examined the relationship between specific attention network functioning and driving ability, with none of the attention networks accounting for unsafe driving behaviors independently (131). However, conceptual understanding of the networks functions can provide insight into their relationships with driving behaviors. The alerting network is a foundational network and, therefore, is likely to be involved in all three unsafe driving behaviors (i.e., difficulty maintaining speed, tailgating, swerving). The orienting network is responsible for selecting information from the environment for further processing. Orienting network deficits are likely be related to the unsafe driving behaviors of difficulty maintaining speed and swerving due to an individual focusing on other information in the environment, opposed to the speedometer or vehicles position in the lane. The executive network is responsible for monitoring and resolving conflicts within the attention networks. The executive network is predicted to be related to the unsafe behaviors of difficulty maintaining speed and tailgating, due the individual failing to adjust speed or distance based on environmental cues (e.g., notice signs are moving past faster or slower but not switching attention to speedometer).

Analytic Plan

Power Analysis

There is limited research examining the effect sizes of relevance to the study hypotheses. In one study, simulator performance was found to be significantly related to family member ratings of driving skills at a ten-month follow-up, producing a large to very large effect size ($r = 0.66, p = 0.01$)(70). Simulator performance was also found to be significantly related to self-reported unsafe driving behaviors, with medium effect sizes for speeding (Adjusted $R^2=.18$) and lane variability (Adjusted $R^2=.09$) (108). An attention task with similar attention cues to those used in BEAM for the current study was found to be significantly related to driving simulator performance, accounting for nine percent of the variance beyond that accounted for by age, $F(1, 35) = 6.80, p = .013$ (131). For the current study, moderate effect sizes were considered the minimum effect size to be of clinical utility for detection of individuals at high risk for impaired driving. Power analysis (*G*Power*, (35) indicates that the sample size (20 - 25) for this aim can detect large effect sizes ($F^2=.577 - .443$) using hierarchical regressions with 0.80 power and two predictors.

Variable Analysis

Prior to analyses, the primary attention (alerting, orienting, executive network), VR driving (operational and tactical driving quotients, accidents, tailgating, swerving, difficulty maintaining speed), and self-reported driving variables were screened for sources of bias, including outliers and violations of assumptions (additivity and linearity, independent errors, homoscedasticity, and normally distributed errors). Z-scores were calculated to identify outliers ($z > \text{absolute value of } 3.29$); no outliers were observed for any of the primary variables. Potential cases which could influence the regression models were identified by examining

Cook's distance (value > 1) following each of the primary analyses. No influential cases were identified for any of the analyses.

Normality was assessed using visual inspection of histograms and examination of skewness and kurtosis. Skewness and kurtosis were significant ($z > \text{absolute value of } 1.96$) for the primary independent variables: alerting (Skewness $z = -2.61$, Kurtosis $z = 2.58$), orienting (Skewness $z = -3.95$, Kurtosis $z = 4.45$), and executive (Skewness $z = -2.01$, Kurtosis $z = 2.03$) attention. The operational and tactical driving quotients were also significantly negatively skewed with z -scores of -2.39 and -3.88 , respectively. To evaluate linearity and homogeneity of variance (homoscedasticity), plots of standardized residuals against standardized predicted values were visually inspected for each of the primary analyses. Visual identification was difficult due to the small sample sizes. However, there appeared to be potential heteroscedasticity in the relationships between orienting attention and two VR driving behaviors (tailgating, swerving). The examination of independent errors using the Durbin-Watson d statistics for each of the primary analyses indicate that the residuals for the majority the primary analyses were independent from one another ($1.5 < d < 2.5$). Skewness and kurtosis of the variables, as well as potential heteroscedasticity, did not impact the accuracy of the parameter estimates, as bootstrapping was used, which is a method robust to violations of assumptions and does not rely on assumptions of normality or homoscedasticity (38). See Table 7 for means and standard deviations for each of the primary variables.

Table 7. Means and Standard Deviations for Primary Variables

	M (sd)
Attention	
Alerting	4.77 (5.31)
Orienting	2.60 (4.97)
Executive	-5.11 (6.20)
VR Driving	
Operational DQ	85.90 (23.24)
Tactical DQ	97.79 (18.32)
Swerving	0.33 (0.04)
Difficulty Maintaining Speed	9.41 (1.40)
Tailgating	2.46 (1.22)
Real-world Driving Survey	2.46 (1.52)

Bootstrapping

For the current study, bootstrapping was used to evaluate the precision of the regression estimates and confidence intervals (134). Bootstrapping provides an estimate of the sampling distribution for the sample data by using the sample as a population from which smaller samples are drawn (39). The mean is calculated in each bootstrap sample, resulting in multiple parameter estimates. This information is used to compute the standard deviation of the parameter estimates, which is then used as the standard error (39). With this information, confidence intervals and *p*-values are also computed. 95% Bias-corrected and accelerated (BCa) confidence intervals were used as a conservative estimate due to bootstrapped distribution skewness (134). Confidence intervals, standard errors, and *p*-values are based on 1000 bootstrap samples.

Chapter 3: Results

SAMPLE CHARACTERISTICS

Demographic and Injury Characteristics

Descriptive statistics were evaluated for age, education, ethnicity, gender, TBI severity, and time since injury. See Table 8 for breakdown of demographics and injury characteristics.

Table 8. Demographic and Injury Characteristics

	M (sd)	
Age	50.10 (13.80)	
Years Driving	32.52 (13.50)	
Education	%	N
GED/HS	20.7	6
Vocational Training	3.4	1
Associates Degree	13.8	4
Bachelor's Degree	31	9
Master's degree	31	9
Doctoral Degree	0	0
Gender (Male)	69	20
Race		
Caucasian	65.6	19
African American	17.2	5
Hispanic	3.4	1
Asian	10.3	3
Other	3.4	1
TBI Severity		
Mild	58.6	17
Moderate	20.7	6
Severe	20.7	6
Time Since Injury (Months)	114 (119)	
M (sd)		

Relationships between Demographics and Study Variables

Correlational analyses examining the relationships between demographic and study variables were conducted to identify potential covariates which could influence the study findings. Number of years driving was also examined to determine if the age effects discussed above may be influenced by driving experience. As expected, number of years driving was highly correlated with age ($r = .948, p < .001$). Number of years driving was also significantly correlated with operational driving quotient ($r = -.406, p = .029$). Partial correlations controlling for age found that the relationship between years driving and the operational driving quotient decreased but was still significant ($r = .375, p = .049$). These findings indicate that age influenced the relationships between the driving variables and number of years driving. Education was also found to be significantly correlated with one driving variable (Swerving: $r_s = .450, p = .027$). Education was also significantly related to age ($r_s = .425, p = .022$). Swerving was not significantly related to age ($r = .245, p = .248$). However, partial correlations controlling for age found that the relationship between swerving and education were no longer significant ($p = .089$), indicating that age influenced the relationship.

The relationship between study variables and factors that may influence performance, such as hours of sleep the previous night, level of fatigue, and recent substance use (caffeine, alcohol, nicotine) were also analyzed. Nicotine and alcohol use were not expected to impact performance as only one individual endorsed nicotine use, and three individuals endorsed alcohol use, reporting having two or less alcoholic beverages more than twelve hours before the start of the session. Individuals who consumed caffeine did not perform significantly different than those who did not consume caffeine on any of the IVs or DVs. Of those who consumed caffeine, there were no significant relationships between amount of caffeine consumed and any

of the study variables. Previous night sleep was significantly related to tactical driving quotient score ($r = -.601$, $p = .002$). Level of fatigue was related to alerting attention ($r = .467$, $p = .019$), with performance improving as level of fatigue increased. Scatterplot analysis suggests that influential cases may have skewed the findings (i.e., only four individuals reported a fatigue level of four or higher, with three of those producing RTs above 100ms [only four RTs were above 100ms total]). Amount of sleep and level of fatigue were not related to each other ($r = -.062$, $p = .260$), or other variables. The effects of sleep and fatigue are likely artifacts based on nonsignificant correlations with other variables and their inconsistent relationships with driving variables (i.e., increased fatigue was associated with improved alerting attention performance).

In summary, age was found to be related to two driving variables. Education was related to one driving variable though this relationship is likely artificially increased by age. Amount of sleep was related to two driving variables, while level of fatigue was related to one primary independent variable, though these variables produced inconsistent findings (i.e., improved performance on one tasks, but decreased performance on another). Analyses conducted with, and without, the three potential confounds (education, fatigue, and sleep) indicated that these variables did not influence the results. Recent substance use was also not related to any of the study variables. Therefore, only age will be included as a covariate in the analyses.

PRIMARY ANALYSES

Specific Aim 1: Examine the relationship between attention deficits and unsafe driving behaviors

A series of hierarchical regressions were conducted to evaluate the relationships between attention network performance (alerting, orienting, and executive networks measured by BEAM RT difference scores for nondirectional, directional, and misdirectional cues, respectively) and VRDS performance after accounting for the effects of age.

Hypothesis 1a.

Poorer attention network performance (alerting, orienting, executive attention) will be related to poorer VRDS performance in the form of significantly worse overall cognitive component scores, measured by the operational driving quotient.

For each hierarchical regression, the first step produced a significant change in R^2 ($\Delta R^2 = .371$, $p = .001$), accounting for 37 percent of the variance. None of the attention network variables produced a significant change in R^2 in the second step, with alerting, orienting, and executive accounting for three percent, four percent, and four percent of the variance, respectively. Based on beta values, the relationships between two attention variables (alerting and orienting) and operational driving performance were in the expected direction (i.e., positive relationship). The beta value for executive attention is in the unexpected direction, with the operational driving quotient decreasing as executive attention score increased. The bootstrapped confidence intervals for each of the variables overlap with zero. Therefore, the results do not provide evidence for significant relationships between the attention variables and the operational driving quotient in the population. Results are summarized in Tables 9 – 11.

Table 9. Alerting Attention as Predictor of Operational Driving Quotient

	b	SE B	β	p
Step 1				
Constant	139.02 (113.65, 186.43)	15.34		.001
Age	-1.10 (-1.82, -0.60)	0.33	-.61	.004
Step 2				
Constant	131.32 (96.40, 184.49)	19.04		.001
Age	-1.02 (-1.73, -0.50)	0.36	-.57	.009
Alerting	0.83 (-1.25, 2.37)	0.90	.18	.294

Note. $R^2 = .371$ for Step 1 ($p = .001$); $\Delta R^2 = .030$ for Step 2 ($p = .308$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 10. Orienting Attention as Predictor of Operational Driving Quotient

	b	SE B	β	p
Step 1				
Constant	139.02 (112.72, 177.57)	15.11		.001
Age	-1.10 (-1.77, -0.56)	0.33	-.61	.004
Step 2				
Constant	134.92 (111.22, 161.00)	15.79		.001
Age	-1.07 (-1.86, -0.45)	0.33	-.59	.006
Orienting	1.02 (-0.98, 3.33)	1.05	.21	.273

Note. $R^2 = .371$ for Step 1 ($p = .001$); $\Delta R^2 = .042$ for Step 2 ($p = .224$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 11. Executive Attention as Predictor of Operational Driving Quotient

	b	SE B	β	p
Step 1				
Constant	139.02 (114.04, 180.21)	15.93		.001
Age	-1.10 (-1.87, -0.54)	0.35	-.61	.007
Step 2				
Constant	133.47 (109.18, 166.60)	16.92		.001
Age	-1.07 (-1.93, -0.47)	0.34	-.59	.005
Executive	-0.78 (-2.29, 0.54)	0.65	-.20	.208

Note. $R^2 = .371$ for Step 1 ($p = .001$); $\Delta R^2 = .038$ for Step 2 ($p = .250$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Hypothesis 1b.

Poorer attention network performance (alerting, orienting, and executive attention) will be related to poorer VRDS performance in the form of significantly worse overall driving performance scores, measured by the tactical driving quotient.

For each hierarchical regression, the first step produced significant changes in R^2 ($\Delta R^2 = .258$, $p = .022$), accounting for 26 percent of the variance. None of the attention network variables produced a significant change in R^2 in the second step, with alerting, orienting, and executive accounting for ten percent, one percent, and less than one percent of the variance, respectively. Based on beta values, the relationship between alerting attention performance and tactical driving performance was in the unexpected direction, with driving quotient score decreasing as alerting attention score increased. The beta value for orienting and executive attention were in the expected direction. The bootstrapped confidence intervals for each of the variables overlap with zero. Therefore, the results do not provide evidence for significant

relationships between the attention variables and the tactical driving quotient in the population.

Results are summarized in Tables 12 – 14.

Table 12. Alerting Attention as Predictor of Tactical Driving Quotient

	b	SE B	β	p
Step 1				
Constant	128.81 (101.16, 151.59)	14.66		.001
Age	-0.68 (-1.40, 0.13)	0.31	-.51	.053
Step 2				
Constant	136.75 (100.21, 163.12)	17.34		.001
Age	-0.75 (-1.36, 0.13)	0.32	-.55	.030
Alerting	-1.12 (-2.37, 0.38)	0.75	-.32	.089

Note. $R^2 = .258$ for Step 1 ($p = .022$); $\Delta R^2 = .101$ for Step 2 ($p = .121$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 13. Orienting Attention as Predictor of Tactical Driving Quotient

	b	SE B	β	p
Step 1				
Constant	128.81 (101.40, 150.82)	14.35		.001
Age	-0.68 (-1.34, .09)	0.31	-.51	.051
Step 2				
Constant	127.70 (101.55, 146.33)	15.18		.001
Age	-0.68 (-1.33, 0.46)	0.32	-.50	.068
Orienting	0.35 (-1.62, 11.57)	1.50	.09	.509

Note. $R^2 = .258$ for Step 1 ($p = .022$); $\Delta R^2 = .008$ for Step 2 ($p = .670$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 14. Executive Attention as Predictor of Tactical Driving Quotient

	b	SE B	β	p
Step 1				
Constant	128.81 (101.64, 151.55)	14.45		.001
Age	-0.68 (-1.32, 0.09)	0.31	-.51	.055
Step 2				
Constant	128.94 (104.07, 148.94)	13.57		.001
Age	-0.68 (-1.31, 0.13)	0.32	-.51	.066
Executive	0.03 (-1.15, 0.96)	0.71	.01	.962

Note. $R^2 = .258$ for Step 1 ($p = .022$); $\Delta R^2 = .000$ for Step 2 ($p = .971$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Hypothesis 1c.

Poorer attention network performance (alerting, orienting, and executive attention) will predict accidents on the VRDS.

A series of hierarchical logistic regression analyses were conducted to test the hypothesis that attention network performance predicts driving simulator accidents (1 = yes, 0 = no) beyond age. None of the attention network variables were significant predictors of being involved in an accident on the driving simulator. Overall classification percentage accuracy was 65% (83% for no accidents, 38% for accidents) for alerting attention, 75% (100% for no accidents, 38% for accidents) for orienting attention, and 60% (75% for no accidents, 38% for accidents) for executive attention. The bootstrapped confidence intervals for the beta values overlap with zero. Also, the bootstrapped confidence intervals for the odds ratios contains one, suggesting that the direction of the relationships between accidents and the attention network variables cannot be determined, as attention network performance may either increase or decrease the odds of being involved in an accident on the driving simulator. Therefore, the results do not provide evidence

for significant relationships between the attention networks and VR accidents in the population. Results are summarized in Tables 15 – 17. Of note, only the results from the final step of the analyses were included in the tables to improve readability due to the large quantity of results that are produced for each step of the model.

Table 15. Coefficients of Model for Alerting Attention as Predictor of Accidents

	b	95% CI for Odds Ratio		
		<i>Lower</i>	<i>Odds</i>	<i>Upper</i>
Constant	-4.17 (-11.34, -1.00)			
Age	0.05 (-0.13, 2.61)	0.97	1.05	1.14
Alerting	0.26 (-0.16, 4.18)	0.93	1.29	1.79

Note. $R^2 = .228$ (Cox & Snell), $.308$ (Nagelkerke). Model $\chi^2(2) = 5.16$, $p = .076$. Confidence Intervals for the unstandardized coefficient (reported in parentheses) are based on 1000 bootstrap samples. Odds Ratio information was obtained from empirical analyses. Presented data are from final step of analysis.

Table 16. Coefficients of Model for Orienting Attention as Predictor of Accidents

	b	95% CI for Odds Ratio		
		<i>Lower</i>	<i>Odds</i>	<i>Upper</i>
Constant	-2.05 (-10.65, 3.33)			
Age	0.04 (-0.17, 11.82)	0.97	1.04	1.11
Orienting	-0.03 (-0.77, 0.13)	0.81	0.97	1.18

Note. $R^2 = .054$ (Cox & Snell), $.073$ (Nagelkerke). Model $\chi^2(2) = 1.12$, $p = .572$. Confidence Intervals for the unstandardized coefficient (reported in parentheses) are based on 1000 bootstrap samples. Odds Ratio information is from empirical analyses. Presented data are from final step of analysis.

Table 17. Coefficients of Model for Executive Attention as Predictor of Accidents

	b	95% CI for Odds Ratio		
		<i>Lower</i>	<i>Odds</i>	<i>Upper</i>
Constant	-2.80 (-13.22, 0.81)			
Age	0.04 (-0.10, 3.57)	0.97	1.04	1.11
Executive	-0.11 (-0.52, 0.07)	0.72	0.89	1.11

Note. $R^2 = .109$ (Cox & Snell), $.148$ (Nagelkerke). Model $\chi^2(2) = 2.32$, $p = .314$. Confidence Intervals for the unstandardized coefficient (reported in parentheses) are based on 1000 bootstrap samples. Odds Ratio information is from empirical analyses. Presented data are from final step of analysis.

Hypothesis 1d.

Poorer alerting attention will be related to poorer VRDS performance in the form of significantly more occurrences of tailgating and greater standard deviations for speed (difficulty maintaining speed) and lane position (swerving).

For each hierarchical regression, the first step did not produce significant changes in R^2 . Alerting attention did not produce a significant change in R^2 in the second step, with difficulty maintaining speed, swerving, and tailgating accounting for one percent, one percent, and six percent of the variances, respectively. Based on beta values, the relationships between alerting attention and the three driving variables were in the unexpected direction, with unsafe driving behaviors increasing as alerting attention score increased. However, the bootstrapped confidence intervals overlap with zero. Therefore, the results do not provide evidence for significant relationships between alerting attention score and the driving variables in the population. Results are summarized in Tables 18 – 20.

Table 18. Alerting Attention as Predictor of Difficulty Maintaining Speed

	b	SE B	β	p
Step 1				
Constant	11.58 (9.21, 13.33)	1.02		.001
Age	-0.05 (-0.81, -0.002)	0.02	-.44	.024
Step 2				
Constant	11.40 (9.33, 13.40)	1.15		.001
Age	-0.04 (-0.08, -0.002)	0.19	-.42	.029
Alerting	0.03 (-0.10, 0.17)	0.06	.10	.613

Note. $R^2 = .189$ for Step 1 ($p = .055$); $\Delta R^2 = .009$ for Step 2 ($p = .670$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 19. Alerting Attention as Predictor of Swerving

	b	SE B	β	p
Step 1				
Constant	0.31 (0.24, 0.42)	0.04		.001
Age	0.00 (-0.001, 0.001)	0.001	.17	.480
Step 2				
Constant	0.31 (0.23, 0.46)	0.04		.001
Age	0.00 (-0.001, 0.001)	0.001	.18	.437
Alerting	0.001 (-0.002, 0.003)	0.002	.10	.599

Note. $R^2 = .028$ for Step 1 ($p = .479$); $\Delta R^2 = .008$ for Step 2 ($p = .712$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 20. Alerting Attention as Predictor of Tailgating

	b	SE B	β	P
Step 1				
Constant	3.27 (1.60, 5.15)	1.03		.011
Age	-0.01 (-0.06, 0.03)	0.02	-.17	.462
Step 2				
Constant	2.92 (1.08, 4.66)	1.15		.027
Age	-0.01 (-0.06, 0.05)	0.02	-.14	.562
Alerting	0.05 (-0.02, 0.13)	0.04	.24	.138

Note. $R^2 = .029$ for Step 1 ($p = .471$); $\Delta R^2 = .055$ for Step 2 ($p = .328$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Hypothesis 1e.

Poorer orienting attention will be related to poorer VRDS performance in the form of significantly greater standard deviations for speed (difficulty maintaining speed) and lane position (swerving).

For each hierarchical regression, the first step did not produce significant changes in R^2 . Orienting attention did not produce a significant change in R^2 in the second step, accounting for eleven percent and two percent of the variances for difficulty maintaining speed and swerving, respectively. Based on beta values, the relationships between orienting attention score and the two driving variables were in the unexpected direction, with unsafe driving behaviors increasing as orienting attention score increased. However, the bootstrapped confidence intervals overlap with zero. Therefore, the results do not provide evidence for significant relationships between

orienting attention score and the driving variables in the population. Results are summarized in Tables 21 & 22.

Table 21. Orienting Attention as Predictor of Difficulty Maintaining Speed

	B	SE B	β	<i>p</i>
Step 1				
Constant	11.58 (9.00, 13.60)	1.01		.001
Age	-0.05 (-0.08, -0.13)	0.02	-.44	.024
Step 2				
Constant	11.26 (8.61, 13.95)	1.06		.001
Age	-0.04 (-0.08, -0.12)	0.02	-.42	.045
Orienting	0.10 (-0.09, 0.19)	0.08	.34	.111

Note. $R^2 = .189$ for Step 1 ($p = .055$); $\Delta R^2 = .113$ for Step 2 ($p = .116$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 22. Orienting Attention as Predictor of Swerving

	B	SE B	β	<i>p</i>
Step 1				
Constant	0.31 (0.26, 0.38)	0.03		.001
Age	0.00 (-0.001, 0.002)	0.001	.17	.452
Step 2				
Constant	0.31 (0.25, 0.39)	0.04		.001
Age	0.00 (-0.001, 0.002)	0.001	.17	.454
Orienting	0.001 (-0.003, 0.003)	0.002	.13	.339

Note. $R^2 = .028$ for Step 1 ($p = .479$); $\Delta R^2 = .018$ for Step 2 ($p = .582$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Hypothesis 1f.

Poorer executive attention will be related to poorer VRDS performance in the form of significantly more occurrences of tailgating and greater standard deviation for speed (difficulty maintaining speed).

For each hierarchical regression, the first step did not produce a significant change in R^2 . Executive attention did not produce a significant change in R^2 in the second step, accounting for nine percent and five percent of the variance for difficulty maintaining speed and tailgating, respectively. Based on beta values, the relationships between executive attention score and the two driving variables were in the expected direction. The bootstrapped confidence intervals overlap with zero. Therefore, the results do not provide evidence for significant relationships between executive attention score and the driving variables in the population. Results are summarized in Tables 23 & 24.

Table 23. Executive Attention as Predictor of Difficulty Maintaining Speed

	b	SE B	β	p
Step 1				
Constant	11.58 (9.07, 13.27)	1.02		.001
Age	-0.05 (-0.08, -0.001)	0.02	-.44	.020
Step 2				
Constant	11.19 (8.75, 13.74)	1.15		.001
Age	-0.05 (-0.08, -0.01)	0.02	-.44	.026
Executive	-0.08 (-0.15, 0.09)	0.06	-.31	.092

Note. $R^2 = .189$ for Step 1 ($p = .055$); $\Delta R^2 = .094$ for Step 2 ($p = .153$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 24. Executive Attention as Predictor of Tailgating

	b	SE B	β	p
Step 1				
Constant	3.27 (1.29, 5.73)	1.05		.005
Age	-0.01 (-0.05, 0.02)	0.02	-.17	.452
Step 2				
Constant	3.05 (1.06, 5.61)	1.12		.017
Age	-0.01 (-0.06, 0.03)	0.02	-.17	.471
Executive	-0.05 (-0.15, 0.06)	0.05	-.23	.213

Note. $R^2 = .029$ for Step 1 ($p = .471$); $\Delta R^2 = .053$ for Step 2 ($p = .337$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Specific Aim 2: Evaluate the predictive validity of two novel assessment tools (BEAM and VRDS) in predicting unsafe driving behaviors in the real world

Hypothesis 2a.

There will be an inverse relationship between BEAM performance and indicators of real-world unsafe driving behaviors, such that worse attention network performance will be related to significantly more occurrences of self-reported, real-world unsafe driving behaviors.

For each hierarchical regression, the first step did not produce a significant change in R^2 . Orienting attention produced a significant change in R^2 , accounting for fourteen percent of the variance in real-world unsafe driving behaviors. Alerting and executive attention did not produce significant changes in R^2 , accounting for seven percent and one percent of the variances in real-world unsafe driving behaviors, respectively. Based on beta values, the relationships between two attention network scores (alerting and executive) and real-world driving behaviors were in the expected direction, with number of unsafe driving behaviors decreasing as attention performance increased. The relationship with orienting attention score was in the unexpected

direction. For alerting and executive attention, the bootstrapped confidence intervals overlap with zero. Therefore, the results do not provide evidence for significant relationships between the attention network scores and real-world unsafe driving behaviors in the population. Results are summarized in Tables 25 - 27.

Table 25. Alerting Attention as Predictor of Real-World Unsafe Driving Behaviors

	b	SE B	β	p
Step 1				
Constant	2.50 (0.15, 5.93)	1.22		.045
Age	-0.001 (-0.05, 0.04)	0.03	-.01	.977
Step 2				
Constant	3.33 (0.27, 5.94)	1.38		.016
Age	-0.01 (-0.06, 0.04)	0.03	-.09	.642
Alerting	-0.08 (-0.22, 0.12)	0.07	-.27	.191

Note. $R^2 = .000$ for Step 1 ($p = .979$); $\Delta R^2 = .067$ for Step 2 ($p = .271$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 26. Orienting Attention as Predictor of Real-World Unsafe Driving Behaviors

	b	SE B	β	p
Step 1				
Constant	2.50 (0.07, 5.72)	1.17		.041
Age	-0.001 (-0.04, 0.04)	0.02	-.01	.973
Step 2				
Constant	1.97 (-0.20, 4.58)	1.13		.080
Age	0.005 (-0.03, 0.05)	0.02	.04	.804
Orienting	0.11 (0.04, 0.27)	0.06	.37	.026

Note. $R^2 = .000$ for Step 1 ($p = .979$); $\Delta R^2 = .135$ for Step 2 ($p = .111$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 27. Executive Attention as Predictor of Real-World Unsafe Driving Behaviors

	b	SE B	β	p
Step 1				
Constant	2.50 (0.41, 5.18)	1.15		.041
Age	-0.001 (-0.05, 0.04)	0.02	-.01	.984
Step 2				
Constant	2.46 (0.25, 5.76)	1.26		.062
Age	-0.001 (-0.05, 0.05)	0.03	-.01	.977
Executive	-0.006 (-0.08, 0.20)	0.06	-.03	.897

Note. $R^2 = .000$ for Step 1 ($p = .979$); $\Delta R^2 = .011$ for Step 2 ($p = .918$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Hypothesis 2b.

There will be an inverse relationship between VRDS performance and indicators of real-world unsafe driving behaviors, such that poorer performance on the VRDS operational and tactical driving quotients will be related to significantly more occurrences of self-reported, real-world unsafe driving behaviors.

For each hierarchical regression, the first step did not produce a significant change in R^2 . Neither driving quotients produced a significant change in R^2 in the second step. However, Operational driving quotient displayed a nonsignificant trend, accounting for twelve percent of the variance. However, based on beta values, the relationships between the driving quotients and self-reported driving behaviors were in the unexpected direction, with number of reported unsafe driving behaviors increasing as driving quotient increased. The bootstrapped confidence intervals overlap with zero. Therefore, the results do not provide evidence for significant relationships between the VR driving quotients and real-world unsafe driving behaviors in the population. Results are summarized in Tables 28 & 29.

Table 28. Operational Driving Quotient as Predictor of Real-World Unsafe Driving Behaviors

	B	SE B	β	<i>p</i>
Step 1				
Constant	2.86 (1.02, 5.32)	1.03		.017
Age	-0.01 (-0.06, 0.04)	0.02	-.08	.686
Step 2				
Constant	-0.60 (-4.83, 3.56)	2.14		.779
Age	0.02 (-0.04, 0.08)	0.03	.14	.560
Operational DQ	0.03 (-0.001, 0.05)	0.01	.41	.059

Note. $R^2 = .006$ for Step 1 ($p = .722$); $\Delta R^2 = .123$ for Step 2 ($p = .091$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 29. Tactical Driving Quotient as Predictor of Real-World Unsafe Driving Behaviors

	B	SE B	β	<i>p</i>
Step 1				
Constant	2.74 (0.77, 5.20)	1.04		.017
Age	-0.01 (-0.05, 0.04)	0.02	-.09	.600
Step 2				
Constant	1.51 (-7.52, 15.23)	5.44		.765
Age	-0.01 (-0.08, 0.05)	0.03	-.05	.834
Tactical DQ	0.01 (-0.10, 0.08)	0.04	.08	.813

Note. $R^2 = .008$ for Step 1 ($p = .700$); $\Delta R^2 = .004$ for Step 2 ($p = .791$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

EXPLORATORY ANALYSES

Additional analyses were also conducted to potentially help describe the findings and elucidate possible trends not captured in the primary analyses. These analyses included examination of unaltered BEAM RT scores, the Trail Making Test-B, TBI severity, level of

BEAM impairment, and specific unsafe driving behaviors (e.g., instances of speeding) for both virtual and real-world driving. Similar to the primary analyses, the exploratory analyses did not significantly predict driving performance beyond age and the bootstrapped confidence intervals overlapped with zero. Therefore, the results do not provide evidence for significant relationships in the population. While not significant, multiple analyses produced findings of interest that can provide future directions for both research and clinical applications (discussed below). See Appendix B for results.

NON-DRIVER QUALITATIVE ANALYSIS

Four of the participants did not drive for the duration of the baseline portion of the study. These individuals were not included in the hypotheses for Specific Aim 2 but were examined qualitatively to identify factors which may have contributed to their lack of driving. Head injury severity for this group consisted of 2 severe, 1 moderate, and 1 mild TBI (25% of all moderate-severe participants). During baseline assessment and intervention, three individuals indicated that they no longer drove due to concerns about cognitive deficits. When compared to the other participants, this group was approximately four years older but had been driving for the same amount of time (32 years). In regard to time since injury (TSI), this group had a drastically shorter period between sustaining the TBI and participating in the study (20 months vs. 131 months). VR driving performance was worse for those individuals who did not drive, performing approximately one and one-and-a-half standard deviations below those participants who drove on the operational and tactical driving quotients, respectively. The non-driving group was also responsible for half of the accidents during the tactical drive (seven), which were committed by two individuals. Both individuals had sustained severe TBI and were less than 24 months post-injury. The participant with the more recent injury (twelve months) had more than

twice as many accidents (5 vs. 2) as the participant who was 23 months post-injury. None of the non-drivers had an impaired BEAM RT score on the index. For the participants who drove, those involved in an accident on the VRDS were 4 with mild TBI, 1 with severe TBI, and two accidents for one individual with moderate TBI. These individuals had an average TSI of 178, ranging from 76 to 268 months.

Chapter 4: Discussion

Attention is a necessary cognitive domain for safe driving, with inattention and distraction being the primary causes of motor vehicle accidents. The current study examined the influence of attention deficits on specific driving behaviors using a novel eye tracking assessment tool, the Bethesda Eye and Attention Measure (BEAM), to detect unsafe driving behaviors on a virtual reality driving simulator (VRDS). A second objective of the study was to examine the predictive validity of both the BEAM and VRDS by examining their relationships with self-reported unsafe driving behaviors on a driving questionnaire over a four-week period.

SPECIFIC AIM 1: RELATIONSHIPS BETWEEN BEAM AND VR DRIVING

Attention network performances (alerting, orienting, executive) measured by BEAM difference scores for NDC, DC, and MDC, were not significantly related to the VR driving variables. Based on effect size analysis, executive attention performance was the best predictor of unsafe driving behaviors, producing primarily small to medium effect sizes for four of the six VR variables: accidents ($\Delta R^2 = .15$), difficulty maintaining speed ($\Delta R^2 = .09$), swerving ($\Delta R^2 = .09$), and tailgating ($\Delta R^2 = .05$). Only one relationship in the unexpected direction was observed (operational driving quotient, $\Delta R^2 = .04$). Alerting attention performance accounted for three percent of the operational driving quotient and had two relationships in the unexpected direction, accidents ($\Delta R^2 = .02$) and tactical driving quotient ($\Delta R^2 = .10$). Orienting attention performance produced small effect sizes for two variables (accidents, $\Delta R^2 = .07$; operational driving quotient, $\Delta R^2 = .04$), and had two relationships in the unexpected direction (difficulty maintaining speed, $\Delta R^2 = .11$; swerving, $\Delta R^2 = .02$). Evaluation of the combined BEAM variable performances, using an impairment index, was not significantly related to VR unsafe driving behaviors. The index only displayed one relationship in the expected direction (difficulty maintaining speed,

$\Delta R^2 = .02$) and three in the unexpected direction (tactical driving quotient, $\Delta R^2 = .06$; accidents, $\Delta R^2 = .07$; and tailgating, $\Delta R^2 = .02$).

While the findings were not significant, the observed effect sizes and patterns of attention network performance are similar to the findings from another study which used an attention task with similar cues to the BEAM. That study found that overall task performance accounted for nine percent of the variance (small-to-moderate effect size) of driving simulator performance, measured by observer-rated total score, beyond that accounted for by age in 38 healthy participants (mean age = 45.3 years, range = 18-63) (131). Individual attention network performance was not found to be significantly related to driving performance, but executive attention produced a small effect size ($R^2 = .03$). The study also found variable relationships between alerting and orienting attention network performances and driving, with 34 percent (13 of 38) displaying performances that were in the unexpected direction (i.e., driving performance increasing as attention performance decreased). In the current study, overall BEAM performance was assessed using an impairment index which identified the number of impaired scores across the three attention network performances, opposed to the overall score (total mean/total standard deviation) used in the previously mentioned study. Therefore, a comparison between two performances cannot be made. However, multiple effect sizes for the relationships between BEAM individual network performances and VR variables were in the small-to-moderate range, particularly those for executive attention which were almost all in the expected direction. Similarly, alerting and orienting attention network performances were also variable, producing regression coefficients, of at least a small effect size, that were both in the expected and unexpected directions.

The authors of the previous study hypothesized that the unexpected findings may have been caused by the alerting and orienting trial cues serving as distractors that increased reaction time, rather than facilitators that primed the attention networks. Examination of the current study data found that 24 percent (6 of 25) displayed these counterintuitive alerting and orienting attention difference scores, with three scores for each. Two individuals with discrepant orienting attention scores produced counterintuitive scores for executive attention. When examining the findings of the Posner's cuing paradigm, which the ANT and BEAM cues were based, only the overall scores for the cues were provided (97). Therefore, the number of participants that produced counterintuitive findings is unknown. However, another Posner study found that knowledge of spatial position only improves performance in complex tasks, and that the presentation of either temporal (alerting) cues or temporal/spatial (orienting) cues in a simple task may decrease performance compared to an uncued trial (99). The authors stated that the costs of the cues (use of attentional resources) were the same in both the simple and complex tasks. However, the benefits (faster reaction time) only outweighed the costs in the complex tasks. Thus, the unexpected findings in the relationships between alerting and orienting attention networks and the driving variables may be partially explained by the cues not facilitating, and potentially hindering, performance.

Exploratory analyses conducted to supplement the primary analyses findings also did not elucidate significant relationships. TMT-B, the only currently used measure previously shown to have utility in assessing driving performance, displayed a nonsignificant trend ($p = .059$) with the operational driving quotient, producing a moderate effect size ($\Delta R^2 = .14$). However, it was not significantly related to any of the driving variables, producing small effect sizes for accidents ($\Delta R^2 = .03$) and the tactical driving quotient ($\Delta R^2 = .04$). One relationship (tailgating, $\Delta R^2 = .05$)

was in the unexpected direction. One hypothesis for the different relationships between TMT-B and the two driving quotients is that the TMT-B and the operational driving quotients are both cognitive measures, opposed to the tactical driving quotient which is a driving-behavior measure. A related hypothesis is that while the TMT-B may be able to detect difficulties in cognitive abilities typically involved in driving, such as divided attention, individuals may have utilized strategies to compensate for these cognitive difficulties while performing the tactical drive. This hypothesis is discussed further in the Specific Aim 2 discussion.

Exploratory analyses examining the impact of TBI severity (mild and moderate-severe) on VRDS performance found a nonsignificant trend with swerving, producing a moderate effect size ($\Delta R^2 = .15$). While not significant, TBI severity also produced small and medium effect sizes for multiple variables, including the driving quotients (operational, $\Delta R^2 = .02$; tactical, $\Delta R^2 = .02$) and tailgating ($\Delta R^2 = .03$), and accidents ($\Delta R^2 = .15$). The impact of TBI severity becomes more apparent when comparing those who did not drive due to cognitive difficulties to those who drove, with performances on the operational and tactical driving quotients being one and one-and-a-half standard deviations below those participants who drove, respectively. The non-driving group was also responsible for half of the accidents during the tactical drive. There is limited research evaluating the impact of TBI severity on driving abilities, both in individuals with mild TBI and those who experienced a TBI of sufficient severity that precludes returning to driving due to cognitive deficits. Therefore, it is difficult to compare findings from the current study to the existing literature. However, the medium effect size seen in the relationship between TBI severity and swerving is similar to prior driving simulator studies which found that individuals with both mild and moderate-severe TBI may not have increased occurrences of broad driving events (e.g., accidents) but may display more difficulty with subtle driving

behaviors (e.g., difficulty maintaining speed or lane position)(7, 70, 111). This finding highlights the ability of simulators to detect subtle deficits that may not be observed during an on-road driving test.

In summary, while the BEAM did not display significant relationships with the VR driving behaviors, the observed effect sizes and general patterns were consistent with findings from previous research. However, based on the inconsistent relationships between BEAM and VR variables, and the bootstrapped confidence intervals that overlap with zero, there is limited evidence to indicate that these relationships exist in the population. Therefore, hypotheses for specific aim 1 were not supported. The findings were also likely impacted by sample and measure characteristics, which also influenced the findings for Specific Aim 2, and therefore will be discussed below.

SPECIFIC AIM 2: RELATIONSHIPS BETWEEN NOVEL ASSESSMENT TOOLS AND REAL-WORLD DRIVING

Most of the BEAM and VRDS variables were not significantly related to the self-reported driving behaviors, with many of the regression coefficients being in the unexpected direction. Orienting attention performance and the operational driving quotient had significant ($p = .028$) and near-significant ($p = .059$) relationships with the unsafe driving behaviors, respectively. However, these relationships were also in the unexpected direction, with the number of unsafe driving behaviors increasing as either orienting attention performance or operational driving quotient increased. No other BEAM or VRDS variables were significantly related to the unsafe driving behaviors. Only two variables (alerting attention and difficulty maintaining speed) had relationships with the unsafe driving behaviors that were in the expected direction, accounting for seven percent and two percent of the variances, respectively. While not

significant, age accounted for 27 percent of the variance in relationship to self-reported speeding, with instances of self-reported speeding decreasing as age increased.

In all, 10 of the 15 variables displayed unexpected relationships that produced small to moderate effect sizes, including: the three BEAM RTs (NDC $\Delta R^2 = .02$; MDC, $\Delta R^2 = .14$; DC, $\Delta R^2 = .17$), VR unsafe driving behaviors (accidents, $\Delta R^2 = .02$; swerving, $\Delta R^2 = .18$), and exploratory variables (impairment index, $\Delta R^2 = .05$; TMT-B, $\Delta R^2 = .09$; TBI severity, $\Delta R^2 = .07$). These findings contrast with previous studies evaluating simulator performance and self-reported unsafe driving behaviors. One study of individuals with ADHD (mean age = 30.41, SD = 8.49, range = 18 – 51) found small-to-medium and medium effect sizes for the relationships between self-reported driving and simulator lane variability ($\Delta R^2 = .09$) and speeding ($\Delta R^2 = .18$), respectively (108). A study examining eleven individuals with moderate-severe TBI found that simulator performance may show promise in potentially predicting real-world accidents ($r = -.47$, $p = .07$), but was not able to predict traffic citations and license revocations ($r = -.05$, $p = .40$) at a ten-month follow-up (70).

One hypothesis for these finding is that those individuals with poorer performance could have been aware of their deficits, and therefore, were less likely to resume driving or drive in traffic and may be more likely to drive cautiously, which has been found in a previous TBI study (103). In the current study, self-reported unsafe driving behaviors decreased as cognitive test performance (BEAM RTs and TMT-B) decreased and injury severity increased. Also, three of the four participants who reported not driving during the study indicated that they did not drive due to concerns about their cognitive functioning. As mentioned previously, their performance was primarily poorer across VRDS variables, including operational and tactical DQs, tailgating, and lane variability. Also, they accounted for half of the accidents despite being fourteen percent

of the sample. Two individuals who had not driven with more recent injuries accounted for half of the total accidents in the sample, with the participant whose TSI was half as long having more than twice as many accidents. This finding suggests that these individuals are likely still in the recovery phase, with deficits seen primarily in the first two years (112). They also may not have developed strategies to adjust to their cognitive deficits. However, this hypothesis cannot be tested due to lack of information about various driving-related factors, such as strategies implemented to limit risk, confidence in driving ability, and perception of cognitive functioning level. Therefore, hypotheses for specific aim 2 were not supported.

GENERAL DISCUSSION

Overall, the current study found what has typically been found in driving ability assessment research - methods used to assess driving ability have not been found to consistently predict driving behaviors. The BEAM and VRDS produced variable findings, including nonsignificant trends, effect sizes that suggests further research may be warranted, and regression coefficients that were in the unexpected direction. The Trail Making Test- Part B, which is the closest “gold standard” available for neuropsychological tests, displayed similar variable findings. Two factors that likely contributed to the inconsistent findings in both the current study and the driving assessment literature, in general, are the heterogeneity of TBI and the complexity of driving. Heterogeneity of TBI, including injury characteristics (e.g., severity, location, time since injury) and influencing factors (e.g., age, education level), can lead to various deficits that make it difficult to assess the impact of TBI on driving ability, as well as evaluate the predictive validity of measures, negatively impacting assessment and prognosis in clinical settings (7, 78). Failure to account for these factors in studies can greatly obscure the relationships between driving ability and TBI. For example, if time since injury is not examined,

studies could find different driving performances in individuals with the same injury severity, despite the differences being potentially better explained by the individuals being in different phases of recovery. Also, driving is a complex, multifactorial activity that requires constant processing of various information and can be influenced by a wide variety strategies and attitudes, making it difficult to predict driving behaviors. The combination of these factors dramatically increases the difficulty of assessing and predicting driving ability following TBI. Potential reasons for the inconsistent, and nonsignificant, findings that are more specific to the current study are discussed below.

LIMITATIONS

Sample Characteristics

The study included a relatively small sample size, ranging from 20 - 25 participants, depending on the hypothesis. Despite the use of bootstrapping, a larger sample would better represent the population. Multiple variables produced a range of small to medium effect sizes, however these relationships were not detected due to current study only being able to detect large effects because of sample size. This limitation is commonly found in driving simulator research involving individuals with TBI, with a mean sample size of 28 participants (range: 3 – 87) across multiple studies (7). Another potential limitation of the study is that the average time since injury (TSI) was over nine years, with the minimum TSI being twelve months. These individuals may have developed their own adaptive strategies to account for cognitive deficits. For the tactical and operational driving quotients, 88 percent and 72 percent of the participants produced scores that were at least in the low average range, respectively, suggesting that they may have adapted well to their cognitive deficits. The two individuals with severe TBI that did not drive during the study, and displayed impaired driving variable scores, were less than two

years since injury, and were likely still in the recovery phase and had not yet developed compensatory strategies.

Another potential issue is that the participants may not reflect the general TBI population. The individuals in the study were interested in attending a rehabilitation program that could potentially address both cognitive and driving deficits. Therefore, these individuals may experience greater deficits than other individuals with TBI who do not seek treatment. Also, individuals were excluded from the parent study if they were less than three months post-injury or if they were asymptomatic (mild TBI only). Therefore, over half of the sample (59 percent) was individuals with mild TBI who reported persistent symptoms past the expected resolution time-frame, which typically occurs in approximately ten percent of the mild TBI population and is often attributed to other factors, such as psychological comorbidities (15). Thus, the symptoms may reflect psychological factors and not actual cognitive deficits (e.g., fatigue and difficulty concentrating). The lack of a control group precludes comparing performances to evaluate the possible influence of psychological symptoms.

While this sample may not reflect the general TBI population, the participants may be similar to those individuals who are seen in clinical settings. Like the participants in the current study, those individuals who present for neuropsychological assessment and/or neurocognitive rehabilitation, whether referred by self or others, express concerns about decrements in cognitive and/or real-world functioning. The study participants had an average of nine years since injury; this chronicity can be seen in clinical settings, as individuals with severe TBI have been shown to display deficits for 10 to 15 years after injury (79). However, this study excluded individuals who were in the acute injury phase, which is also commonly seen in clinical settings. Regarding TBI severity, this sample does not reflect the population of individuals in rehabilitation

programs, as rehabilitation is used primarily by individuals with severe TBI (116) and the majority of the current study is of mild severity. One reason for this difference is that rehabilitation has been shown to provide benefit in severe injury but has not shown consistent ability to benefit those with mild TBI and may actually contribute to symptom exacerbation due to iatrogenic effects (116). Therefore, the finding from this study may not reflect the level of impairment typically seen in cognitive rehabilitation settings due to overrepresentation of individuals with mild TBI.

Level of education in the sample may also not reflect the general population. Sixty-two percent of the sample had at least a college degree (31% bachelor's degree; 31% master's degree). The high level of education may also suggest a higher level of cognitive reserve, meaning that these individuals may be less impacted by cognitive deficits, and/or be better able to adapt to their cognitive deficits (51). Lastly, while no participants reported recent substance use (last 24 hours) which could impact performance on the BEAM or VRDS, more general substance use, presence of substance use disorder, or the impact of potential substance use on self-reported driving behaviors over the previous week, were not assessed. Therefore, it is unknown if substance use may have contributed to unsafe real-world driving behaviors.

Study Instruments

BEAM

The instruments selected for the current study also have limitations which likely contributed to the nonsignificant findings. The BEAM displayed variable split-half reliability for the difference scores, particularly orienting attention (Alerting = .81, Orienting = .38, Executive = .72), increasing the measurement error. The VR operational driving quotient also displayed poor test-retest reliability (.49). Thus, the measurement error is likely to be greatly increased

when examining the relationships between these variables. When conducting research examining the individual differences between participants, such as the current study, adequate reliability is needed in order to consistently measure performance; otherwise, the measures will not be able to detect relationships between constructs due to the inability to distinguish between individual differences and measurement error (49). Therefore, the nonsignificant findings may be partially related to measurement error obscuring relationships between the study variables.

Also, BEAM and eye-tracking, in general, are relatively new measures with limited research support as predictors of functional performance. The BEAM has been shown to be related to severity of TBI (33), however, this is the first study evaluating its validity as a predictor of real-world functioning. Potentially, BEAM may be more useful as a biomarker of injury as opposed to an assessment tool for cognitive and real-world functioning. Additionally, the primary analyses utilized variables that were the closest representatives of the visual attention networks. Eye-tracking measurement produces various scores, some of which may be able to better predict driving performance (discussed further in future directions section below).

VRDS

Similarly, there is limited research evaluating the psychometric properties of VR driving simulators. The available validity of the simulator used in the current study focuses on the ability of the simulator to discriminate between healthy controls and individuals with conditions that may negatively impact cognitive functioning (e.g., Parkinson's disease, Alzheimer's Disease, and stroke) (79), not its ability to predict real-world driving. The driving simulator may also not be sensitive to subtle deficits seen in mild TBI, or to the compensatory strategies used by individuals with more severe TBI. Recommendations for potentially improving sensitivity are discussed in the future research section below.

Driving Survey

As mentioned in the background, driving surveys are susceptible to multiple biases which may impact the accurate measurement of the variable being assessed. However, the current study relies on individual's providing answers about unsafe driving behaviors over the previous week. The short latency period may hinder bias and help provide more accurate recall of driving events but may also contribute to other confounds. For example, after completing the driving assessment and the driving survey, individuals may have become more aware of their driving behaviors and adjusted their behavior based on the knowledge that they were going to complete another driving assessment the following week. Also, four weeks may not have been enough time to capture more unsafe behaviors and driving violations.

The greatest limitation of the survey is that time driven over the previous week was assessed, but it was not possible to capture all of the conditions in which individuals drove (e.g., heavy traffic, interstate driving, nighttime driving) nor strategies implemented to decrease the likelihood of driving in complex situations (e.g., taking backroads to avoid major highways, driving only during off-peak hours). Those individuals with poorer attention network, and driving simulator, performance reported fewer real-world unsafe driving behaviors, which is contrary to expected outcomes. As mentioned previously, some individuals with TBI may not be aware of cognitive deficits, potentially due to the severity of the deficits (i.e., anosognosia), and may be at greater risk of performing unsafe driving behaviors and/or being involved in an accident. However, individuals with cognitive deficits who are aware of their limitations and heightened accident risk may employ tactical-level (e.g., drive slower) and operational-level (e.g., avoiding highways to limit exposure to potential hazards) strategies. Relatedly, they may also be inclined to intentionally avoid unsafe driving behaviors, such as speeding, tailgating, or talking on a cellphone. The participants in the current study are more likely to be aware of

potential cognitive and/or driving deficits due to volunteering to participate in a cognitive and driving rehabilitation intervention (discussed above). As such, while the survey scores account for amount of time driven, they do not account for the probability of performing an unsafe driving behavior. The driving survey was developed for the study as an outcome measure to assess the presence of specific driving behaviors. However, the lack of information about confidence in driving ability, attitudes toward unsafe driving behaviors, and implementation of strategies to cope with potential deficits, prevents the examination of why an individual chose not to drive or why this pattern was observed. However, even if this information were available, attempting to account for all of the factors that could impact driving ability would not be feasible due to the complex and multifactorial nature of driving (130). This difficulty in collecting information on, and addressing, the various factors that could impact driving is evidenced by the lack of information about confidence level, attitudes, and strategy utilization in the current literature, with most of the known studies assessing the impact of TBI on driving ability using self-report measures focusing on the occurrences of unsafe driving behaviors. This limitation is discussed further in the future directions section.

STRENGTHS

The current study utilized multiple novel approaches in the assessment of driving behaviors, both in general and in a TBI sample. The assessment of real-world driving behaviors involved measurement at multiple time points over a four-week period following cognitive testing, which differs from the retrospective nature of most studies. The prospective survey may help improve reporting accuracy, while also limiting potential biases, such as consistency motif. The survey also allowed the participants to annotate the number of specific instances of unsafe driving behaviors, resulting in the potential for a range of responses opposed to the restricted

responses on nominal- and ordinal-scaled surveys. These two strengths may better reflect actual real-world driving.

The use of translational research methodology was another strength of the current study. This is the first known study of real-world driving behaviors to utilize a cognitive model of attention and eye-tracking measure previously used only in basic research. The historical division between clinical and cognitive neuropsychology, each with their own measures and conceptual models of cognitive domains, has changed due to the current nature of neuropsychological assessment. Two primary issues have been noted in the field of neuropsychology: the need for translational research where cognitive and clinical disciplines utilize similar instruments and terminology, and the development of instruments that can assess real-world functioning. However, the integration of clinical and research domains has been lacking, and neuropsychological measures continue to show limited utility in assessing functional outcomes. This study attempted to address these issues by utilizing a cognitive framework of attention, as well as an eye-tracking measure previously used only in cognitive research and assessing their ability to predict real-world functioning. Lessons learned from the current study can provide future directions for subsequent driving research and improving assessment and prognosis in clinical settings.

FUTURE DIRECTIONS

Measures

Driving assessment research has largely focused on neuropsychological tests as measures of cognitive and real-world functioning. Due to the highly structured nature of the tests and the testing environment, they may not detect subtle deficits, or how those deficits relate to real-world performance in a complex activity, such as driving. Future assessment research should focus on

using measures that may be more sensitive to subtle deficits and may better reflect real-world activities. From the current study, examining different variables, such as eye-tracking reaction time variability, individual operational components of VR driving, and specific unsafe real-world driving behaviors, may elucidate significant relationships that were not evaluated in the current study.

In general, more research is needed to evaluate the ability of both VR driving simulators and eye-tracking measures to detect both cognitive deficits and predict real-world functioning. Refinement of eye-tracking measures and VR driving simulation, including improved hardware and software, could help improve sensitivity (e.g., new technology to better accurately and consistently track eye movement to provide better measurement), as well as reliability. In the current study, the driving simulator scenario might not have been demanding enough to fully assess performance, and/or capture the complexity of real-world driving. Research using simulators has typically found that more subtle aspects of driving, such as lane and speed variability, differentiated performances between groups, opposed to more broad characteristics, such as accidents (7). The development of driving simulator scenarios with greater complexity, as well as variations in duration and complexity, might better assess potential unsafe driving behaviors and how they are impacted by attention deficits. The integration of eye-tracking measures and VR simulation may also be able to better elucidate attention deficits that result from increased stimuli presentation that is not captured in a standard eye-tracking measure administration. Similarly, eye-tracking measures could also potentially be combined with currently used neuropsychological instruments to enhance assessment of cognitive functioning.

Questionnaires

Another future direction for driving assessment is evaluating factors, such as perceived driving ability, attitudes concerning safe driving behaviors, and potential strategies used to cope with cognitive and/or motor deficits. This information has not been typically evaluated in the current literature, especially for individuals with TBI, which hinders the ability to determine the true impact of cognitive deficits on real-world driving. Questionnaires which assess for some of this information, such as the Barriers to Driving questionnaire (101), can be used in research (both real-world and virtual reality scenarios) to examine their potential utility as tools to predict driving ability, as well as identify areas for intervention, in clinical settings. Another avenue for research is the further assessment of compensatory strategies using driving simulation where individuals can provide real-time discussion of strategies as they are being implemented and researchers can assess their effectiveness.

The development of questionnaires and surveys that use collateral information from significant others is another method which could prove useful in assessing driving ability. Collateral questionnaires could provide many of the benefits of self-report surveys, such as ability to assess behaviors that would be generally difficult to collect otherwise (e.g., was driver slow to react to changing traffic light?), while having the added benefit of assessing driving behaviors in individuals who may not be aware of their deficits (e.g. elderly individuals). Use of collateral report could also be developed for research settings, such as an examiner recording qualitative information while a participant drives in a simulator, potentially providing additional information that is not captured by data measurement (e.g., did the driver appear anxious when merging into traffic?).

Research Design

Implementing strategies to help manage the influence of TBI heterogeneity is another issue to address in future research. The current TBI diagnostic framework classifies injury severity by the acute injury characteristics (e.g., loss of consciousness, post-traumatic amnesia), and as such, are not representative of subsequent cognitive and functional impairments. Other factors (e.g., time since injury, age, premorbid functioning) also influence symptoms and may be more important in predicting outcome. Despite the multitude of characteristics that influence symptoms and outcome in TBI, systematic approaches to address these characteristics have not been developed. Current efforts to standardize and integrate research findings have focused on the development of committees that provide recommendations for research (e.g. World Health Organization's Mild TBI Task Force) and systematic reviews of existing literature. Utilizing a standardized framework can guide research in various domains (e.g., biological, social, cognitive, affective) and provide more consistency in terminology and procedures, resulting in findings that can be integrated across different biopsychosocial factors. One practical approach that would be particularly useful in TBI is to implement a pre-existing framework, such as the National Institute of Mental Health Research Domain Criteria Project (RDoC), which was developed to address heterogeneity by assessing biopsychosocial factors in conditions where these factors may have greater influence on outcomes than the diagnostic criteria alone (e.g., major depressive disorder).

One approach to address these various factors in research is to develop groups based on specific injury characteristics, such as injury severity and stage of recovery (e.g., mild TBI in acute phase), opposed to combining individuals of different injury severity and time since injury, which would likely help elucidate potential group differences in the pattern and severity of driving difficulties. Employing matched-group designs to account for the effects of injury

characteristics (e.g., time since injury) and demographic factors (e.g., age, education), would aid in decreasing the impact of confounds.

Driving assessment research would also likely benefit from the examination of populations that previously have not received sufficient attention. Driving survey research in TBI populations has focused on individuals who resumed driving, even though approximately half of individuals who sustain a severe TBI no longer drive (76). The inclusion of nondrivers in research could provide insight into factors that influence the decision to resume driving (e.g., perceived driving ability, perceived cognitive functioning). Additionally, examination of how common comorbid conditions that can also negatively influence cognitive and daily functioning, such as depression and anxiety, influence driving ability and/or decision to resume driving following TBI could help identify difficulties that are mistakenly attributed to TBI.

Clinical Practice

Standard clinical practice regarding driving assessment typically relies on inferences about driving ability derived from neuropsychological evaluations, including cognitive testing and collateral report of functioning in various activities of daily living (e.g., paying bills, basic self-care). Assessment may also include an on-road driving test, and more recently, virtual reality driving simulation. However, most individuals do not receive any type of driving assessment following insult that could cause deficits in cognitive functioning and driving ability (e.g., TBI, stroke). Therefore, standard clinical practice guidelines should be developed that identify when an individual should have a formal driving assessment (e.g., four accidents in a one-year period), what domains should be assessed (e.g., cognitive and sensory functioning, motor skills, pain, sleep, psychiatric conditions), what measures should be included in the evaluation, and potential referral options to help address concerns (e.g., neurocognitive or motor

rehabilitation, social work, psychiatry, arrangements for assistive technology equipment).

Current assessment measures (cognitive testing, on-road and virtual driving evaluations) have limitations which impact their ability to assess driving fitness. Therefore, formal driving assessment should include a combination of these methods to provide a more robust assessment of driving ability. Recent research efforts, including the current study, have emphasized the use of novel assessment measures that may be more sensitive to subtle deficits and may better reflect the complexity of real-world driving. As the limitations of the methodology and measures are addressed, the impact of cognitive functioning on driving performance and the ability to better predict driving fitness will likely improve.

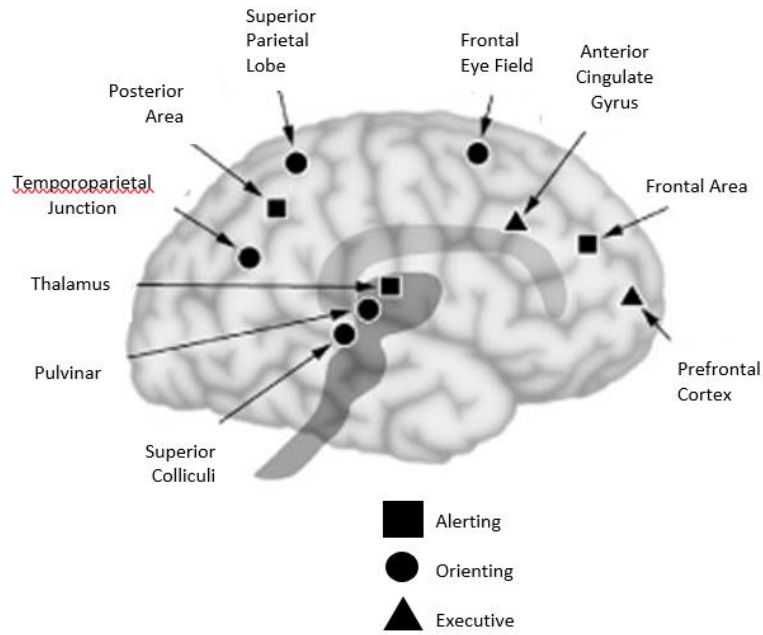


Figure 1. Schematic of attention networks by brain region. Figure adapted from (97).

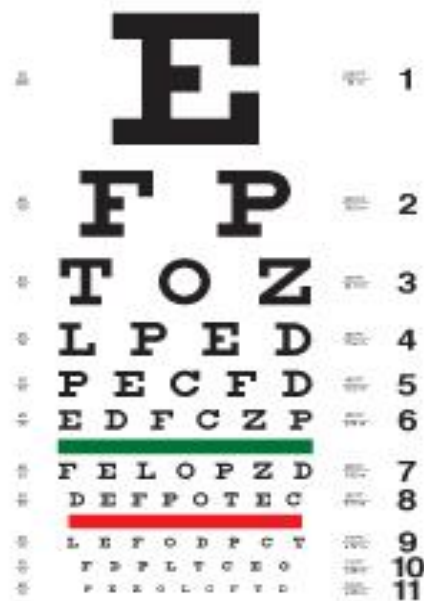


Figure 2. Snellen eye chart



Figure 3. T3 VRDS.

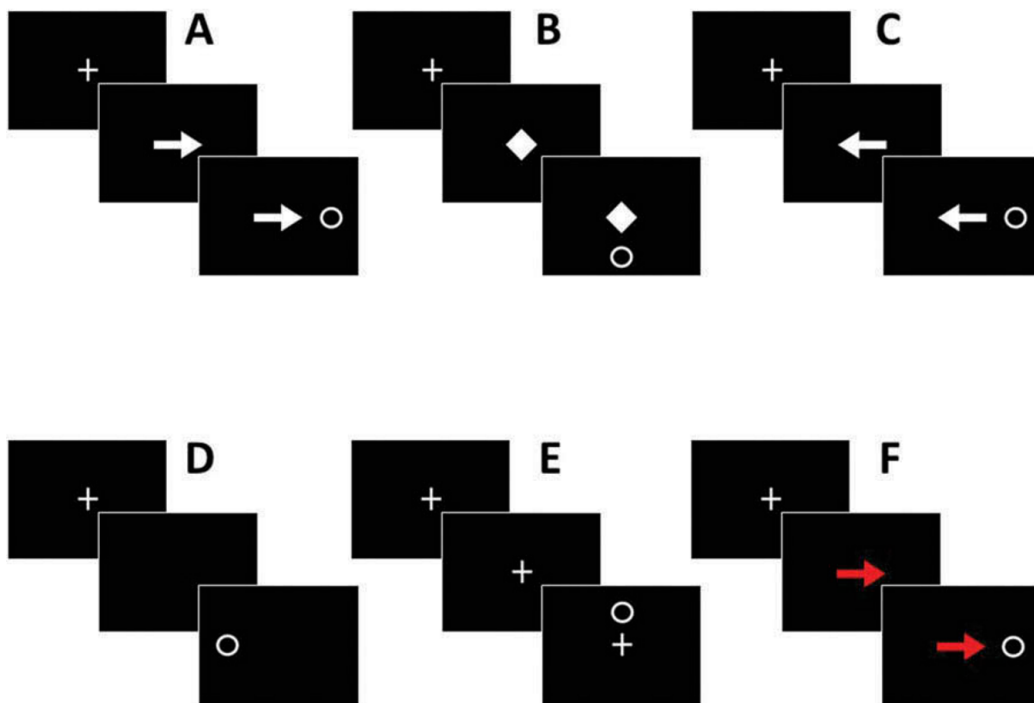


Figure 4. Bethesda Eye & Attention Measure v.34 (BEAM) example trials.
A = directional cue; B = nondirectional cue; C = misdirectional cue; D = gap cue;
E = uncued; F = no-go cue. Figure from (34).

<u>Operational Variables</u>	<u>Test-Retest correlations R values</u>	<u>Internal- Consistency</u>	<u>Between sites differences P values(Sig. Level)</u>
<u>Vision</u>			
<i>Static Visual Acuity</i>	a	NA	ns
<i>Contrast Sensitivity</i>	-.04	NA	.02*
<i>Dynamic Vision</i>	.84 **	NA	ns
<i>Peripheral Vision</i>	-.03	NA	ns
<u>Motor</u>			
<i>Arm/Hand Reaction Time</i>	.31*	.85**	ns
<i>Foot/Leg Reaction Time</i>	.56**	.96**	ns
<u>Cognitive</u>			
<i>Rapid Information Processing</i>	1.00**	NA	ns
<i>Divided Attention</i>	-.04	NA	ns
<i>Divided/Selective Attention</i>	.08	NA	.042*
<i>Dual Processing</i>	.35*	.82**	.006**
<i>Response Inhibition</i>	.17	.59*	.001**
<i>Working Memory</i>	.82**	1 sign = 1.00** 2 signs = .86** 3 signs = .81**	ns
Operational Driving Quotient	.49**	NA	ns

a. Cannot be computed because at least one of the variables is constant.
 *. Correlation is significant at the .05 level.
 **. Correlation is significant at the .01 level.
 ns. Mean difference is not significant.

Figure 5. Reliability of operational driving variables. From (79).

<u>Operational Variables</u>	<u>Test-Retest correlations R values</u>	<u>Between sites differences P values(Sig. Level)</u>
Speed Control		
<i>Tailgating</i>	.18	ns
<i>Speeding</i>	.68**	.046*
<i>Reckless Driving</i>	.8**	ns
<i>Acceleration Smoothness</i>	.94**	ns
Steering		
<i>Off Road Events</i>	a	ns
<i>Across Midline</i>	.58**	ns
<i>Swerving</i>	.83**	ns
<i>Time Off Road</i>	.29	ns
Braking		
<i>Rolling Stops</i>	-.04	ns
<i>Deceleration Smoothness</i>	.67**	.000**
<i>Crashes</i>	-.12	ns
<i>Bumps</i>	.49**	ns
Judgment		
<i>Driving Slow</i>	.38*	ns
<i>Lane Changes</i>	.53**	ns
Tactical Driving Quotient	.80**	ns
a. Cannot be computed because at least one of the variables is constant.		
*. Correlation is significant at the .05 level.		
**. Correlation is significant at the .01 level.		
ns. Mean difference is not significant.		

Figure 6. Reliability of tactical driving variables. From (79).

APPENDIX A.

Internet Driving Survey

Please answer the following questions about typical driving behavior over the past week. Remember, all answers will be kept confidential, and answering them will not affect your driving record in any way so please answer as honestly as possible. If you cannot remember the exact number, please make your best estimate.

1. How many hours have you driven in the past week?
 - a. I have not driven at all in the last week
 - b. Specify: ____
2. In the past week, how many times have you accidentally sat at a traffic light (red light) even after the signal turns green?
 - a. N/A - I have not driven at all in the last week
 - b. 0 times
 - c. 1 time
 - d. 2 times
 - e. 3 times
 - f. 4 times
 - g. More than 4 times (Specify a number: _____)
3. In the past week, how many times have you been pulled over by police for a traffic violation, regardless if you received a ticket or fine?
 - a. N/A - I have not driven at all in the last week
 - b. 0 times
 - c. 1 time
 - d. 2 times
 - e. 3 times
 - f. 4 times
 - g. More than 4 times (Specify a number: _____)
4. In the past week, how many times did you disregard a traffic sign or signal?
 - a. N/A - I have not driven at all in the last week
 - b. 0 times
 - c. 1 time
 - d. 2 times
 - e. 3 times
 - f. 4 times
 - g. More than 4 times (Specify a number: _____)
5. In the past week, how frequently has your mind wandered while driving?
 - a. N/A - I have not driven at all in the last week
 - b. Never

- c. Rarely
- d. Sometime
- e. Frequently
- f. Always

6. In the past week, how many times has your vehicle bumped or hit another vehicle, person, animal, or object while you were driving or parking? Please count all bumps/hits regardless of who was at fault.
 - a. N/A - I have not driven at all in the last week
 - b. 0 times
 - c. 1 time
 - d. 2 times
 - e. 3 times
 - f. 4 times
 - g. More than 4 times (Specify a number: _____)

7. In the past week, how many times did you drive 10 mph or more over the posted speed limit?
 - a. N/A - I have not driven at all in the last week
 - b. 0 times
 - c. 1 to 2 times
 - d. 3 to 4 times
 - e. 5 to 6 times
 - f. 7 to 8 times
 - g. More than 8 times (Specify a number: _____)

8. In the past week, how many times have you checked your phone while driving?
 - a. N/A - I have not driven at all in the last week
 - b. 0 times
 - c. 1 to 3 times
 - d. 4 to 6 times
 - e. 7 to 9 times
 - f. 10 to 11 times
 - g. More than 11 times (Specify a number: _____)

9. In the past week, how many times have you answered or made a phone call while driving?
 - a. N/A - I have not driven at all in the last week
 - b. 0 times
 - c. 1 to 2 times
 - d. 3 to 4 times
 - e. 5 to 6 times
 - f. 7 to 8 times
 - g. More than 8 times (Specify a number: _____)

10. In the past week, how many times have you answered or sent a text message while driving?
- a. N/A - I have not driven at all in the last week
 - b. 0 times
 - c. 1 to 2 times
 - d. 3 to 4 times
 - e. 5 to 6 times
 - f. 7 to 8 times
 - g. More than 8 times (Specify a number: _____)
11. In the past week, how many times have you experienced a near miss (almost bumped or hit another vehicle, person, animal, or object) while driving?
- a. N/A - I have not driven at all in the last week
 - b. 0 times
 - c. 1 time
 - d. 2 times
 - e. 3 times
 - f. 4 times
 - g. More than 4 times (Specify a number: _____)
12. In the past week, how many times have you become lost or disoriented while driving?
- a. N/A - I have not driven at all in the last week
 - b. 0 times
 - c. 1 to 2 times
 - d. 3 to 4 times
 - e. 5 to 6 times
 - f. 7 to 8 times
 - g. More than 8 times (Specify a number: _____)
13. In the past week, how many times did you find it difficult to judge when it was safe to pass a car or change lanes?
- a. N/A - I have not driven at all in the last week
 - b. 0 times
 - c. 1 to 2 times
 - d. 3 to 4 times
 - e. 5 to 6 times
 - f. 7 to 8 times
 - g. More than 8 times (Specify a number: _____)
14. In the past week, how many times have you cut off another driver (purposefully or accidentally)?
- a. N/A - I have not driven at all in the last week
 - b. 0 times
 - c. 1 time
 - d. 2 times
 - e. 3 times

- f. 4 times
- g. More than 4 times (Specify a number: _____)

15. In the past week, how many times have you arrived at your destination, and did not remember driving there?

- a. N/A - I have not driven at all in the last week
- b. 0 times
- c. 1 time
- d. 2 times
- e. 3 times
- f. 4 times
- g. More than 4 times (Specify a number: _____)

APPENDIX B.

Table 30. Impairment Index as Predictor of Operational Driving Quotient

	B	SE B	β	<i>p</i>
Step 1				
Constant	139.02 (115.29, 182.19)	15.01		.001
Age	-1.10 (-1.74, -0.61)	0.33	-.61	.009
Step 2				
Constant	138.87 (110.47, 191.41)	16.20		.001
Age	-1.08 (-1.73, -0.58)	0.34	-.60	.015
Impairment Index	-0.72 (-7.66, 5.91)	3.96	-.04	.861

Note. $R^2 = .371$ for Step 1 ($p = .001$); $\Delta R^2 = .001$ for Step 2 ($p = .844$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 31. Impairment Index as Predictor of Tactical Driving Quotient

	B	SE B	β	<i>p</i>
Step 1				
Constant	128.81 (98.11, 156.36)	14.44		.001
Age	-0.68 (-1.27, -0.04)	0.31	-.51	.050
Step 2				
Constant	127.74 (96.52, 152.18)	14.81		.001
Age	-0.74 (-1.41, 0.05)	0.34	-.55	.049
Impairment Index	3.80 (-3.25, 11.48)	3.46	.24	.255

Note. $R^2 = .258$ for Step 1 ($p = .022$); $\Delta R^2 = .057$ for Step 2 ($p = .250$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 32. Coefficients of Model for the Impairment Index as Predictor of Accidents

	B	95% CI for Odds Ratio		
		<i>Lower</i>	<i>Odds</i>	<i>Upper</i>
Constant	-1.57 (-23.26, 26.27)			
Age	0.03 (-5.97, 6.64)	0.96	1.03	1.11
Impairment	0.08 (-23.12, 20.18)	0.49	1.08	2.39

Note. $R^2 = .053$ (Cox & Snell), $.071$ (Nagelkerke). Model $\chi^2(2) = 1.082$, $p = .582$. Confidence Intervals for the unstandardized coefficient (reported in parentheses) are based on 1000 bootstrap samples. Odds Ratio information is from empirical analyses. Presented data are from final step of analysis.

Table 33. Impairment Index as Predictor of Difficulty Maintaining Speed

	B	SE B	β	<i>p</i>
Step 1				
Constant	11.58 (9.22, 13.18)	1.00		.001
Age	-0.05 (-0.08, 0.00)	0.02	-.44	.024
Step 2				
Constant	11.53 (9.11, 13.46)	1.06		.001
Age	-0.05 (-0.08, -0.01)	0.02	-.46	.013
Impairment Index	0.18 (-0.21, 0.53)	0.20	.15	.314

Note. $R^2 = .189$ for Step 1 ($p = .055$); $\Delta R^2 = .023$ for Step 2 ($p = .495$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 34. Impairment Index as Predictor of Tailgating

	B	SE B	β	<i>p</i>
Step 1				
Constant	3.27 (1.20, 6.02)	1.09		.017
Age	-0.01 (-0.05, 0.02)	0.02	-.17	.477
Step 2				
Constant	3.31 (1.03, 6.05)	1.19		.017
Age	-0.01 (-0.05, 0.03)	0.02	-.15	.546
Impairment Index	-0.12 (-0.41, 0.14)	0.18	-.13	.506

Note. $R^2 = .029$ for Step 1 ($p = .471$); $\Delta R^2 = .015$ for Step 2 ($p = .607$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 35. Impairment Index as Predictor of Swerving

	B	SE B	β	<i>p</i>
Step 1				
Constant	0.31 (0.25, 0.39)	0.03		.001
Age	0.00 (-0.001, 0.001)	0.001	.17	.490
Step 2				
Constant	0.31 (0.23, 0.41)	0.04		.001
Age	0.000 (-0.001, 0.001)	0.001	.16	.605
Impairment Index	0.002 (-0.02, 0.02)	0.01	.08	.796

Note. $R^2 = .028$ for Step 1 ($p = .479$); $\Delta R^2 = .006$ for Step 2 ($p = .754$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 36. Impairment Index as Predictor of Real-World Unsafe Driving Behaviors

	B	SE B	β	<i>p</i>
Step 1				
Constant	2.50 (0.36, 5.00)	1.11		.031
Age	-0.001 (-0.04, 0.04)	0.02	-.01	.976
Step 2				
Constant	2.33 (-0.63, 4.83)	1.25		.070
Age	0.01 (-0.03, 0.08)	0.03	.10	.672
Impairment Index	-0.33 (-1.31, 0.39)	0.38	-.25	.353

Note. $R^2 = .000$ for Step 1 ($p = .979$); $\Delta R^2 = .052$ for Step 2 ($p = .336$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 37. TMT-B as Predictor of Operational Driving Quotient

	B	SE B	β	<i>p</i>
Step 1				
Constant	133.59 (113.96, 171.36)	13.55		.001
Age	-0.91 (-1.65, -0.48)	0.30	-.52	.014
Step 2				
Constant	94.12 (52.29, 126.99)	23.00		.005
Age	-0.80 (-1.65, -0.02)	0.25	-.46	.012
TMT-B	0.69 (-0.10, 1.54)	0.34	.38	.070

Note. $R^2 = .271$ for Step 1 ($p = .006$); $\Delta R^2 = .139$ for Step 2 ($p = .029$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 38. TMT-B as Predictor of Tactical Driving Quotient

	B	SE B	β	<i>p</i>
Step 1				
Constant	128.86 (89.98, 157.12)	17.32		.001
Age	-0.62 (-1.31, 0.26)	0.36	-.43	.126
Step 2				
Constant	113.57 (54.66, 150.84)	21.63		.001
Age	-0.63 (-1.28, 0.57)	0.36	-.44	.146
TMT-B	0.33 (-0.48, 0.96)	0.46	.19	.590

Note. $R^2 = .185$ for Step 1 ($p = .051$); $\Delta R^2 = .037$ for Step 2 ($p = .364$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 39. Coefficients of Model for TMT-B as Predictor of Accidents

	B	95% CI for Odds Ratio		
		<i>Lower</i>	<i>Odds</i>	<i>Upper</i>
Constant	-1.44 (-9.11, 3.92)			
Age	0.03 (-0.52, 5.90)	0.95	1.03	1.11
TMT-B	-0.02 (-0.15, 0.10)	0.90	0.98	1.07

Note. $R^2 = .026$ (Cox & Snell), .037 (Nagelkerke). Model $\chi^2(2) = .556$, $p = .757$. Confidence Intervals for the unstandardized coefficient (reported in parentheses) are based on 1000 bootstrap samples. Odds Ratio information is from empirical analyses. Presented data are from final step of analysis.

Table 40. TMT-B as Predictor of Difficulty Maintaining Speed

	B	SE B	β	p
Step 1				
Constant	10.84 (7.91, 12.77)	1.23		.001
Age	-0.03 (-0.07, 0.02)	0.02	-.28	.170
Step 2				
Constant	10.33 (5.91, 13.29)	1.84		.001
Age	-0.03 (-0.07, 0.04)	0.02	-.28	.193
TMT-B	0.01 (-0.05, 0.06)	0.03	.09	.601

Note. $R^2 = .078$ for Step 1 ($p = .220$); $\Delta R^2 = .007$ for Step 2 ($p = .707$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 41. TMT-B as Predictor of Swerving

	B	SE B	β	p
Step 1				
Constant	0.29 (0.23, 0.37)	0.03		.001
Age	0.001 (-0.001, 0.002)	0.001	.30	.164
Step 2				
Constant	0.28 (0.21, 0.39)	0.05		.001
Age	0.001 (-0.001, 0.002)	0.001	.29	.181
TMT-B	0.000 (-0.001, 0.001)	0.001	.07	.669

Note. $R^2 = .087$ for Step 1 ($p = .195$); $\Delta R^2 = .005$ for Step 2 ($p = .751$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 42. TMT-B as Predictor of Tailgating

	B	SE B	β	<i>p</i>
Step 1				
Constant	3.14 (1.18, 6.23)	1.26		.014
Age	-0.02 (-0.07, 0.02)	0.02	-.16	.513
Step 2				
Constant	2.04 (-0.63, 4.62)	1.65		.202
Age	-0.02 (-0.07, 0.02)	0.02	-.17	.521
TMT-B	0.02 (-0.02, 0.10)	0.03	.21	.314

Note. $R^2 = .026$ for Step 1 ($p = .485$); $\Delta R^2 = .046$ for Step 2 ($p = .359$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 43. TMT-B as Predictor of Real-World Unsafe Driving Behaviors

	B	SE B	β	<i>p</i>
Step 1				
Constant	2.81 (0.92, 6.10)	1.21		.026
Age	-0.01 (-0.05, 0.03)	0.02	-.04	.801
Step 2				
Constant	0.60 (-2.12, 4.79)	1.76		.696
Age	-0.004 (-0.05, 0.03)	0.02	-.03	.874
TMT-B	0.04 (-0.03, 0.09)	0.03	.31	.122

Note. $R^2 = .002$ for Step 1 ($p = .847$); $\Delta R^2 = .094$ for Step 2 ($p = .176$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 44. Difficulty Maintaining Speed as Predictor of Real-World Unsafe Driving Behaviors

	B	SE B	β	p
Step 1				
Constant	2.73 (0.86, 5.38)	0.99		.012
Age	-0.01 (-0.05, 0.03)	0.02	-.09	.589
Step 2				
Constant	0.99 (-5.33, 5.50)	2.96		.717
Age	-0.004 (-0.05, 0.05)	0.02	-.04	.846
Speed	0.16 (-0.34, 0.79)	0.25	.16	.533

Note. $R^2 = .008$ for Step 1 ($p = .700$); $\Delta R^2 = .022$ for Step 2 ($p = .545$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 45. Swerving as Predictor of Real-World Unsafe Driving Behaviors

	B	SE B	β	p
Step 1				
Constant	2.74 (1.29, 4.62)	0.97		.007
Age	-0.01 (-0.05, 0.04)	0.02	-.09	.590
Step 2				
Constant	8.19 (2.55, 15.51)	3.56		.037
Age	0.01 (-0.04, 0.05)	0.02	.09	.652
Swerving	-19.15 (-43.74, 3.15)	12.03	-.46	.147

Note. $R^2 = .008$ for Step 1 ($p = .700$); $\Delta R^2 = .176$ for Step 2 ($p = .072$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 46. Tailgating as Predictor of Real-World Unsafe Driving Behaviors

	B	SE B	β	p
Step 1				
Constant	2.73 (1.16, 4.81)	0.95		.013
Age	-0.01 (-0.05, 0.03)	0.02	-.09	.604
Step 2				
Constant	3.26 (-0.08, 7.98)	1.63		.063
Age	-0.01 (-0.06, 0.02)	0.02	-.13	.560
Tailgating	-0.15 (-0.58, 0.27)	0.27	-.11	.567

Note. $R^2 = .008$ for Step 1 ($p = .700$); $\Delta R^2 = .011$ for Step 2 ($p = .666$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 47. Difficulty Maintaining Speed as Predictor of Real-World Accidents

	B	SE B	β	p
Step 1				
Constant	5.35 (-0.26, 11.23)	2.84		.096
Age	-0.03 (-0.14, 0.09)	0.06	-.14	.682
Step 2				
Constant	-0.39 (-40.36, 17.94)	17.91		.984
Age	-0.01 (-0.21, 0.24)	0.10	-.04	.947
Speed	0.48 (-1.27, 5.19)	1.42	.19	.711

Note. $R^2 = .020$ for Step 1 ($p = .619$); $\Delta R^2 = .027$ for Step 2 ($p = .573$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 48. Swerving as Predictor of Real-World Accidents

	B	SE B	β	p
Step 1				
Constant	5.35 (-0.46, 11.70)	2.89		.096
Age	-0.03 (-0.14, 0.08)	0.07	-.14	.657
Step 2				
Constant	0.19 (-17.69, 15.89)	8.51		.984
Age	-0.04 (-0.16, 0.08)	0.07	-.18	.619
Swerving	16.64 (-28.87, 80.60)	27.79	.22	.558

Note. $R^2 = .020$ for Step 1 ($p = .619$); $\Delta R^2 = .045$ for Step 2 ($p = .462$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 49. Tailgating as Predictor of Real-World Accidents

	B	SE B	β	p
Step 1				
Constant	5.35 (-0.22, 11.14)	2.79		.080
Age	-0.03 (-0.14, 0.08)	0.06	-.14	.668
Step 2				
Constant	11.35 (1.88, 17.75)	4.09		.018
Age	-0.07 (-0.17, 0.06)	0.06	-.32	.349
Tailgating	-1.42 (-2.92, 1.35)	0.84	-.45	.087

Note. $R^2 = .020$ for Step 1 ($p = .619$); $\Delta R^2 = .168$ for Step 2 ($p = .142$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 50. Difficulty Maintaining Speed as Predictor of Real-World Speeding

	B	SE B	β	<i>p</i>
Step 1				
Constant	32.95 (17.90, 51.26)	8.54		.016
Age	-0.37 (-0.72, -0.07)	0.18	-.52	.064
Step 2				
Constant	1.55 (-111.48, 50.74)	48.89		.974
Age	-0.25 (-0.76, 0.41)	0.26	-.36	.346
Speed	2.64 (-1.79, 13.31)	3.85	.31	.461

Note. $R^2 = .268$ for Step 1 ($p = .048$); $\Delta R^2 = .070$ for Step 2 ($p = .282$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 51. Swerving as Predictor of Real-World Speeding

	B	SE B	β	<i>p</i>
Step 1				
Constant	32.95 (12.76, 58.95)	9.02		.016
Age	-0.37 (-0.73, -0.09)	0.19	-.52	.086
Step 2				
Constant	19.27 (-26.02, 74.47)	28.54		.566
Age	-0.39 (-0.71, -0.15)	0.21	-.55	.161
Swerving	44.14 (-144.05, 234.48)	95.72	.17	.703

Note. $R^2 = .268$ for Step 1 ($p = .048$); $\Delta R^2 = .028$ for Step 2 ($p = .506$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 52. Tailgating as Predictor of Real-World Speeding

	B	SE B	β	<i>p</i>
Step 1				
Constant	32.95 (15.09, 54.68)	8.84		.015
Age	-0.37 (-0.74, -0.09)	0.18	-.52	.066
Step 2				
Constant	54.00 (5.37, 86.00)	14.55		.006
Age	-0.50 (-0.85, -0.22)	0.19	-.71	.038
Tailgating	-4.99 (-9.14, 3.28)	3.05	-.46	.115

Note. $R^2 = .268$ for Step 1 ($p = .048$); $\Delta R^2 = .179$ for Step 2 ($p = .072$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 53. TBI Severity as Predictor of Operational Driving Quotient

	B	SE B	β	<i>p</i>
Step 1				
Constant	130.96 (108.38, 164.53)	12.43		.001
Age	-0.90 (-1.46, -0.44)	0.28	-.53	.012
Step 2				
Constant	131.75 (109.72, 164.69)	12.49		.001
Age	-0.86 (-1.43, -0.42)	0.28	-.51	.014
TBI Severity	-6.28 (-24.20, 11.29)	8.03	-.14	.457

Note. $R^2 = .285$ for Step 1 ($p = .003$); $\Delta R^2 = .018$ for Step 2 ($p = .421$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 54. TBI Severity as Predictor of Tactical Driving Quotient

	B	SE B	β	<i>p</i>
Step 1				
Constant	125.63 (101.72, 146.51)	12.45		.001
Age	-0.56 (-1.11, 0.06)	0.26	-.43	.062
Step 2				
Constant	126.15 (102.35, 147.00)	12.40		.001
Age	-0.53 (-1.05, 0.14)	0.28	-.41	.101
TBI Severity	-4.47 (-18.86, 09.62)	7.03	-.13	.530

Note. $R^2 = .187$ for Step 1 ($p = .035$); $\Delta R^2 = .015$ for Step 2 ($p = .391$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 55. Coefficients of Model for TBI Severity as Predictor of Accidents

	B	95% CI for Odds Ratio		
		<i>Lower</i>	<i>Odds</i>	<i>Upper</i>
Constant	-1.80 (-5.72, 0.76)			
Age	0.02 (-0.10, 0.19)	0.96	1.02	1.09
TBI Severity	-0.13 (-3.16, 2.29)	0.15	0.88	5.05

Note. $R^2 = .021$ (Cox & Snell), .030 (Nagelkerke). Model $\chi^2(2) = .516$, $p = .773$. Confidence Intervals for the unstandardized coefficient (reported in parentheses) are based on 1000 bootstrap samples. Odds Ratio information is from empirical analyses. Presented data are from final step of analysis.

Table 56. TBI Severity as Predictor of Tailgating

	B	SE B	β	<i>p</i>
Step 1				
Constant	3.57 (1.55, 6.20)	1.03		.002
Age	-0.02 (-0.06, 0.01)	0.02	-.26	.240
Step 2				
Constant	3.52 (1.68, 5.98)	1.04		.002
Age	-0.03 (-0.07, 0.01)	0.02	-.30	.206
TBI Severity	0.40 (-0.47, 1.26)	0.50	.17	.425

Note. $R^2 = .068$ for Step 1 ($p = .220$); $\Delta R^2 = .027$ for Step 2 ($p = .437$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 57. TBI Severity as Predictor of Difficulty Maintaining Speed

	B	SE B	β	<i>p</i>
Step 1				
Constant	11.26 (8.36, 13.01)	0.95		.001
Age	-0.04 (-0.06, -0.01)	0.02	-.38	.030
Step 2				
Constant	11.24 (8.29, 13.20)	0.99		.001
Age	-0.04 (-0.07, -0.01)	0.02	-.39	.029
TBI Severity	0.14 (-0.96, 1.34)	0.56	.05	.794

Note. $R^2 = .142$ for Step 1 ($p = .070$); $\Delta R^2 = .003$ for Step 2 ($p = .802$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 58. TBI Severity as Predictor of Swerving

	B	SE B	β	<i>p</i>
Step 1				
Constant	0.30 (0.24, 0.37)	0.03		.001
Age	0.001 (0.000, 0.001)	0.001	.25	.225
Step 2				
Constant	0.30 (0.24, 0.36)	0.03		.001
Age	0.000 (-0.001, 0.001)	0.001	.16	.473
TBI Severity	0.03 (-0.01, 0.06)	0.02	.39	.109

Note. $R^2 = .060$ for Step 1 ($p = .248$); $\Delta R^2 = .148$ for Step 2 ($p = .060$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 59. TBI Severity as Predictor of Real-World Unsafe Driving Behaviors

	B	SE B	β	<i>p</i>
Step 1				
Constant	2.86 (1.08, 5.34)	1.00		.015
Age	-0.01 (-0.05, 0.02)	0.02	-.08	.672
Step 2				
Constant	2.94 (1.19, 5.38)	1.04		.012
Age	-0.004 (-0.05, 0.04)	0.02	-.03	.875
TBI Severity	-0.84 (-2.10, 0.34)	0.65	-.27	.205

Note. $R^2 = .006$ for Step 1 ($p = .722$); $\Delta R^2 = .072$ for Step 2 ($p = .204$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap sample.

Table 60. Nondirectional Cue as Predictor of Operational Driving Quotient

	B	SE B	β	<i>p</i>
Step 1				
Constant	139.02 (113.56, 176.15)	14.40		.001
Age	-1.10 (-1.75, -0.59)	0.32	-.61	.007
Step 2				
Constant	149.57 (93.55, 210.49)	27.16		.001
Age	-1.04 (-1.66, -0.51)	0.34	-.58	.011
NDC	-0.36 (-1.63, 1.21)	0.75	-.09	.585

Note. $R^2 = .371$ for Step 1 ($p = .001$); $\Delta R^2 = .006$ for Step 2 ($p = .643$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 61. Directional Cue as Predictor of Operational Driving Quotient

	B	SE B	β	<i>p</i>
Step 1				
Constant	139.02 (110.63, 178.03)	14.90		.001
Age	-1.10 (-1.68, -0.64)	0.33	-.61	.007
Step 2				
Constant	160.56 (111.41, 205.06)	21.61		.001
Age	-0.94 (-1.61, -0.38)	0.35	-.52	.021
DC	-0.85 (-2.01, 0.62)	0.61	-.24	.159

Note. $R^2 = .371$ for Step 1 ($p = .001$); $\Delta R^2 = .050$ for Step 2 ($p = .183$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 62. Misdirectional Cue as Predictor of Operational Driving Quotient

	B	SE B	β	<i>p</i>
Step 1				
Constant	139.02 (112.23, 176.95)	14.91		.001
Age	-1.10 (-1.79, -0.56)	0.33	-.61	.007
Step 2				
Constant	143.39 (92.22, 208.55)	26.86		.001
Age	-1.08 (-1.79, -0.49)	0.34	-.60	.011
MDC	-0.14 (-1.29, 1.02)	0.58	-.04	.820

Note. $R^2 = .371$ for Step 1 ($p = .001$); $\Delta R^2 = .001$ for Step 2 ($p = .830$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 63. Nondirectional Cue as Predictor of Tactical Driving Quotient

	B	SE B	β	<i>p</i>
Step 1				
Constant	128.81 (102.03, 151.40)	14.44		.001
Age	-0.68 (-1.42, 0.09)	0.31	-.51	.060
Step 2				
Constant	109.74 (59.74, 145.55)	19.97		.001
Age	-0.75 (-1.53, 0.54)	0.33	-.55	.062
NDC	0.61 (-0.13, 1.33)	0.49	.19	.195

Note. $R^2 = .258$ for Step 1 ($p = .022$); $\Delta R^2 = .035$ for Step 2 ($p = .374$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 64. Directional Cue as Predictor of Tactical Driving Quotient

	B	SE B	β	<i>p</i>
Step 1				
Constant	128.81 (101.40, 153.72)	14.72		.001
Age	-0.68 (-1.28, 0.08)	0.31	-.51	.047
Step 2				
Constant	119.99 (77.98, 153.40)	18.93		.001
Age	-0.72 (-1.40, 0.13)	0.35	-.54	.062
DC	0.31 (-0.54, 1.26)	0.54	.11	.500

Note. $R^2 = .258$ for Step 1 ($p = .022$); $\Delta R^2 = .011$ for Step 2 ($p = .626$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 65. Misdirectional Cue as Predictor of Tactical Driving Quotient

	B	SE B	β	<i>p</i>
Step 1				
Constant	128.81 (101.24, 151.89)	14.45		.001
Age	-0.68 (-1.30, 0.10)	0.31	-.51	.059
Step 2				
Constant	121.55 (92.49, 143.53)	15.21		.002
Age	-0.71 (-1.43, 0.18)	0.36	-.53	.086
MDC	0.22 (-0.92, 1.32)	0.47	.09	.648

Note. $R^2 = .258$ for Step 1 ($p = .022$); $\Delta R^2 = .007$ for Step 2 ($p = .693$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 66. Coefficients of Model for Nondirectional Cue as Predictor of Accidents

	B	95% CI for Odds Ratio		
		<i>Lower</i>	<i>Odds</i>	<i>Upper</i>
Constant	-3.25 (-13.86, 4.87)			
Age	0.03 (-0.06, 0.13)	0.96	1.03	1.11
NDC	0.04 (-0.27, 1.68)	0.88	1.04	1.22

Note. $R^2 = .059$ (Cox & Snell), .080 (Nagelkerke). Model $\chi^2(2) = 1.22$, $p = .543$. Confidence Intervals for the unstandardized coefficient (reported in parentheses) are based on 1000 bootstrap samples. Odds Ratio information is from empirical analyses. Presented data are from final step of analysis.

Table 67. Coefficients of Model for Directional Cue as Predictor of Accidents

	B	95% CI for Odds Ratio		
		<i>Lower</i>	<i>Odds</i>	<i>Upper</i>
Constant	-3.47 (-11.53, 2.05)			
Age	0.03 (-0.08, 0.20)	0.96	1.03	1.11
DC	0.05 (-0.18, 3.76)	0.90	1.05	1.22

Note. $R^2 = .068$ (Cox & Snell), .092 (Nagelkerke). Model $\chi^2(2) = 1.416$, $p = .493$. Confidence Intervals for the unstandardized coefficient (reported in parentheses) are based on 1000 bootstrap samples. Odds Ratio information is from empirical analyses. Presented data are from final step of analysis.

Table 68. Coefficients of Model for Misdirectional Cue as Predictor of Accidents

	B	95% CI for Odds Ratio		
		<i>Lower</i>	<i>Odds</i>	<i>Upper</i>
Constant	-5.45 (-12.89, -1.31)			
Age	0.03 (-3.90, 7.29)	0.95	1.03	1.10
MDC	0.10 (-0.07, 4.84)	0.96	1.10	1.27

Note. $R^2 = .136$ (Cox & Snell), .185 (Nagelkerke). Model $\chi^2(2) = 2.935$, $p = .231$. Confidence Intervals for the unstandardized coefficient (reported in parentheses) are based on 1000 bootstrap samples. Odds Ratio information is from empirical analyses. Presented data are from final step of analysis.

Table 69. Nondirectional Cue as Predictor of Difficulty Maintaining Speed

	B	SE B	β	<i>p</i>
Step 1				
Constant	11.58 (9.25, 13.27)	0.98		.001
Age	-0.05 (-0.80, -0.001)	0.02	-.44	.015
Step 2				
Constant	11.22 (5.82, 14.84)	2.18		.001
Age	-0.05 (-0.09, -0.003)	0.19	-.45	.020
NDC	0.01 (-0.08, 0.13)	0.06	.05	.844

Note. $R^2 = .189$ for Step 1 ($p = .055$); $\Delta R^2 = .002$ for Step 2 ($p = .834$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 70. Directional Cue as Predictor of Tailgating

	B	SE B	β	<i>p</i>
Step 1				
Constant	3.27 (1.00, 6.04)	1.08		.013
Age	-0.01 (-0.05, 0.02)	0.02	-.17	.454
Step 2				
Constant	3.28 (0.52, 6.89)	1.70		.083
Age	-0.01 (-0.05, 0.02)	0.02	-.17	.448
NDC	0.000 (-0.08, 0.08)	0.04	-.001	.992

Note. $R^2 = .029$ for Step 1 ($p = .471$); $\Delta R^2 = .000$ for Step 2 ($p = .996$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 71. Directional Cue as Predictor of Difficulty Maintaining Speed

	B	SE B	β	<i>p</i>
Step 1				
Constant	11.58 (8.72, 13.82)	1.03		.001
Age	-0.05 (-0.08, -0.13)	0.02	-.44	.029
Step 2				
Constant	13.03 (9.14, 17.53)	1.87		.002
Age	-0.04 (-0.08, 0.01)	0.02	-.37	.099
DC	-0.05 (-0.15, 0.03)	0.05	-.23	.322

Note. $R^2 = .189$ for Step 1 ($p = .055$); $\Delta R^2 = .048$ for Step 2 ($p = .313$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 72. Directional Cue as Predictor of Swerving

	B	SE B	β	<i>p</i>
Step 1				
Constant	0.31 (0.25, 0.39)	0.03		.001
Age	0.000 (-0.001, 0.001)	0.001	.17	.469
Step 2				
Constant	0.30 (0.19, 0.43)	0.05		.001
Age	0.00 (-0.001, -0.001)	0.001	.15	.553
DC	0.00 (-0.003, 0.003)	0.001	.05	.795

Note. $R^2 = .028$ for Step 1 ($p = .479$); $\Delta R^2 = .003$ for Step 2 ($p = .836$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 73. Misdirectional Cue as Predictor of Difficulty Maintaining Speed

	B	SE B	β	<i>p</i>
Step 1				
Constant	11.58 (8.86, 13.32)	1.04		.001
Age	-0.05 (-0.08, -0.01)	0.02	-.44	.021
Step 2				
Constant	11.29 (6.81, 14.93)	2.12		.001
Age	-0.05 (-0.08, -0.01)	0.02	-.45	.019
MDC	0.01 (-0.08, 0.11)	0.04	.05	.817

Note. $R^2 = .189$ for Step 1 ($p = .055$); $\Delta R^2 = .002$ for Step 2 ($p = .845$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 74. Misdirectional Cue as Predictor of Tailgating

	B	SE B	β	<i>p</i>
Step 1				
Constant	3.27 (1.17, 5.51)	1.06		.008
Age	-0.01 (-0.05, 0.02)	0.02	-.17	.467
Step 2				
Constant	2.36 (-0.87, 5.60)	1.69		.173
Age	-0.02 (-0.06, 0.02)	0.02	-.22	.384
MDC	0.03 (-0.05, 0.13)	0.04	.18	.437

Note. $R^2 = .029$ for Step 1 ($p = .471$); $\Delta R^2 = .030$ for Step 2 ($p = .469$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 75. Nondirectional Cue as Predictor of Real-World Unsafe Driving Behaviors

	B	SE B	β	<i>p</i>
Step 1				
Constant	2.50 (0.18, 5.48)	1.20		.039
Age	-0.001 (-0.04, 0.04)	0.03	-.01	.976
Step 2				
Constant	3.63 (-1.23, 9.70)	2.83		.247
Age	0.01 (-0.04, 0.06)	0.03	.06	.823
NDC	-0.04 (-0.22, 0.12)	0.09	-.16	.654

Note. $R^2 = .000$ for Step 1 ($p = .979$); $\Delta R^2 = .020$ for Step 2 ($p = .552$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 76. Directional Cue as Predictor of Real-World Unsafe Driving Behaviors

	B	SE B	β	<i>p</i>
Step 1				
Constant	2.50 (0.61, 4.61)	1.12		.030
Age	-0.001 (-0.04, 0.05)	0.03	-.01	.978
Step 2				
Constant	4.88 (1.52, 8.38)	1.81		.013
Age	0.02 (-0.03, 0.08)	0.03	.21	.392
DC	-0.10 (-0.21, 0.01)	0.06	-.46	.112

Note. $R^2 = .000$ for Step 1 ($p = .979$); $\Delta R^2 = .171$ for Step 2 ($p = .070$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

Table 77. Misdirectional Cue as Predictor of Real-World Unsafe Driving Behaviors

	B	SE B	β	<i>p</i>
Step 1				
Constant	2.50 (0.36, 5.40)	1.12		.039
Age	-0.001 (-0.05, 0.04)	0.02	-.01	.972
Step 2				
Constant	5.17 (0.51, 10.22)	2.24		.045
Age	0.02 (-0.03, 0.07)	0.03	.16	.514
MDC	-0.09 (-0.20, 0.04)	0.06	-.41	.166

Note. $R^2 = .000$ for Step 1 ($p = .979$); $\Delta R^2 = .143$ for Step 2 ($p = .100$). Confidence Intervals reported in parentheses. Confidence intervals, standard errors, and p -values are based on 1000 bootstrap samples.

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