The Pennsylvania State University

The Graduate School

College of Health and Human Development

# CHARACTERISTICS AND PREDICTORS OF DISTRACTED DRIVING BEHAVIORS IN OLDER ADULTS

A Thesis in

Human Development and Family Studies

by

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Submitted in Partial Fulfillment

of the Requirements

for the Degree of

Master of Science

August 2018

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**ABSTRACT**

Distracted driving is a major public health concern, increasing the risk of motor vehicle crashes that can result in injury or death. Despite research indicating that older adults engage in distracted driving behaviors, there is limited work characterizing distracted driving and its predictors in older adults. The majority of research on older adult driving behavior has utilized insufficient methods to understand the nature of distracted driving behavior. The use of multiple assessments of driving behavior is needed to examine day-to-day variations in driving behavior, allowing for more accurate and specific assessments of driving. The current study examined the variability of and predictors of objectively-assessed older adult distracted driving in a naturalistic study of healthy older adults in the Senior and Adolescent Naturalistic Driving Study. Participants (N=72) were between 65 and 85 years of age (*M*=72.29, SD=5.36) and 56% were women. The majority of older adults did not engage in distracted driving behaviors during the study, and participants who did engage in them did so infrequently. The most common distracted driving behaviors were interacting with a cell phone, reaching, and grooming. Multilevel models predicting distracted driving behavior across trips revealed that better physical function significantly predicted more grooming during a trip. Multilevel models predicting distracted driving behavior within a trip revealed that men were more likely to interact with a cell phone during a trip than women. The results of this study highlight the importance of studying variability in distracted driving. Future studies should examine within-trip and within-person predictors of distracted driving such as driving environment or daily cognition.

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# ACKNOWLEDGEMENTS

This work was made possible due to the financial support provided by the University of Alabama at Birmingham Faculty Development Grant Program, Southeastern Transportation Research, Innovation, Development & Education Center (STRIDE), Alabama Department of Transportation, and the UAB Roybal Center for Translational Research on Aging and Mobility. This work could not have been done without the efforts of research participants and staff involved in the Senior and Adolescent Naturalistic Driving Study.

I would like to thank my primary adviser, Dr. Lesley Ross, who worked closely with me on this project and provided invaluable support during every step of this project. I would also like to thank Dr. Alyssa Gamaldo, my second committee member, for her valuable insights and support.

## Introduction

Distracted driving is a major public health concern. In 2015, 391,000 people were injured as a result of motor vehicle crashes involving distracted drivers (National Highway Traffic Safety Administration, 2017a). In addition to national datasets, experimental studies have also demonstrated the link between distracted driving and driving safety (Atchley, Tran, & Salehinejad, 2017; Caird, Johnston, Willness, & Asbridge, 2014; Ferdinand & Menachemi, 2014; Oviedo-Trespalacios, Haque, King, & Washington, 2016). Though it is commonly discussed as a problem of young adult drivers, distracted driving is a problem for older adults as well. In fact, recent large observational studies have indicated that older adults engage in distracted driving behaviors such as talking on a cell phone (National Highway Traffic Safety Administration, 2016). Though older adults engage in distracted driving behaviors less frequently than other age groups, distracted driving may be a greater problem for older adults, whose driving behavior may be more vulnerable to distractions while driving due to declines in cognition, vision, and physical function. Despite older adults' potential vulnerability to the effects of distracted driving, little research has been done on the role of age-related declines in physical, cognitive, and visual function in distracted driving. Further, naturalistic studies of older adult driving to date have not assessed variability in distracted driving, which may be vital to understanding specific contexts in which distracted driving occurs.

The National Highway Traffic Safety Administration (NHTSA) has identified distracted driving behavior as a significant safety problem and identified a need for improved understanding of the nature of driver distraction (National Highway Traffic Safety Administration, 2010). However, the majority of research on older adult driving behavior has utilized insufficient methods to understand the nature of distracted driving behavior. Methods such as self-report, driving simulator, and experimental test drives are unable to capture older adult driving behavior as it occurs in a naturalistic setting. Additionally, distracted driving research in older adults frequently includes only one-time assessments. The use of multiple assessments of driving behavior is needed to examine day to day variations in driving behavior, allowing for more accurate and specific assessments of driving and circumstances around driving. The primary aim of this research study is to examine the variability of and predictors of older adult distracted driving in a unique naturalistic dataset that combines video data of participant behavior in-vehicle and detailed baseline and post-test assessments of function in a sample of healthy older adults.

## Literature Review

**Distracted driving behavior.** Distracted driving behavior occurs when a person's attention is averted from fundamental driving tasks due to a competing activity (Regan, Hallett, & Gordon, 2011). Distracted driving behavior can take many forms as long as the implicit assumption is that the behavior is taking attention away from fundamental driving tasks. The National Highway Traffic Safety Administration (NHTSA) identifies three types of distracted driving: *visual distraction*, which requires the driver to look away from the road; *manual distraction*, which requires the driver to take a hand off the steering wheel; and *cognitive distraction*, which involves thinking about something other than driving (National Highway Traffic Safety Administration, 2010). Cognitive distraction is similar to driving inattention, which results from fatigue and other physical and emotional conditions of the driver (Regan et al., 2011). Cognitive distraction and inattention are more difficult to assess objectively than visual and manual distraction because they are defined by internal conditions of the driver rather than outward behavior. As a result, most research on distracted driving does not include cognitive distraction or inattention as measures of distracted driving.

A common element of distracted driving definitions is that the behavior impacts the ability to drive safely (Regan et al., 2011). State crash records support this link between driver distraction and safety outcomes: In 2015, distracted driving was involved in 10% of all fatal crashes and 15% of all injury crashes (National Highway Traffic Safety Administration, 2017a). Cell phone use is a common distracted driving behavior linked to driving safety, accounting for 14% of fatal distraction-involved crashes in 2015 (National Highway Traffic Safety Administration, 2017a). However, distracted driving behavior can take many forms, including eating, drinking, and adjusting the radio. Distracted driving is also not just a problem for young adults: in 2015, 17% of distracted drivers involved in fatal crashes were adults 60 years and older (National Highway Traffic Safety Administration, 2017a). In addition to state crash records, research on prevalence of distracted driving behaviors among older adults has also been conducted through self-report and observational methods.

*Self-report methods of assessing distracted driving.* The majority of research on older adult distracted driving behavior is conducted via self-report methods. Older adults report engaging in a variety of distracted driving behaviors, including using a mobile phone (Young & Lenné, 2010), listening to music (Young & Lenné, 2010), interacting with passengers (Fofanova & Vollrath, 2012; Young & Lenné, 2010), using an in-car device (adjusting controls/operating the radio/adjusting seatbelt; Fofanova & Vollrath, 2012; Young & Lenné, 2010), eating or drinking (Fofanova & Vollrath, 2012; Young & Lenné, 2010), or smoking (Fofanova & Vollrath, 2012). Self-report is widely used to assess a variety of driving behaviors, including frequency, mileage, and engagement in or avoidance of specific behaviors such as driving at night or making left-hand turns. However, self-reported measures of driving behavior do not always correspond to actual driving behavior. Blanchard and colleagues conducted a study to determine the correspondence between self-reported and objective driving behavior in a sample of 61 older drivers in Canada (2010). The authors compared self-reported driving behavior via questionnaires and activity diaries with objective data from two in-vehicle devices. The authors found agreement between self-reported and objective measures for some driving behaviors, such as driving in the evening and at night, but disagreement for other driving behaviors, including avoiding left-hand turns and avoiding driving in rush hour. Participants also misestimated their time spent driving and weekly driving distance. Many participants did not attempt to estimate weekly distance, suggesting that self-report of driving distance may be too difficult or burdensome. Staplin and colleagues also examined the correspondence between self-reported and objective driving data across several data sources (2008). Across studies, they found discrepancies among self-reported driving mileage in participants who participated in two studies, miles driven per week and annual mileage, and self-reported driving mileage and objectively assessed driving mileage via GPS. The authors identified a pattern in misestimating driving mileage: older adults who objectively drove the most mileage tended to overestimate their annual mileage in self-report questionnaires, while older adults who objectively drove the lowest mileage tended to underestimate their self-reported mileage. The findings from these studies suggest that self-reported driving behavior of older adults does not always correspond to actual behavior. Therefore, caution should be used when interpreting the results of driving studies that solely rely on self-report methods.

*Roadside observational methods of assessing distracted driving.* In addition to self-report, distracted driving is also assessed by roadside naturalistic observation methods in a small number of studies. In the United States, the National Occupant Protection Use Survey (NOPUS) is an annual survey that collects nationwide observational data on in-vehicle electronic device use (National Highway Traffic Safety Administration, 2016). NOPUS is the largest observational study to date on distraction while driving, examining demographic and environmental correlates with distraction. In 2015, NOPUS observed 45,916 stopped vehicles during summer daytime hours across the United States. A small percentage of older adults 70 years and older were manipulating phones (0.5%) and talking on a handheld cell phone (1.1%) at the time of observation. Though the percentage of older adults who engaged in distracted driving behaviors was small in NOPUS, it is important to note that NOPUS only recorded interactions with electronic devices. Older drivers may have been conducting other distracted driving behaviors not coded by the observers.

Other large observational driving studies have found higher rates of distracted driving among older adults when recording general distracted driving behaviors. A large-scale daytime observational study in Spain observed general distracted driving behavior among 6,578 drivers and found higher rates of older adults conducting distracted driving behaviors than rates found in NOPUS (Prat, Planes, Gras, & Sullman, 2014). At the time of observation, 18% of older drivers (50 years and older, total n=2217) were engaged in at least one distracted driving behavior (Prat et al., 2014). An observational study of 7,168 drivers in England found that 13% of older adults (50 years and older, total n=1633) were engaged in some form of distraction while driving, including mobile phone use, eating/drinking, smoking, talking to a passenger, adjusting controls, and other distractions, with talking to a passenger as the most common distraction (Sullman, 2012). It is important to note that these studies are not directly comparable to NOPUS since their age ranges of older adults are different (70 and older in NOPUS versus 50 and older in the studies in Spain and England). These studies were also conducted in other countries, where distracted driving laws and cultural norms may be different. In addition, their sample sizes are also smaller than NOPUS, though large in comparison to self-report driving studies.

Roadside observational studies of distracted driving suggest that older adults participate in a variety of distracted driving behaviors; the most frequent behavior observed being talking to a passenger (Prat et al., 2014; Sullman, 2012). Though these studies found older adults less likely to engage in distracted driving behaviors than other age groups, a small percent of older adults still participated in these behaviors. These percentages are particularly meaningful in studies with large sample sizes, such as NOPUS, which has a total sample size of over 38,000 drivers.

Roadside observational studies of distracted driving have several limitations, including the inability to include fine-grained assessments of age. Roadside observational studies rely on rater's subjective assessment of driver age range (National Highway Traffic Safety Administration, 2016, 2017a; Prat et al., 2014; Sullman, 2012). As a result, driver age can only be represented in broad ranges, such as "50 years and older." However, crash statistics indicate that risk of crashes among adult age groups only begins to increase around age seventy (Staplin et al., 2008). Broad age ranges used in roadside observational studies may therefore misrepresent risk. Another issue with roadside observational studies is that they are unable to assess driver-specific variables beyond basic demographics such as age and gender. Driver-specific variables such as cognition, vision, and physical function are known to impact driving safety and are therefore important to capture when assessing driving (Anstey, Wood, Lord, & Walker, 2005) Finally, roadside observational studies are often restricted to specific days and times of assessment to ensure consistency across measurements. The day and time in which a roadside observational study takes place may have a large impact on what types of behaviors drivers engage in. For example, a person may display unsafe driving on the day he or she is observed, such as driving above the speed limit, but this behavior may be due to unusual circumstances rather than characteristic of typical driving behavior.

**Distracted driving and unsafe driving behaviors.** The impact of distracted driving behavior on unsafe driving has been well-documented in systematic reviews and meta-analyses (Atchley et al., 2017; Caird et al., 2014; Ferdinand & Menachemi, 2014; Oviedo-Trespalacios et al., 2016). However, the majority of studies on distracted driving and unsafe driving behaviors have been conducted with samples of younger adults. There are a few studies examining the impact of distracted driving on unsafe driving behaviors among older adults, utilizing a variety of methods, including driving simulators and experimental test-drives.

*Driving simulators.* The use of a driving simulator is a common method of assessing objective driving performance in an attempt to address concerns of self-report driving data. A driving simulator is defined as “a computer-controlled environment that presents selected aspects of the driving experience considered representational of real-world driving and that allows objective measurements of users’ responses to designated driving tasks” (Board, 2016). The majority of studies examining the impact of distracted driving on unsafe driving behavior have been conducted using driving simulators. Driving simulators allow for a safer assessment of driving safety than on-road assessments because any safety errors or crashes are simulated. Driving simulators also allow researchers to manipulate the driving situation through different experimental conditions. A common method of assessing the impact of distracted driving is to compare driving simulator performance in a condition with distraction tasks versus a condition of normal driving (Choudhary & Velaga, 2017; Cuenen et al., 2015; Fofanova & Vollrath, 2011; Horberry, Anderson, Regan, Triggs, & Brown, 2006). Distraction tasks are designed to simulate real-world driving distractions and typically require either visual/manual (designed to simulate manipulation of a cell phone or in-vehicle system) or auditory/vocal (designed to simulate conversation on a cell phone or with a passenger) participation by the driver while driving in the simulator. For example, three simulator studies ask participants to respond verbally to a question presented through a speaker (Choudhary & Velaga, 2017; Cuenen et al., 2015; Horberry et al., 2006). Other studies ask participants to engage in tasks using the car radio while driving in the simulator (Horberry et al., 2006) or respond manually to changes on a computer screen while in the driving simulator (Fofanova & Vollrath, 2011). Simulator performance is calculated through a number of scores including speed, lateral lane position, following distance, and steering wheel measures. Simulator studies with older adult participants generally find that simulator performance is worse during driving conditions with distraction tasks compared with conditions of normal driving (Choudhary & Velaga, 2017; Cuenen et al., 2015; Fofanova & Vollrath, 2011; Horberry et al., 2006). However, results are not always consistent across all driving simulator performance measures. For example, Cuenen and colleagues (2015) assessed performance in a driving simulator in four experimental conditions: no visual distraction, visual distraction, no cognitive distraction, and cognitive distraction in a sample of older adults. The authors found mixed results in regards to the impact of distraction on driving behavior: Cognitive distraction was significantly associated with incomplete stops at stop signs, later initiation of braking at pedestrian crossings, and more crashes, while visual distraction was not associated with any driving behaviors (Cuenen et al., 2015). The authors also examined the impact of cognitive function on driving performance changes with distraction and found only one marginally significant cognition by distraction interaction: Distraction significantly interacted with attention capacity to predict lane position but no other driving performance measure.

A few driving simulator studies also examine the differential impact of distractions on driving performance for people of different ages (Choudhary & Velaga, 2017; Fofanova & Vollrath, 2011; Horberry et al., 2006). In a simulator experiment comparing 10 older drivers (age 60-73) and 10 middle-age drivers (31-44), older adults' simulator performance was more affected by visual-manual distraction than middle-age adults (Fofanova & Vollrath, 2011). In a similar study of 100 drivers in three age groups (less than 30 years, 30-50 years, and 50 and older), there was also a differential impact of visual-manual distraction on simulator performance. (Choudhary & Velaga, 2017) A third study of 31 drivers using similar methods compared three similar age groups and found no age differences in the impact of distractions on simulator performance (Horberry et al., 2006). In general, older adults reached a lower speed upon approaching a hazard in the simulator than younger adults, though there was no interaction with age and presence of a distraction task. In general, simulator studies find that distraction impacts driving performance, though results are mixed depending on age of participant and the driving performance measure examined.

Performance in a driving simulator does not necessarily indicate how a person will drive on the road. External validity of driving simulators, or how performance in a driving simulator can be generalized to on-the-road driving performance, is a concern (Mullen, Charlton, Devlin, & Bédard, 2011). External validity of driving simulators may be threatened if participants do not "buy in" to the driving simulator. Particularly in the case of unsafe driving behaviors, participants may perform these behaviors more frequently because there is no "real" threat in a driving simulator compared to driving on the road. Another concern with driving simulators is simulator sickness. Driving simulators may produce nausea or other discomfort in participants. Simulator sickness can impact both ability to perform the task as well as impact data collected during the simulator (Stoner, Fisher, & Mollenhauer Jr., 2011). For example, in one study, 22 out of 77 participants were unable to participate in the driving simulator due to simulator sickness (Cuenen et al., 2015). Older adults may also be more vulnerable to simulator sickness: One small study (N=32) found that 29% of older adult participants experienced simulator sickness compared to only 6% of younger adults (Kawano et al., 2012). Driving simulators are a promising method of data collection but are not truly "naturalistic".

*Experimental test drives and distracted driving.* In addition to driving simulators, experimental test drives are also used to assess the association between distracted and unsafe driving. In a typical experimental test drive, participants drive a test vehicle with an experimenter observing in the passenger or back seat. Experimental test drives may occur on a closed track or out on the road. Two experimental studies using an instrumented vehicle assessed the impact of experimenter-initiated distractors on older adult driving. In one study, middle-age and older participants drove an instrumented vehicle on a 1.5 mile suburban commercial road (Aksan et al., 2013). Participants were instructed to verbally identify traffic signs and restaurants on the side of the road; this task served as a distraction. Older adults committed more safety errors than middle-age drivers. Among older drivers, visual cognition and general cognition predicted number of safety errors. Interestingly, visual perception, recall, executive function, motor function, basic vision, age, gender, and education did not significantly predict number of safety errors. However, this study did not assess baseline driving ability without the presence of distractors, so it is impossible to assess the effect of distraction on driving behavior and the differential effect by age.

Thompson and colleagues also conducted a distracted driving study in an instrumented vehicle with a middle-age and older adult sample (Thompson et al., 2012). Participants completed a baseline drive followed by a distracted drive. During the distracted drive, participants completed the Paced Auditory Serial Addition Task (PASAT). Participants also completed the PASAT in the laboratory. The difference in PASAT performance between the lab and the drive did not differ significantly between the older and middle-age groups. Older drivers committed more safety errors during the distracted drive than middle-age drivers. The authors report mixed results for the impact of distraction on safety errors: some safety errors increased from baseline to distracted driving, while others did not. Cognitive, visual, and physical function predicted the difference in safety errors between baseline and distracted driving among older adults. Specifically, contrast sensitivity, far visual acuity, functional reach, recall, and a cognitive composite significantly predicted a difference in safety errors between baseline and distraction.

**Naturalistic Studies of Older Adult Driving.** Until recently, self-report, roadside observation, simulator, and experimental test drives were the primary methods of assessing older adult driving behavior. In response to concerns about how representative of actual driving these data are, coupled with advances in technology, researchers have begun to use naturalistic methods to assess driving in-vehicle. Naturalistic studies utilize technology such as smartphones and vehicle sensors to assess driving behavior as it occurs in daily life. Though older adults represent a large proportion of drivers, few naturalistic studies have assessed older adult drivers. As of now, the main naturalistic studies of older adult drivers are the 100-Car Naturalistic Driving Study, Longitudinal Research on Aging Drivers, Candrive II/Ozcandrive, and integrated vehicle-based safety system field operation tests.

*100-Car Naturalistic Driving Study (100-Car Study).* The 100-Car Study is one of the first studies to utilize naturalistic data collection to assess older adult driving behavior. The 100-Car study includes 109 participants between the ages of 18 and 72 years from Washington, D.C. and surrounding areas (Klauer, Guo, Sudweeks, & Dingus, 2010). Participants drove an instrumented vehicle, either their own vehicle or one leased by the study, for 12 months. Participants were instructed to drive as they normally would during this time. Data were collected between 2003 and 2004. Participant vehicles were outfitted with four cameras and a set of vehicle sensors in order to obtain objective data on driving behaviors, near-crashes, and crashes. A study of 100-Car Study participants found that only cell phone dialing was associated with increased crash or near-crash risk (Klauer et al., 2013). The final report of the 100-Car Study, published in 2010, reported a number of secondary tasks (i.e., distracted driving behaviors) engaged in by participants (Klauer et al., 2010). Secondary tasks included a range of behaviors including using a cell phone, adjusting controls, eating, drinking, smoking, adjusting contact lenses, biting nails, dancing, and other behaviors. Drivers were engaged in secondary tasks 23.5% of the time that they were driving. Overall, secondary task engagement was associated with increased odds of a crash or near-crash.

The 100-Car Study collected a large amount of naturalistic driving data on a large sample. However, it is difficult to assess distracted driving differences across age due to the wide age range of the sample (18 to 72 years). Further, the 100-Car Study did not collect information on participants' health or cognitive, physical, and visual functioning. Therefore, it is not possible to examine moderators of the association between distracted driving and crashes or near-crashes in this dataset. As simulator and test-track research has indicated, cognitive, vision, and physical function moderate the association between distraction and safety errors. This association has not yet been assessed in a naturalistic driving setting. The study authors also report summary-level statistics, reporting percentages of driving trips in which distracted behavior occurs.

*Longitudinal Research on Aging Drivers (LongROAD Study).* The LongROAD Study is a multi-site naturalistic driving study of drivers between 65 and 79 years of age (Li et al., 2017). Participants drove their own vehicles, which were instrumented with devices that collected vehicle information (including time and date, speed, distance, right- and left-hand turns, and other vehicle parameters) as well as global positioning system (GPS). The LongROAD Study also includes detailed participant information, including self-reported driving data, dementia status, mental health, social variables, and measures of cognition and physical function. However, the LongROAD Study did not collect video data of participants while driving, so the study is not able to objectively assess distracted driving behaviors.

*Candrive II/Ozcandrive.* The Candrive II/Ozcandrive study is a multisite naturalistic driving study of 1230 drivers over 70 years of age in Canada, Australia, and New Zealand. Participants will drive their own vehicles for four years (Marshall et al., 2013). The vehicles will be instrumented with a data collection system that assesses speed, acceleration, braking, steering wheel angle, indicator use, and GPS information. Additionally, participants will be assessed on a variety of cognitive, physical function, health, vision, and other variables. The Candrive II/Ozcandrive study will not collect video data of drivers, so it will not be possible to examine objective distracted driving behaviors using this sample.

*Integrated vehicle-based safety system field operation tests.* Two large naturalistic studies, designed for the purpose of examining the effect of integrated vehicle-based safety systems (IVBSS), collected naturalistic driving data on older adults. The University of Michigan Transportation Research Institute (UMTRI) conducted a field operation test (FOT) in 2009-2010 (Sayer et al., 2011), Participants drove instrumented vehicles provided by researchers that were equipped with safety systems, which included feature such as blind spot detection. Instrumented vehicles also included five cameras and devices to collect vehicle information such as speed and following distance. Participants drove instrumented vehicles for 40 days, but IVBSS were not activated until after the first 12 days, allowing researchers to examine driver behavior not influenced by these systems. Participants represented three age groups: 20-30 years, 40-50 years, and 60-70 years of age. Two published studies examined driver distraction in the UMTRI FOT study. In one study drivers drove slower when talking on a cell phone and interacting with a phone (Xiong, Bao, Sayer, & Kato, 2015). Dozza and colleagues also examined the UMTRI FOT study and found evidence for compensatory behavior: Older drivers exhibited larger safety margins when using the phone while driving (Dozza, Flannagan, & Sayer, 2015). Further, drivers across all ages experienced less critical longitudinal threats (shorter time-to-collision) when talking on the phone. These results suggest that people may compensate for distracted driving by altering their driving behavior. Neither paper using UMTRI FOT data examined driver-specific predictors of distraction or moderators of distraction and driving behavior, such as cognitive and physical function. Dozza and colleagues call for more research on characteristics of drivers and how they impact self-regulation of driving behaviors while distracted (2015).

**Distracted driving theory**. There is a large number of driver behavior theories. Four theories of driving behavior address the skills and abilities needed to successfully drive safely: Michon's Hierarchical Driver Model (Michon, 1985), the Task-Capability Interface Model (Fuller, 2005), the Multifactorial Model for Enabling Driving Safety (Anstey et al., 2005) and the low-mileage bias hypothesis (Janke, 1991).

*Michon's Hierarchical Driver Model (Michon, 1985).* John Michon's Hierarchical Driver Model defines three nested levels of driver control: strategic, tactical, and operational. At the *strategic level*, driver control occurs in the form of trip planning. Before a trip, a driver must make a number of decisions, including where to go, when to leave, etc. At the *tactical level*, driver control occurs while driving. During a trip, a driver must make decisions about when to change lanes, whether or not to stop at a yellow light, etc. Decisions made at the tactical level are influenced by decisions made at the higher strategic level as well as environmental input. For example, if a driver decides at the strategic level to leave late for a trip, at the tactical level the driver may decide to drive through a yellow light rather than stopping. At the *operational level*, driver control occurs in the form of rapid automatic decisions while driving. At this lowest level, drivers make rapid decisions to break, swerve, use a turn signal, etc. The operational level is also influenced by environmental input, as well as decisions made at the higher tactical level. For example, if a driver decides at the tactical level to overtake the car in front, at the operational level the driver would use a turn signal (or not), accelerate, and move the steering wheel.

*Task-Capability Interface Model (Fuller, 2005).* According to TCI, driving safety is related to the interface of driver capability and task demand. *Driver capability* is influenced by factors such as driver experience, driver cognition, and driver physical functioning. *Task demand* is influenced by the environment, such as road curvature, but also by driver-controlled factors such as speed and distraction. Therefore, the role of behavior in the model is in the task demand, as well as in determining whether or not a loss of control will result in a crash (swerving at the last minute to avoid a pedestrian). According to the TCI model, the amount of control a driver has, and therefore the risk for crashes, depends on the distance between driver capability and task demand. In situations where task demand is greater than driver capability, crash risk increases.

*Multifactorial Model for Enabling Driving Safety (Anstey et al., 2005).* The multifactorial model synthesizes literature on the large number of factors related to safe driving in older adults. The multifactorial model predicts driving behavior, which is defined broadly and can include safe or unsafe driving behavior. The factors are divided into three main categories: cognition, vision, and physical function. *Cognitive domains* that have been found to be associated with crash risk or on-road driving performance include attention, perceptual and visuo-spatial ability, speed and reaction time, and executive function (Anstey et al., 2005). *Visual performance* measures that have been found to be associated with crash risk or on-road driving performance include visual acuity and contrast sensitivity (Anstey et al., 2005). The association between *physical function* measures and crash risk or on-road driving performance are less consistent in Anstey and colleagues' review. At the time of publication, the authors' review identified only neck rotation as predicting crash risk in one study (Marottoli et al., 1998). A recent paper identified grip strength, Turn 360, and self-reported physical function as significant predictors of change in driving exposure measures (Phillips, Sprague, Freed, & Ross, 2016). The paper did not examine crash risk or on-road driving performance.

Cognition, vision, and physical function influence the capacity to drive safely, but there is no direct path between cognition, vision, and physical function, and driving behavior. Instead, cognition impacts self-rating of capacity to drive safely, which in turn affects driving behavior. Additionally, cognition, vision, and physical function impact actual capacity to drive safely, which in turn impacts driving behavior. Overall, driving behavior is influenced by self-monitoring beliefs about driving capacity as well as actual driving capacity. In this model, two drivers with the same level of physical, cognitive, and visual function can have different driving behavior. Both drivers have the same capacity to drive safely, but they may have different self-monitoring and beliefs about driving capacity that differentially impact their driving behavior. One driver who is aware of her limitations may choose to not drive at night, whereas another driver unaware of her limitations may continue to drive at night.

Driver distraction is one such variable that influences driving safety. According to TCI, driver distraction would influence task demand. Distraction takes away resources from focusing on the road and therefore increases demand of driving. In the multifactorial model, these resources include cognition, vision, and physical function abilities.

*Low-mileage bias (LMB) hypothesis***.** The low-mileage bias hypothesis was originally proposed by Janke and colleagues in 1991 in response to a commonly-cited U-shaped curve representing the association between driver age and crash risk, with older adults and young adults having the highest crash risk. According to the low-mileage bias hypothesis, the safety risk of older drivers is exaggerated (Janke, 1991). Several studies have examined annual mileage as a predictor of older adult drivers' crash risk and reported that older adults who drive the least miles per year are at the highest risk for crashes (Langford, Methorst, & Hakamies-Blomqvist, 2006). The failure to take into account annual mileage when computing crash risk is known as the low-mileage bias, and the LMB hypothesis posits that it is only a small number of older adults who drive few miles per year who are at risk for crashing and skew the numbers of older adults as a whole.

The low-mileage bias hypothesis is sometimes used as justification for why older adult driving safety is not a concern, implying that it is only a few severely impaired individuals that are the greatest concern. However, there are two main criticisms of the data used to support the low mileage bias hypothesis. First, the majority of data collected in the papers used to support the low mileage bias hypothesis were collected in countries outside of the United States, including the Netherlands (Langford, Methorst, et al., 2006), Finland (Hakamies-Blomqvist, Raitanen, & O'Neill, 2002), New Zealand (Langford, Koppel, Charlton, Fildes, & Newstead, 2006), and Australia and Canada (Langford et al., 2013). The results of these studies may not be generalizable to the United States due to differences in driver's licensing regulations, availability of public transportation, and road makeup (i.e., urban versus rural roads). The issue of how well the LMB hypothesis fits with rural drivers was examined by Hanson and colleagues, who examined travel behavior of 53 rural older drivers in Canada between 56 and 92 years of age (Hanson & Hildebrand, 2011). The authors separated rural older drivers into four groups based on self-reported annual mileage driven. As annual mileage increased, proportion of travel on urban roads increased while proportion of travel on rural roads decreased. The lowest-mileage group of rural older drivers spent the greatest proportion of driving miles on rural roads, which are considered safer and have a lower crash risk than urban roads. Though the study did not collect information on crashes, the authors conclude that the LMB hypothesis may not apply to rural older drivers.

A second criticism is that the data used to support the low mileage bias hypothesis were collected primarily from self-report questionnaires (Langford, Methorst, et al., 2006). In these studies, older adults self-reported crash involvement and yearly mileage driven. However, Staplin and colleagues conducted an analysis of discrepancies between self-reported and actual crash involvement and mileage driven and found that discrepancies differed depending on mileage (Staplin et al., 2008). A similar pattern emerged across several datasets: Older drivers who drove the highest mileage tended to overestimate their self-reported driving exposure, while older drivers who drove the lowest mileage tended to underestimate their self-reported driving exposure. Hanson and colleagues (2011) also found that low-mileage groups under-reported their annual mileage (assessed via GPS data for up to 6 days of driving), while high-mileage groups over-estimated their annual mileage. These findings suggest that self-reported data on driving exposure may not reflect actual driving behavior and that results of studies should be interpreted with caution. Objective measures of miles driven should be used in studies of older adult driving exposure. Even if there is a large proportion of crashes attributable to a small number of older adults, older adults are still involved in crashes (National Highway Traffic Safety Administration, 2017b) and therefore it is important to address older adult driving safety. Based on findings of the above studies, it is also important to take into account annual miles driven when examining older adult driving safety.

**Importance of studying variability in driving.** A major methodological piece missing from studies of naturalistic driving behavior is the study of within-person variability in driving behavior. The majority of naturalistic driving studies collapse data across trips, creating summary variables (Klauer et al., 2013). For example, a study may have data on weather during driving trips across ten days. A common method of analyzing these data is to calculate the proportion of days in which driving trips occurred during rain. However, this method of condensing data does not allow for examination of *within-person* variability and instead only *between-person* differences can be analyzed. Obtaining within-person variability allows us to obtain both a more accurate/specific assessment of driving as well as being able to examine specific circumstances that led up to driving behaviors of interest.

Multilevel modeling (MLM) is an effective way of capturing and comparing within-person and between-person variability. MLM allows us to account for nested data structure, such as multiple trips per individual as well as multiple individuals. MLM allows us to obtain measures on comparing within- and between-person variability in driving behaviors (How much of this behavior is due to within-person versus between-person differences?) as well as analyze associations among variables while accounting for the data structure. Information on within-person predictors of driving behavior has the potential to inform both public health interventions and in-vehicle product development. However, we did not find any articles that used a multilevel modeling method to analyze driving behavior of older adults in a naturalistic setting, making the present study the first of its kind.

## Current Study

The present study used a multilevel modeling approach to examine distracted driving behaviors within-person and between-person in older adults. The first aim was to characterize distracted driving behaviors of older adults during driving trips using objective assessments of real-world driving. Specifically, I examined variability at three levels: within a driving trip (within-person variability), across driving trips (within-person variability), and at a summary level (between-person variability). Based on previous work and the age of the sample, I hypothesized that participants will engage in distracted driving behaviors during driving trips at a low rate and that rates of interacting with a cell phone will be lower than other distracted driving behaviors. Based on theories of driving that specify a variety of conditions and fluctuating participant characteristics that influence driving behavior, I hypothesized that a large amount of variability in distracted driving behaviors across driving trips will be accounted for by within-person differences. The second aim is to examine between-person predictors of distracted driving behavior across driving trips. Based on the Multifactorial Model for Enabling Driving Safety, in which cognition, vision, and physical function impact driving behavior through driving capacity and self-monitoring, I hypothesize that older adults with better functioning will be more comfortable driving and in turn will be more likely to engage in distracted driving behaviors (Anstey et al., 2005). Specifically, I hypothesize that participants who are younger, are men, and have better physical function, executive function, contrast sensitivity, visual acuity, and useful field of view will engage in distracted driving behaviors more across trips. The third aim is to examine between-person predictors of distracted driving behavior within a driving trip. I hypothesize that age, gender, physical function, executive function, contrast sensitivity, visual acuity, and useful field of view will also predict distracted driving behavior within a driving trip.

## Methods

**Data.** Secondary data analyses were conducted using the Senior and Adolescent Naturalistic Driving Study (SANDS). Participants were recruited through recruitment databases and community advertisements. In order to be eligible for the study, participants had to hold a valid driver's license and insurance, own a vehicle and be the primary driver of a vehicle, drive at least three days per week, and demonstrate no evidence of dementia as assessed by a score of 22 or higher on the Modified Telephone Interview for Cognitive Status (TICS-M). Participants 65 years of age and older were included in the current analyses. Participants underwent a telephone screening, completed mailed questionnaires, and attended a baseline appointment. After baseline testing, participant's vehicles were installed with a Naturalistic Data Acquisition Device (N-DAD), and participants were instructed to drive as they normally would for a two-week period. After the two-week driving period, participants returned for a post-test appointment. All study activities were approved by the University of Alabama at Birmingham's Institutional Review Board for Human Use and all participants signed an informed consent document prior to participation in the study. Detailed information study procedures can be found elsewhere (Stavrinos, Ross, & Sisiopiku, 2014).

**Naturalistic Data Acquisition Device (N-DAD).** The N-DAD was developed for the SANDS study in order to obtain objective measures of real-world driving behavior. The N-DAD was installed in participants' personal vehicles and mounted on the front windshield of the vehicle. The system consisted of an Android smart phone (Samsung HTC EVO 4G LTE®) with two detachable wide-angle lenses. Three types of systems within the smart phone collected data: (1) An accelerometer collected data on acceleration, (2) A global position system (GPS) collected latitude and longitude coordinates of the vehicle, and (3) A duel camera system collected photographic images approximately every two seconds of the front exterior of the vehicle and the interior of the vehicle. A 15 minute driving trip would have approximately 450 interior images, or frames. The N-DAD was initiated by vehicle motion and continued collecting data until five minutes after no vehicle motion was detected. The N-DAD collected data on every driving trip the participant took during the two-week study period. Photographs collected by the N-DAD were then coded by researchers for specific driving behavior and environmental measures with acceptable inter-rater reliability at $r$=0.90 (Stavrinos et al., 2014). The N-DAD was tested and validated against a self-report driving log prior to the start of the SANDS project, with a significant relationship between self-reported and N-DAD collected trip time ($r$=0.82, $p$<.001) and between self-reported and N-DAD collected trip distance ($r$=0.94, $p$<.001).

**Sample.** All participants ($N$=72) completed a baseline assessment and a post-test assessment two weeks later. Table 1 displays demographic characteristics of the sample. Participants ranged in age from 65-85 years ($M$=72.29, $SD$=5.36). Overall, participants were highly educated, ranging from 9 years to 20 years (PhD). The majority of participants completed high school and some college. Only 13% of participants were Black. Most participants were married, though 22% were widowed and 18% were single/separated/divorced. At post-test, participants self-reported having driven an average of 6 days per week in the past two weeks (SD=1.32), driving an average of 3 times per day (SD=1.87). Self-reported driving frequency varied widely, ranging from 0 times per day to 15 times per day.

Table 1. Demographic characteristics of sample (*N*=72)

| | *M* (SD) | Range |
|---|---|---|
| Age in years | 72.29 (5.36) | 65 - 85 |
| Gender (% female) | 55.60% | . |
| Race (% White) | 84.70% | . |
| Marital status (% married) | 59.70% | . |
| Education in years | 14.50 (2.49) | 9 - 20 |
| Days per week driven (past two weeks) | 6.11 (1.32) | 0 - 7 |
| Times per day driven (past two weeks) | 3.35 (1.87) | 0 - 15 |

**Measures.**

**Distracted driving behavior.** Distracted driving behavior was assessed via the coding of the photographs/frames collected by the N-DAD for each driving trip the participant took across the two-week study period. Eating, drinking, talking to passenger, reading, grooming, technology interaction, smoking, and reaching were all considered distracted driving behaviors. The current study conceptualized distracted driving behavior three different ways: summary level, across-trip level, and within-trip level. At the *summary* level, distracted driving behavior was defined as the number of trips in which a distracted driving behavior took place. Each participant has one value for this variable, and this variable accounts for whether or not a behavior took place but not duration of the behavior. At the *across-trip* level, distracted driving behavior was defined as the proportion of each driving trip in which the distracted driving behavior took place, measured as the number of frames in each trip in which the behavior occurred divided by the total number of frames for that trip. The across-trip level of distracted driving behavior accounts for total duration of a trip so that participants can be compared to each other. Each participant has multiple values for this variable depending on the number of driving trips they took during the study period. At the *within-trip* level, distracted driving behavior was defined as presence of absence of a distracted driving behavior during each frame of the driving trip (approximately every two seconds between frames). Within-trip distracted driving behavior is represented as a 0 or 1, where 1 indicates presence of distracted driving behavior during that frame. For example, if frame 500 for driving trip 2 showed the participant interacting with a cell phone, the value for this frame would be 1. Subsequent frames in which the participant continued to interact with a cell phone would be coded as a 1. When the participant was no longer interacting with a cell phone, subsequent frames would be coded as 0.

**Executive function.** Executive function was assessed during the baseline visit with the Mazes Test and Trails B test. The *Mazes Test* is a paper-and-pencil assessment of executive function (Stern & White, 2009). Participants are asked to complete a series of mazes of increasing difficulty without lifting their pen. Score is calculated based on the amount of time it took the participant to complete the maze, converted to a standardized Z score. *Trail Making Test (TMT) B* assessed executive function (Lezak, Howieson, & Loring, 2004). This test asks participants to draw lines connecting consecutively numbered circles (Part A) and then connect consecutively and alternating numbered and lettered circles as fast as they can (Trails B). Both the Mazes Test and Trails B scores are influenced by speed and accuracy. Therefore, psychomotor speed was not subtracted out of the Trails score as is sometimes done (Lezak et al., 2004). An executive function composite was created from the average of z-scores for Mazes and Trails B, where a higher score indicated worse executive function.

**Useful field of view.** Useful field of view was assessed during the baseline visit by the 4 subtests of the Useful Field of View (UFOV) test (Ball, 1990). Participants complete the UFOV task on a personal computer with a standard touch-screen monitor. The UFOV 1 subtest assesses speed of processing. In Subtest 1, an object (either a car or truck) is displayed on the monitor and then removed. Participants are asked to identify whether the object displayed was a car or truck. A higher score indicates slower speed of processing. The UFOV 2 subtest assesses divided attention. The sequence of Subtest 2 is as follows: First, participants are briefly presented with peripheral (car) and central (car or truck) targets. Second, a full-field, white noise, visual mask is presented. Third, participants are asked on a response screen to identify both the central target and the location of the peripheral target. Participant scores on Subtest 2 are calculated as the display duration in milliseconds in which the participant can perform this subtest accurately 75% of the time. A higher Subtest 2 score indicates worse divided attention. The UFOV 3 Subtest assesses selective attention and includes a field of triangles serving as distractors. A higher score indicates worse selective attention. The UFOV 4 subtest is a more difficult version of Subtest 3 in which two targets (either two cars, two trucks, or one car and one truck) are presented in the central target field and participants are asked to identify if the two objects are the same or different. A useful field of view composite was created by calculating the mean of 4 z-scored UFOV subtests, where higher score indicates worse performance.

**Visual function.** Two types of visual function were assessed. *Contrast sensitivity* is an important visual function necessary for driving, particularly at night, and has been linked to risk of driving cessation (Freeman, Muñoz, Turano, & West, 2005). Contrast sensitivity was assessed during the baseline visit by the Pelli Contrast Sensitivity Chart (Pelli, Robson, & Wilkins, 1988). The Pelli chart asks participants to identify black letters against a white background at a distance of 40 inches, with the letters decreasing in contrast down the chart. Higher scores indicate better contrast sensitivity. *Far Visual Acuity* was also assessed at baseline by the Snellen Chart.

Participants are instructed to read letters out loud on a chart from a distance of ten feet. Higher scores indicate better far visual acuity.

**Physical function.** Three measures of physical function were used. The *Turn 360 task* asks participants to make a complete 360-degree turn, with or without an assistive device. Score for the Turn 360 task is calculated by taking the number of steps taken to complete the turn. The score is the average of two trials. Higher scores indicate worse performance. The *functional reach task* measures distance a participant can reach with their arms while their legs remain stationary. Participants are instructed to stand with their feet comfortably apart and reach forward as far as they can comfortably go. The participant receives a score representing the number of inches from the starting point to the furthest point they were reach. The average of two trials was taken. Higher scores indicate better performance. The *Get Up & Go Test* measures the amount of time it takes a participant to get up from a chair, walk to a designated location, and sit back down in the chair, with or without an assistive device. The participant completed two trials and received two scores representing the number of seconds it took them to complete both trials. The average of two trials was taken, where higher scores indicate worse performance. A physical function composite was created by taking the average of z-scores (reversed for functional reach) for the three measures of physical function, where higher scores indicate worse performance.

**Analytic Strategy.** All analyses were conducted in R Studio (R Core Team, 2013). Using a wide dataset (one line per person), I first calculated participant demographic characteristics. To accomplish Aim 1 (characterize distracted driving behaviors of older adults), I calculated frequencies of participants who engaged in each distracted driving behavior at all across trips (summary-level distracted driving). Also using the wide dataset, I calculated means, standard deviations, and ranges of each distracted driving behavior (across-trip distracted driving). Then, I created a long dataset consisting of multiple rows per participant (one row per driving trip) in order to conduct subsequent models. Based on descriptive statistics, I decided to use the three most common distracted driving behaviors in subsequent models: interacting with a cell phone, grooming, and reaching. I first ran an intercept-only multilevel model (also known as an unconditional means model) with a random intercept and no predictors to identify the amount of between- and within-person variation in three distracted driving behaviors, quantified by an intraclass correlation coefficient (ICC). The multilevel model for Aim 1 is represented by the following equations:

Level 1: $Y_{ti} = \beta_{0i} + \beta_{1i} + e_{ti}$

Level 2 $\beta_{0i} = \gamma_{00} + u_{0i}$

$\beta_{1i} = \gamma_{10}$

In the above equation, $Y_{ti}$ represents the outcome (interacting with cell phone, grooming, or reaching) on trip *t* for person $i$. $\beta_{0i}$ represents the intercept with a random component $u_{0i}$ , and $\beta_{1i}$ represents the slope which is constant for all participants. Random within-person variability/error is represented by $e_{ti}$. Analyses for Aim 1 were conducted using the nlme package in R Studio (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2017).

Aim 2 is to examine predictors of distracted driving behavior. I accomplished this by adding the following level 2 predictors to the multilevel model predicting distracted driving behavior: gender, grand-mean centered age, physical function, executive function, contrast sensitivity, visual acuity, and useful field of view. There is no growth represented in the equation because I do not expect driving behaviors to change in a linear fashion across only two weeks. The multilevel model for Aim 2 is represented by the following equations:

Level 1: $Y_{ti} = \beta_{0i} + \beta_{1i} + e_{ti}$

Level 2: $\beta_{0i} = \gamma_{00} + \gamma_{01}AGE_i + \gamma_{02}GENDER_i + \gamma_{03}PHYSFX_i + \gamma_{04}EXFX_i +$

$\gamma_{05}CS_i + \gamma_{06}VISION_i + \gamma_{07}UFOV_i + u_{0i}$

$\beta_{1i} = \gamma_{10}$

In the above equation, age (*AGE*), gender (*GENDER*), physical function (*PHYSFX*), executive function (*EXFX*), contrast sensitivity (*CS*), vision (*VISION*), and useful field of view (*UFOV*) predict the level 1 intercept for the outcome $Y_{ti}$ (interacting with cell phone, grooming, or reaching). The slope $\beta_{1i}$ remains constant for all participants. Analyses for Aim 2 were conducted using the nlme package in R (Pinheiro et al., 2017). In total, three separate multilevel models were conducted to model each distracted driving behavior.

Aim 3 is to examine within-trip distracted driving behavior. To accomplish this, I chose interacting with a cell phone because it had highest mean and standard deviation for percent of driving trip. First, I selected all driving trips in which interacting with a cell phone took place. If a participant had multiple driving trips in which they interacted with a cell phone, I only included the longest trip in order to avoid any shared variance. In total, 15 driving trips were included in this long dataset, with one line of data representing one photographic frame (approximately every two seconds of driving). I ran stepwise multilevel logistic regression models to predict cell phone use at each frame using the lme4 package and specifying a binomial distribution (Bates, Mächler, Bolker, & Walker, 2015). I added the conducted the following three models in a stepwise fashion: random intercept only (Model 1), random intercept, gender, and age (Model 2), and random intercept, gender, age, executive function, physical function, and useful field of view

(Model 3). The models would not converge with the addition of contrast sensitivity and visual acuity. In separate analyses (not shown), these two variables were not significantly associated with cell phone use. As a result, contrast sensitivity and visual acuity were not included in Model 3. The multilevel model for Aim 3 is represented by the equation below:

Level 1: $Y_{ti} = \beta_{0i} + \beta_{1i} + e_{ti}$

Level 2: $\beta_{0i} = \gamma_{00} + \gamma_{01}AGE_i + \gamma_{02}GENDER_i + \gamma_{03}PHYSFX_i + \gamma_{04}EXFX_i + \gamma_{05}UFOV_i + u_{0i}$

$\beta_{1i} = \gamma_{10}$

In the above equation, $Y_{ti}$ represents the outcome (interacting with cell phone) at frame *t* for person *i*. Age (*AGE*), gender (*GENDER*), physical function (*PHYSFX*), executive function (*EXFX*), and useful field of view (*UFOV*) predict the level 1 intercept for the outcome. The slope $\beta_{1i}$ remains constant for all participants.

# Results

**Aim 1 (Characterize distracted driving behaviors of older adults).** Descriptive statistics of distracted driving behaviors summarized across trips are located in Table 2. In general, distracted driving behaviors were uncommon in this sample. Smoking, reading, eating, and drinking were rare, with less than 20% of the sample ever engaging in these behaviors during the course of the study. Reaching and grooming were engaged in by the most participants, with 71% and 43% of participants having reached at least once or groomed at least once during the course of the study. Despite many participants engaging in reaching and grooming at least once, the average percent of the driving trip in which these behaviors occurred was small. For reading, eating, drinking, and smoking, the average percent of the trip in which the behavior occurred was less than 1%, with low variability (ranging from less than 0.5% to 6.78%). In general, few participants ever engaged in reading, eating, drinking, and smoking during trips, and participants who did these behaviors did them for a small percentage of driving trip except for a few outliers (such as one participant who groomed for 91.94% of a driving trip and one participant who smoked for 85.23% of the driving trip).

To further characterize distracted driving behaviors in this sample, I calculated intraclass correlation coefficients (ICCs) for the three most common distracted driving behaviors: interacting with a cell phone, reaching, and grooming. All other distracted driving behaviors were excluded due to low variability and frequency of these behaviors, making ICCs not appropriate. ICCs quantify the percent of variance in distracted driving behavior attributable to between-person differences. Based the ICC, 6.66% of the variation in reaching across driving trips is due to between-person differences, indicating that a large proportion of variation in reaching behavior is explained by within-person differences. In other words, participants differed more from themselves than they did from each other in reaching behavior. Similarly, the ICC for interacting with a cell phone indicated that 7.11% of the variance in interacting with a cell phone was attributable to between-person differences. In contrast, the ICC for grooming was almost 0%, indicating that participants did not differ from one another in their average levels of grooming. Between-person effects for grooming in subsequent models should therefore be interpreted with caution.

Table 2. Descriptive statistics of distracted driving behaviors.

| Distracted driving behavior (% of trip) | *M* (SD) | Range | Valid observations (*N*) | Participants who ever did behavior (%) |
|---|---|---|---|---|
| Reaching | 1.39 (5.21) | 0 – 61.41 | 178 | 70.6% |
| Reading | 0.01 (0.08) | 0 – 0.87 | 181 | 8.8% |
| Eating | 0.03 (0.34) | 0 – 4.50 | 182 | 8.8% |
| Drinking | 0.15 (0.74) | 0 – 6.63 | 182 | 17.6% |
| Grooming | 1.44 (9.54) | 0 – 91.94 | 181 | 42.6% |
| Smoking | 0.75 (6.77) | 0 – 85.23 | 182 | 5.9% |
| Interacting with cell phone | 1.53 (6.77) | 0 – 78.14 | 181 | 26.5% |

**Aim 2 (Predictors of distracted driving behaviors across trips).** Results of multilevel models for interacting with a cell phone, grooming, and reaching are displayed in Table 3. Fixed effects represent the results for the typical participant. The intercept represents the proportion of trip spent engaging in a distracted driving behavior for the average person (based on other predictor variables) at time 0. The fixed effect estimates of each predictor represent how much higher or lower the proportion of trip engaging in a distracted driving behavior is different

according to levels of the predictor at time 0. There is also a random effect for intercept, representing the variability in proportion of trip engaging in a distracted driving behavior across subjects. Multilevel models are based on around 180 data points, coming from 67 participants.

Gender, age, executive function, physical function, contrast sensitivity, visual acuity, and useful field of view did not significantly predict interacting with a cell phone or reaching. The only significant predictor across all three models was physical function significantly predicting grooming. Participants with better physical function groomed significantly more than participants with worse physical function, though the effect was small.

Table 3. Across-trip multilevel models predicting three distracted driving behaviors

| **Model** | Interacting with cell phone | Grooming | Reaching |
|---|---|---|---|
| **Fixed Effects** | Estimate (SE) | Estimate (SE) | Estimate (SE) |
| Intercept | 0.01 (0.11) | 0.24 (0.13) | 0.00 (0.08) |
| Gender | 0.00 (0.01) | 0.00 (0.02) | 0.01 (0.01) |
| Age | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) |
| Executive Function | 0.00 (0.01) | 0.01 (0.01) | 0.00 (0.01) |
| Physical Function | -0.01 (0.01) | -0.03 (0.01)* | -0.01 (0.01) |
| Contrast Sensitivity | 0.02 (0.06) | 0.00 (0.00) | -0.02 (0.04) |
| Visual Acuity | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) |
| UFOV | 0.00 (0.01) | -0.01 (0.01) | 0.01 (0.01) |
| **Random Effects** | | | |
| Intercept (SD) | 0.02 | 0.00 | 0.01 |
| Residual (SD) | 0.07 | 0.09 | 0.05 |
| *N* Observations | 180 | 180 | 177 |
| *N* Participants | 67 | 67 | 67 |

*Note.* *p<.05

**Aim 3 (Predictors of interacting with cell phone within trips).** The results for within-trip analyses on a subsample of 15 participants who interacted with a cellphone at least once are displayed in Table 4. The 15 participants included in this model were similar in age to the full sample, ranging from 66 to 81 years of age (*M*=72.73, SD=5.4). This subsample was also similar to the full sample in terms of gender, with 8 women and 7 men. Using this subsample, Model 1 represents an intercept-only unconditional means model and was estimated using 7282 data points. In Model 2 (estimated using 7282 data points), gender and age centered at the subsample's grand mean were added as predictors of cell phone use. Fixed effects are represented as odds ratios and 95% confidence intervals. Age is not significantly associated with the odds of using a cell phone during a particular frame. However, gender is significantly associated with cell phone within a trip: Men were 1.01 times likely to use a cell phone during a given frame than women, though the confidence interval is very wide for this estimate so results should be interpreted with caution. In Model 3 (estimated using 6707 data points), executive function, physical function, and useful field of view are added as predictors. None of the added predictors were associated with greater odds of using a cell phone during a given frame. The significant effect of gender also disappears with the addition of predictors. Despite non-significance of predictors, model fit statistics across all three models indicate better fit with addition of subsequent predictors. Model 3 has the lowest AIC and BIC, indicating the best fit out of all three models.

Table 4. Within-trip logistic models predicting cell-phone use (n=15)

| **Model** | M1 | M2 | M3 |
|---|---|---|---|
| **Fixed Effects** | OR (95% CI) | OR (95% CI) | OR (95% CI) |
| Intercept | 0.25 (0.06, 1.03) | 20.19 (0.01, 0.32)* | 10.92 (0.01, 0.69)* |
| Gender | - | 1.01 (1.77, 230.75)* | 0.91 (0.66, 181.16) |
| Age | - | 0.06 (0.80, 1.28) | 0.08 (0.63, 1.32) |
| Executive Function | - | - | 0.94 (0.34, 212.28) |
| Physical Function | - | - | 8.45 (0.00, 2.54) |
| UFOV | - | - | 0.09 (0.03, 30.87) |
| | | | |
| **Random Effects** | | | |
| Intercept (SD) | 2.81 | 2.35 | 2.19 |
| | | | |
| **Fit Statistics** | | | |
| AIC | 4594.0 | 4592.9 | 4163.0 |
| BIC | 4607.8 | 44620.5 | 4210.7 |
| | | | |
| *N* Observations | 7282 | 7282 | 6707 |
| *N* Participants | 15 | 15 | 14 |

*Note*. *p<.05. AIC = Akaike information criteria; BIC = Bayesian information criteria; CI = confidence intervals.

## Discussion

The present study examined the prevalence of distracted driving behaviors in a sample of older adults across two weeks. Distracted driving behaviors were relatively rare in this study, with some behaviors (smoking, eating, drinking, and reading) almost never being engaged in. Grooming, interacting with a cell phone, and reaching were more common among participants but still were not engaged in by a majority of participants. The prevalence of distracted driving behavior in this sample is in line with other observational and naturalistic work of older adult drivers. For example, the 2015 National Occupant Protection Use Survey, a roadside observational study, found that only 0.5% of older adults 70 years and older were manipulating phones and 1.1% were talking on a handheld cell phone at the time of observation (National Highway Traffic Safety Administration, 2016). A survey of drivers in Germany also found very low frequency of distracted driving behaviors among older adults, including 4% for eating or drinking, 3% for smoking, and 0% for using a mobile phone and grooming (Fofanova & Vollrath, 2012). The 100-Car naturalistic driving study found slightly higher rates of engagement, reporting that drivers were engaged in any distracted driving behavior an average of 23.5% of driving time (Klauer et al., 2010). Other distracted driving behaviors not included in the current analyses may have had higher engagement, such as interaction with passengers and driver inattention, which are more common in other studies of distracted driving (Fofanova & Vollrath, 2012; Prat et al., 2014).

In this study, a large amount of variation in two distracted driving behaviors (interacting with a cell phone and reaching) was due to within-person differences, suggesting that people vary greatly across trip in how they drive. To date, no study has looked at *variability* in distracted driving behavior, making this study the first of its kind. The within-trip analysis included over 7,000 data points despite only representing 15 participants. By collapsing to number of frames per trip or even a binary variable for whether a behavior occurred during a trip, a large amount of data is being condensed. Roadside observational studies, surveys asking about behaviors on a typical day or averaged across a time frame, and naturalistic observational studies that condense driving behavior data to summary level statistics are not able to capture this variability in distracted driving behavior. Future work could also look at dynamic associations between distracted driving and other within-trip measures such as driving safety.

Researchers have called for more research on how driver characteristics impact self-regulation of driving behaviors, including distraction (Dozza et al., 2015). The SANDS study is one of the first studies to include in-depth assessments of physical, cognitive, and visual function in conjunction with common naturalistic driving data (i.e., interior and exterior vehicle video data, accelerometer, and GPS data). Based on this rich dataset, I was able to examine variability and predictors of distracted driving behavior. Interestingly, executive function, age, gender, contrast sensitivity, visual acuity, and useful field of view did not predict distracted driving behavior across trips. This result was surprising since older age and useful field of view have been identified as predictors of longitudinal driving cessation (Edwards, Bart, O'Connor, & Cissell, 2009). However, an experimental test track study of distracted driving found that visual perception, recall, executive function, motor function, basic vision, age, gender, and education did not significantly predict driving safety during distraction (Aksan et al., 2013).

Physical function was the only predictor to be related to distracted driving across-trip. Specifically, participants with better physical function groomed more during driving trips than participants with worse physical function, though this effect was small. Participants in this study with better physical function may have felt more confident that grooming during driving would not impact their driving behavior because grooming may be easier for them than participants with worse physical function. Functional reach was included in the physical function composite, and the abilities required in this test are very similar to the type of movement needed to groom during a drive. Interestingly, physical function did not predict reaching, which would also require similar abilities. The association between better physical function and increased grooming behavior makes sense given recent work identifying better physical function as a significant predictor of greater driving exposure (Phillips et al., 2016). Physical function is clearly a functional ability central to driving in older adults, and the results of the current study suggest that participants may adjust their driving behavior in response to their function ability. Self-report of driving modification or longitudinal changes in physical function would be needed to determine whether participants are truly modifying their behavior in response to physical function.

The current study conducted an innovative within-trip analysis in a subsample of 15 driving trips in which interaction with a cell phone occurred. Within a trip, gender was significantly associated with the odds of interacting with a cell phone such that men were more likely to use a cell phone during a given frame than women. Previous work on gender differences in distracted driving is mixed. The National Occupant Protection Use Survey using roadside observational methods found that handheld cell phone use was higher among female drivers than male drivers, though there was only a 1% difference between males and females and differences were not broken down by age so results may have been driven by younger age groups (National Highway Traffic Safety Administration, 2016). Another study found that women self-report less engagement in using an in-car device, eating or drinking, and smoking than men (Fofanova & Vollrath, 2012). In contrast, a large roadside observational study of driver distraction conducted in England found no gender differences in a variety of distracted driving behaviors (Sullman, 2012). A national phone survey of distracted driving attitudes and behaviors found that men were less likely to perceive interacting with a cell phone while driving as dangerous (Tison, Chaudhary, & Cosgrove, 2011). This study also did not examine the interaction of gender and age, so it is not possible to determine if older men were also less likely to perceive interacting with a cell phone while driving as dangerous. The fact that men in the current study were more likely to interact with a cell phone while driving is not very surprising given the previous work described above. However, these gender effects should be interpreted with caution because the within-trip analyses they came from were conducted on only 15 participants and the confidence intervals for these effects were very wide. Future work should examine the role of gender in older adults specifically.

This work was guided by the Multifactorial Model for Enabling Driving Safety (Anstey et al., 2005). In this model, driving behavior is predicted both by actual driving capacity and self-monitoring/beliefs about driving capacity, which in turn are predicted by cognition, vision, and physical function. Distracted driving can be considered a type of driving behavior impacted by self-monitoring/beliefs about driving capacity as well as the capacity to drive safely. Specifically, better physical function predicted more grooming behavior in this sample. These results are in line with the Multifactorial Model for Enabling Driving Safety if distracted driving is considered to be a form of driving behavior. Participants with better physical function may have perceived their driving capacity to be better and therefore their driving behavior (i.e., propensity to engage in distracted driving behavior) was impacted. Interestingly, useful field of view and vision did not impact distracted driving in this sample. Not only are they specified in the multifactorial model as predictors of self-monitoring beliefs about driving capacity, but empirical studies have demonstrated that they play a role in driving modification. Specifically, participants with worse performance on useful field of view limited their driving over time more than participants who did not have poor useful field of view (Ross et al., 2009). In another study, problems with eyesight was the leading reason for limitation of driving for both men and women (Ragland, 2004). Given these findings about older adults' driving restriction, it was surprising that participants in this study who had poorer useful field of view and visual acuity did not engage in distracted driving behaviors less than other participants.

The multifactorial model does not specify other influences on self-monitoring beliefs, but it is likely that other factors may play a role in people's likelihood to engage in distracted driving behavior. In this study, gender was associated with greater likelihood to interact with a cell phone while driving. Based on within-trip results of the current study, men may be more likely than women to believe that they are able to drive safely while distracted and so therefore may be more likely to engage in these behaviors. Another variable that may impact distracted driving not mentioned in the multifactorial model and not included in the current study is sleep. Within-person daily fluctuations in sleep duration are associated with worse daily cognition (Gamaldo, Allaire, & Whitfield, 2010). Considering cognition's link to driving safety, sleep is important to consider when examining driving. In the context of distracted driving, older adults may be less likely to engage in distracted driving behaviors when they are more tired. However, older adults' driving safety may also be more impacted by distracted driving when they do not get enough sleep the night before the drive. Future naturalistic studies should incorporate daily assessments of sleep, either through daily diary self-assessments or actigraphy measures, in order to understand sleep's role in distracted driving.

**Limitations and future directions.** There were several limitations of the current study that warrant discussion and lead to future directions for research. A main issue in conducting these analyses was missing data. Due to technical difficulties and bad weather, the N-DAD system malfunctioned and only a handful of participant trips were recorded. As a result, the current study may have had reduced power to detect effects due to a smaller number of observations per person. Fortunately, the data can be considered missing at random since the missingness was a result of technical issues and not any systematic differences between participants or trips. As a result, analyses of the current study are likely to not be biased as a result of missingness.

In addition to missing data due to technical limitations, the analyses were limited by participant behavior. Initially, I proposed to examine within-person associations between distracted driving behaviors and unsafe driving behaviors, such as running a stop sign, lane deviation, and sudden braking. After examining frequencies of these behaviors, it became apparent that including these as level 1 predictors would not be appropriate because the behaviors were so close to zero in the dataset. Participants in this sample did not engage in distracted driving behaviors frequently and almost no participants engaged in unsafe driving behaviors such as running a stop sign, lane deviation, and sudden braking. Several possibilities exist to explain why there was such a low frequency of these behaviors in this dataset. First, it is likely that participant behavior was impacted by the fact that participants knew they were being observed. Participants may have been "better" drivers and therefore less likely to engage in distracted or unsafe driving behaviors because of a social desirability bias. It would be interesting to examine frequencies of distracted driving behavior in the first few days of data collection to determine if participants returned to their normal baseline behavior after forgetting that they were being observed. Another possibility is that more than two weeks may be needed to capture distracted or unsafe driving behaviors. Based on previous work, we know that distracted driving behaviors do not occur frequently. Extending data collection to more than two weeks may capture more distracted and unsafe driving behaviors. Overall, the older adults in this sample were safe drivers, which is of course good for participant and others' safety.

Given simulator and test-track studies showing that older adults' driving performance is more affected by distraction than younger adults (Aksan et al., 2013; Choudhary & Velaga, 2017; Fofanova & Vollrath, 2011; Thompson et al., 2012), future studies should examine the associations between trip-level distracted driving behavior and trip-level driving safety using naturalistic driving data. Interestingly, one study found no age differences in the impact of distractions on simulator performance (Horberry et al., 2006). Some simulator or test track studies have also found that older adults modify their driving to compensate for distraction, either by reducing speed or increasing safety margins (Dozza et al., 2015; Horberry et al., 2006; Xiong et al., 2015). Inconsistent results of age differences in distracted driving and driving safety could be reconciled by examining variables more salient for driving ability than just age in years. Functional abilities such as physical function, vision, and cognition may be more meaningful for driving safety than just age, which is used as a proxy for these functional variables in studies that do not include these measures. In fact, research using instrumented vehicles has found that cognition predicted driving safety in the presence of distraction (Aksan et al., 2013; Thompson et al., 2012). These studies report discrepant results on the impact of other functional abilities, such as visual perception, recall, executive function, motor function, vision, as well as demographic characteristics such as age, gender, and education, on driving safety in the context of distracted behavior (Aksan et al., 2013; Thompson et al., 2012). Similar to results found in simulator and test track studies, it may be that older adults' driving is more impacted by distractions than younger adults and this may be due to decreased physical function and cognition or vision. The Task-Capability Interface Model states that the amount of control a driver has and therefore the risk for crashes depends on the discrepancy between driver capability and task demand (Fuller, 2005). Physical function, cognition, and vision can be thought of as factors influencing driver capability. Alternatively, older adults may actually regulate their driving in response to distractors more than younger adults as suggested by some simulator and test track studies and the Multifactorial Model for Driving Safety (Anstey et al., 2005). A future study using naturalistic data and multilevel modeling could examine variability in distracted driving behavior and variability in driving safety, with between-person predictors such as age, cognition, physical function, vision, and gender moderating this association.

Future studies should also examine the impact of driving environment on distracted driving. A large amount of variance in the models predicting distracted driving both across- and within-trip was unexplained, suggesting that there may be other aspects of the driving environment playing a role in participants' likelihood to engage in distracted driving. For example, participants may be more likely to engage in distracted driving behaviors when driving conditions are not optimal. Research on driving avoidance would support this hypothesis, which has shown that older adults avoid driving at night, in bad weather, unfamiliar routes, rush hour, and highway driving (Blanchard et al., 2010). In this sample, participants did not frequently drive in conditions with low light level such as night, dusk, or dawn, so I was unable to include light level as a trip-level or frame-level predictor of distracted driving. This result is consistent with previous research showing that older adults do not drive at night as frequently as during the day (Blanchard et al., 2010).

Another avenue for future work is examining longitudinal changes in and predictors of distracted driving behavior. The models in the current study did not include a growth component because I did not expect that driving behavior would change systematically across two weeks. Future work could look at naturalistic driving behavior across a longer period of time so that longitudinal changes in driving in addition to across-trip differences could be assessed. Large datasets such as the 100-Car Study, which followed participants for 12 months (Klauer et al., 2010), and the Candrive II/Ozcandrive study, which will follow participants for 4 years (Marshall et al., 2013), would allow for examination of longitudinal driving changes and how trip-level variability is associated with longitudinal change in driving behavior. For example, as people become older, they may decrease in their variability of trip length, traveling to fewer places. The variability in trip length may be related to variability in within-person characteristics such as physical function, cognition, and vision.

It is important to note that the study sample was very homogenous and may not be representative of the population of older drivers. The sample was highly-educated and was primarily White. In order to be in the study, participants had to satisfy a number of requirements including being the primary driver of a vehicle, driving at least three days per week, and being willing to come to a university for data collection. The results of this study may be biased by these requirements even though they were necessary for naturalistic data collection and extensive assessments of physical function, cognition, and vision. It would be informative to examine driving in a more diverse sample of older adults such as individuals who do not drive frequently or individuals with more functional, visual, or cognitive impairment. Patterns of distracted driving and driving safety may be more pronounced in a more impaired sample, and participants from different demographic backgrounds may have different driving patterns due to sociocultural differences.

**Implications.** This study is the first to assess across- and within-trip associations between distracted driving and extensive objective assessments of physical, cognitive, and visual function utilizing naturalistic driving data in a sample of older adults. The results of this study have elucidated the types of distracted driving behaviors engaged in by older adults and predictors of these behaviors. Distracted driving is a major public health concern not just for adolescents but for older adults, evidenced by the fact that 17% of distracted drivers involved in fatal crashes in 2015 were 60 years and older (National Highway Traffic Safety Administration, 2017a). Distracted driving is a modifiable predictor of driving safety. As a result, this work will inform driver screening, safe driving interventions, and public health campaigns targeting older adults specifically. This work can also inform future uses or potential problems with in-vehicle technology by older adult users. As technology advances and in-vehicle technology gains in popularity, we should be cautious in recommending these technologies for older adults. In-vehicle devices, whether they are entertainment systems, navigation systems, or systems meant to improve safety by delivering beeps or vibrations, may serve as distractors to older adults and impact driving safety. This work also demonstrates the utility of both across-trip and within-trip analysis of naturalistic observation of older adult driving. Naturalistic studies on older adults' driving do not collect video data on participants while driving (Li et al., 2017; Marshall et al., 2013) or detailed information on participant functioning and demographics (Klauer et al., 2010). As demonstrated by this study, video data combined with in-lab assessments, analyzed with minimal data reduction to preserve variability and allow for multilevel modeling techniques, can be informative in understanding driving behavior in older adults.

**References**

Aksan, N., Dawson, J. D., Emerson, J. L., Yu, L., Uc, E. Y., Anderson, S. W., & Rizzo, M. (2013). Naturalistic distraction and driving safety in older drivers. *Human Factors: The Journal of the Human Factors and Ergomanics Society, 55*(4), 841-853. doi:10.1177/0018720812465769

Anstey, K. J., Wood, J., Lord, S., & Walker, J. G. (2005). Cognitive, sensory and physical factors enabling driving safety in older adults. *Clinical Psychology Review, 25*(1), 45-65. doi:10.1016/j.cpr.2004.07.008

Atchley, P., Tran, A. V., & Salehinejad, M. A. (2017). Constructing a publically available distracted driving database and research tool. *Accident Analysis and Prevention, 99*, 306-311. doi:10.1016/j.aap.2016.12.005

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1-48. doi:10.18637/jss.v067.i01

Blanchard, R. A., Myers, A. M., & Porter, M. M. (2010). Correspondence between self-reported and objective measures of driving exposure and patterns in older drivers. *Accident Analysis and Prevention, 42*(2), 523-529. doi:10.1016/j.aap.2009.09.018

Board, T. R. (2016). *Taxonomy and Terms for Stakeholders in Senior Mobility*. Retrieved from https://www.nap.edu/catalog/23666/taxonomy-and-terms-for-stakeholders-in-senior-mobility

Caird, J. K., Johnston, K. A., Willness, C. R., & Asbridge, M. (2014). The use of meta-analysis or research synthesis to combine driving simulation or naturalistic study results on driver distraction. *Journal of Safety Research, 49*, 91-96. doi:http://dx.doi.org/10.1016/j.jsr.2014.02.013

Choudhary, P., & Velaga, N. R. (2017). Analysis of vehicle-based lateral performance measures during distracted driving due to phone use. *Transportation Research Part F*, *44*, 120-133. doi:10.1016/j.trf.2016.11.002

Cuenen, A., Jongen, E. M. M., Brijs, T., Brijs, K., Lutin, M., Vlierden, K. V., & Wets, G. (2015). Does attention capacity moderate the effect of driver distraction in older drivers? *Accident Analysis and Prevention, 77*, 12-20. doi:10.1016/j.aap.2015.01.011

Dozza, M., Flannagan, C. A., & Sayer, J. R. (2015). Real-world effects of using a phone while driving on lateral and longitudinal control of vehicles. *Journal of Safety Research, 55*, 81-87. doi:10.1016/j.jsr.2015.09.005

Edwards, J. D., Bart, E., O'Connor, M. L., & Cissell, G. M. (2009). Ten years down the road: Predictors of driving cessation. *The Gerontologist, 50*(3), 393-399. doi:10.1093/geront/gnp127

Ferdinand, A. O., & Menachemi, N. (2014). Associations between driving performance and engaging in secondary tasks: A systematic review. *American Journal of Public Health, 104*(3), 39-48. doi:10.2105/AJPH.2013.301750

Fofanova, J., & Vollrath, M. (2011). Distraction while driving: The case of older drivers. *Transportation Research Part F: Traffic Psychology and Behavior, 14*(6), 638-648. doi:10.1016/j.trf.2011.08.005

Fofanova, J., & Vollrath, M. (2012). Distraction in older drivers - A face-to-face interview study. *Safety Science*, *50*(3), 502-509. doi:10.1016/j.ssci.2011.10.017

Freeman, E. E., Muñoz, B., Turano, K. A., & West, S. K. (2005). Measures of visual function and time to driving cessation in older adults. *Optometry and Vision Science, 82*(8), 765-773.

Fuller, R. (2005). Towards a general theory of driver behaviour. *Accident Analysis and Prevention, 37*(3), 461-472. doi:10.1016/j.aap.2004.11.003

Gamaldo, A. A., Allaire, J. C., & Whitfield, K. E. (2010). Exploring the within-person coupling of sleep and cognition in older African Americans. *Psychology and Aging, 25*(4), 851-857. doi:10.1037/a0021378.

Hakamies-Blomqvist, L., Raitanen, T., & O'Neill, D. (2002). Driver ageing does not cause higher accident rates per km. *Transportation Research Part F, 5*, 271-274. doi:10.1016/S1369-8478(03)00005-6

Hanson, T. R., & Hildebrand, E. D. (2011). Are rural older drivers subject to low-mileage bias? *Accident Analysis and Prevention, 43*, 1872-1877. doi:10.1016/j.aap.2011.04.028

Horberry, T., Anderson, J., Regan, M. A., Triggs, T. J., & Brown, J. (2006). Driver distraction: The effects of concurrent in-vehicle tasks, road environment complexity and age on driving performance. *Accident Analysis & Prevention, 38,* 185-191. doi:10.1016/j.aap.2005.09.007

Janke, M. K. (1991). Accidents, mileage, and the exaggeration of risk. *Accident Analysis & Prevention, 23*(2/3), 183-188.

Kawano, N., Iwamoto, K., Ebe, K., Aleksic, B., Noda, A., Umegaki, H., . . . Ozaki, N. (2012). Slower adaptation to driving simulator and simulator sickness in older adults. *Aging Clinical and Experimental Research, 24*(3), 285-289. doi:10.1007/BF03325260

Klauer, S. G., Guo, F., Simons-Morton, B. G., Ouimet, M. C., Lee, S. E., & Dingus, T. A. (2013). Distracted driving and risk of road crashes among novice and experienced drivers. *The New England Journal of Medicine, 370*(1), 54-59. doi:10.1056/NEJMsa1204142

Klauer, S. G., Guo, F., Sudweeks, J., & Dingus, T. A. (2010). *An Analysis of Driver Inattention Using a Case-Crossover Approach on 100-Car Data: Final Report*. (DOT HS 811 334). Washington, DC: National Highway Traffic Safety Administration.

Langford, J., Charlton, J. L., Koppel, S., Myers, A., Tuokko, H., Marshall, S., . . . Macdonald, W. (2013). Findings from the Candrive/Ozcandrive study: Low mileage older drivers, crash risk and reduced fitness to drive. *Accident Analysis and Prevention, 61*, 304-310. doi:10.1016/j.aap.2013.02.006

Langford, J., Koppel, S., Charlton, J., Fildes, B., & Newstead, S. (2006). A re-assessment of older drivers as a road safety risk. *IATSS Research*, *30*(1), 27-37. doi:10.1016/S0386-1112(14)60153-9

Langford, J., Methorst, R., & Hakamies-Blomqvist, L. (2006). Older drivers do not have a high crash risk- A replication of low mileage bias. *Accident Analysis and Prevention, 38*(3), 574-578. doi:10.1016/j.aap.2008.08.027

Lezak, M. D., Howieson, D. B., & Loring, D. W. (2004). *Neuropsychological assessment (4th edition)* (4 ed.). New York: Oxford University Press.

Li, G., Eby, D. W., Santos, R., Mielenz, T. J., Molnar, L. J., Strogatz, D., . . . Team, L. R. (2017). Longitudinal research on aging drivers (LongROAD): Study design and methods. *Injury Epidemiology, 4*(22), 1-16. doi:10.1186/s40621-017-0121-z

Marottoli, R. A., Richardson, E. D., Stowe, M. H., Miller, E. G., Brass, L. M., Cooney, L. M., & Tinetti, M. E. (1998). Development of a test battery to identify older drivers at risk for self-reported adverse driving events. *Journal of the American Geriatrics Society, 46*(5), 562-568.

Marshall, S. C., Man-Son-Hing, M., Bedard, M., Charlton, J., Gagnon, S., Gelinas, I., . . . Woolnough, A. (2013). Protocol for Candrive II/Ozcandrive, a multicentre prospective older driver cohort study. *Accident Analysis and Prevention, 61*, 245-252. doi:10.1016/j.aap.2013.02.009

Michon, J. A. (1985). A Critical View of Driver Behavior Models: What Do We Know, What Should We Do? In L. Evans & R. C. Schwing (Eds.), *Human Behavior and Traffic Safety* (pp. 485-520). Boston, MA: Springer.

Mullen, N., Charlton, J., Devlin, A., & Bédard, M. (2011). Simulator validity: Behaviors Observed on the Simulator and on the Road. In D. L. Fisher, M. Rizzo, J. Caird, & J. D. Lee (Eds.), *Handbook of Driving Simulation for Engineering, Medicine, and Psychology*. London: CRC Press.

National Highway Traffic Safety Administration. (2010). *Overview of the National Highway Traffic Safety Administration's Driver Distraction Program*. (DOT HS 811 299). Washington, DC.

National Highway Traffic Safety Administration. (2016). *Driver Electronic Device Use in 2015*. (DOT HS 812 326). Washington, DC: National Center for Statistics and Analysis.

National Highway Traffic Safety Administration. (2017a). *Distracted Driving 2015*. (DOT HS 812 381). Washington, DC: National Center for Statistics and Analysis.

National Highway Traffic Safety Administration. (2017b). *Traffic Safety Facts 2015 Data: Older Population*. (DOT HS 812 372). Washington, DC: National Center for Statistics and Analysis.

Oviedo-Trespalacios, O., Haque, M. M., King, M., & Washington, S. (2016). Understanding the impacts of mobile phone distraction on driving performance: A systematic review. *Transportation Research Part C, 72,* 360-380. doi:10.1016/j.trc.2016.10.006

Phillips, C. B., Sprague, B. N., Freed, S. A., & Ross, L. A. (2016). Longitudinal associations between changes in physical function and driving mobility behaviors of older adults. *Journal of the Transportation Research Board, 2584,* 70-76. doi:10.3141/2584-09

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., & R Core Team. (2017). nlme: Linear and nonlinear mixed effects models. R package version 3.1-131. Retrieved from https://CRAN.R-project.org/package=nlme

Prat, F., Planes, M., Gras, M. E., & Sullman, M. J. M. (2014). An observational study of driving distractions on urban roads in Spain. *Accident Analysis and Prevention, 74*, 8-16. doi:10.1016/j.aap.2014.10.003

R Core Team. (2013). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from http://www.R-project.org.

Ragland, D. R. (2004). Reasons given by older people for limitation or avoidance of driving. *The Gerontologist*, *44*(2), 237-244.

Regan, M. A., Hallett, C., & Gordon, C. P. (2011). Driver distraction and driver inattention: Definition, relationship and taxonomy. *Accident Analysis and Prevention, 43*(1), 1771-1781. doi:10.1016/j.aap.2011.04.008

Ross, L. A., Clay, O. J., Edwards, J. D., Ball, K. K., Wadley, V. G., Vance, D. E., . . . Joyce, J. J. (2009). Do older drivers at-risk for crashes modify their driving over time? *Journals of Gerontology. Series B, Psychological Sciences and Social Sciences, 64*(2), 163-170. doi:10.1093/geronb/gbn034

Sayer, J., LeBlanc, D., Bogard, S., Funkhouser, D., Bao, S., Buonarosa, M. L., & Blankespoor, A. (2011). *Integrated Vehicle-Based Safety Systems Field Operational Test Final Program Report*. (DOT HS 811 482). Washington, DC: National Highway Traffic Safety Administration.

Staplin, L., Gish, K. W., & Joyce, J. (2008). 'Low mileage bias' and related policy implications: A cautionary note. *Accident Analysis and Prevention, 40*(3), 1249-1252. doi:http://dx.doi.org/10.1016/j.aap.2007.10.012

Stavrinos, D., Ross, L., & Sisiopiku, V. (2014). *Final Report: A Naturalistic Driving Study Across the Lifespan*. (2012-095S). Gainesville, FL: Southern Transportation Research, Innovation, Development and Education Center.

Stern, R. A., & White, T. (2009). *NAB Mazes Test Professional Manual*. Lutz, FL: Psychological Assessment Resources, Inc.

Stoner, H. A., Fisher, D. L., & Mollenhauer Jr., M. (2011). Simulator and Scenario Factors Influencing Simulator Sickness. In D. L. Fisher, M. Rizzo, J. Caird, & J. D. Lee (Eds.), *Handbook of Driving Simulation for Engineering, Medicine, and Psychology*. London: CRC Press.

Sullman, M. J. M. (2012). An observational study of driver distraction in England. *Transportation Research Part F: Traffic Psychology and Behaviour, 15*(3), 272-278. doi:10.1016/j.trf.2012.01.001

Thompson, K. R., Johnson, A. M., Emerson, J. L., Dawson, J. D., Boer, E. R., & Rizzo, M. (2012). Distracted driving in elderly and middle-aged drivers. *Accident Analysis and Prevention, 45*(1), 711-717. doi:10.1016/j.aap.2011.09.040

Tison, J., Chaudhary, N., & Cosgrove, L. (2011). *National phone survey on distracted driving attitudes and behaviors*. (DOT HS 811 555). Washington, DC: National Highway Traffic Safety Administration.

Xiong, H., Bao, S., Sayer, J., & Kato, K. (2015). Examination of drivers' cell phone use behavior at intersections by using naturalistic driving data. *Journal of Safety Research*, *54*, 89-93. doi:10.1016/j.jsr.2015.06.012

Young, K. L., & Lenné, M. G. (2010). Driver engagement in distracting activities and the strategies used to minimise risk. *Safety Science*, *48*(3), 326-332. doi:10.1016/j.ssci.2009.10.008