Advanced Driver Assistance Systems and Older Drivers – Mobility, Perception, and Safety

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ABSTRACT

The aging process is often accompanied by declines in one or more physical, vision, and/or cognitive abilities that may impact driving safety. As older drivers become more self-aware of these functional deficits, they have the tendency to engage in self-regulation practices, such as less driving and avoiding challenging driving situations. This tendency may gradually evolve to give up driving altogether.

Advanced Driver Assistance Systems (ADAS) holds promise for improving older drivers' safety on the road as well as maintaining their mobility by compensating for declines in visual, cognitive, and physical capabilities. However, the perception of these technologies can influence the realization of these expected benefits.

The overarching goal of this research is to understand and enhance the safety and mobility of older adults by examining the impact of ADAS. The dissertation addresses this goal by investigating mobility, perception, safety measures, and safety. Study 1 employed structure equation modeling (SEM) on the data from the Second Strategic Highway Research Program (SHRP 2) on driving habits with respect to age, gender, living status, health, and functioning capabilities. The results illustrate that older drivers' health is a reliable predictor of driving exposure, and cognitive and physical declines are predictive of their intention to reduce exposure and actual driving in challenging situations. These findings highlight that the aging population requires support for their mobility and likely road safety given their age-related impairments.

Study 2 employed structure topic modeling on a focus group of older adults driving vehicles equipped with ADAS for six weeks was conducted to reveal five key issues to older drivers (in the order of prevalence): (1) safety, (2) confidence concerning ADAS, (3) ADAS functionality, (4) user interface/usability, and (5) non-ADAS related features. The findings point to a need for holistic ADAS design that not only must consider safety concerns but also user interfaces accommodating older adults' preferences and limitations as well as in-depth training programs to operate ADAS given the technology limitations.

Study 3 employed correlation analysis and logistic regression on SHRP 2 data to reveal that the longitudinal deceleration events at greater than 0.60g and lateral acceleration events at greater than 0.40g appear most associated with older adults' driving risk and are predictive of near future crash and near-crashes (CNCs) occurrence and high-risk older drivers with acceptable accuracy. These findings indicate that high g-force events can be used to assess risk for older drivers, and the selection of thresholds should consider the characteristics of drivers.

Study 4 compared high g-force events between two naturalistic driving studies to reveal that drivers who drove vehicles equipped with ADAS had lower longitudinal declaration rates, indicating the benefits of ADAS presence on older drivers' safety. When lane keeping assist (LKA) was engaged, lower high longitudinal deceleration was observed than when LKA was not engaged, indicating that older drivers tended to apply less aggressive braking when using LKA. Over several weeks of exposure to vehicles with ADAS presence, older drivers showed decreasing longitudinal deceleration but increasing lateral acceleration events. In other words, the potential of ADAS for positive safety-related impacts exists but some refinement in the design to reduce lateral events might be necessary.

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GENERAL AUDIENCE ABSTRACT

As people grow older, they may experience declines in their physical, vision, and cognitive abilities, which can affect their ability to drive safely. Many older drivers become more aware of these limitations and tend to drive less or avoid challenging situations, gradually some eventually stop driving altogether.

Advanced Driver Assistance Systems (ADAS) hold the potential to enhance the safety and mobility of older drivers by compensating for these declines in vision, cognition, and physical capabilities. However, the way older adults perceive and accept these technologies can influence their effectiveness.

This research focuses on understanding and improving the safety and mobility of older adults by examining the impact of ADAS on them through four studies. These studies fill gaps in research and provide insights into the potential of ADAS to enhance both the safety and mobility of older drivers. This research is vital for improving the quality of life for older adults and making our roads safer for all.

To my beloved Dad

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Liang, D., Lau, N., & Antin, J. (2022, September). A Structural Equation Model of older adults' driving exposure and avoidance using objective driving records. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 66, No. 1, pp. 6-7). Sage CA: Los Angeles, CA: SAGE Publications. https://doi.org/10.1177/1071181322661115

Study 2 was adapted from the published articles:

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1 Introduction

1.1 Motivation

Population aging is one of the major social transformations in the current century, posing challenges to the economy, healthcare system, and transportation. Americans are expected to have longer life expectancies, projected to rise from 79.7 years in 2017 to anticipated 85.6 by 2060. This demographic shift is resulting in both a higher number and proportion of people aged 65 and older in the population (Medina, Sabo, & Vespa, 2020). With the population aging, there will be more older drivers on the road. The number of licensed drivers aged over 65 has surpassed 42 million, representing 18% of all drivers in the United States (Federal Highway Administration, 2016). Furthermore, older adults perceived driving a personal automobile as a form of independence and a high quality-of-life and older drivers are expected to drive ever more (Buehler & Nobis, 2010; Santos, McGuckin, Nakamoto, Gray, & Liss, 2011).

Personal mobility includes a range of abilities, from the getting out of bed without assistance to more complex tasks such as ambulation and arranging transportation from one place to another. Mobility directly affects social interactions, independence, and wellness. Older adults in the U.S. primarily rely on driving their personal vehicle to complete daily tasks such as commuting to work, shopping, and visiting the doctor. The restrictions on driving habits pose a threat to older adults' mobility, which may lead to many adverse consequences, such as depression and declined health trajectories (Chihuri et al., 2016; Ragland, Satariano, & MacLeod, 2005; Windsor, Anstey, Butterworth, Luszcz, & Andrews, 2007). Thus, society needs to ensure that older adults can drive safely to maintain their mobility and thus well-being.

The dependence on driving for the mobility of older adults presents potential safety concerns because fatal crash rate per mile driven increase significantly after the age of 69 and peaks among drivers at age of 80 and older (Insurance Institute for Highway Safety, 2020). This elevated fatal crash risk can be attributed to age-related declines in cognitive, vision, and physical abilities, all of which are critical to driving (e.g., Anstey, Wood, Lord, & Walker, 2005; Owsley, Ball, Sloane, Roenker, & Bruni, 1991). Age-related frailty reduces biomechanical tolerance to crash forces leading to more fatalities (Li, Braver, & Chen, 2003).

Emerging vehicle technologies hold promises for improving driving safety as well as maintaining mobility for older adults. Advanced driver assistance systems (ADAS) that commonly includes adaptive cruise control (ACC), blind spot alert (BSA), lane keeping assist (LKA), and lane departure warning (LDW) could improve older drivers' safety by compensating for their age-related declines in visual, cognitive, and physical capabilities (Caird, 2004; Davidse, Hagenzieker, van Wolffelaar, & Brouwer, 2009). Older drivers could also drive more in conditions that they may otherwise avoid given the assistance of these technologies (Caird, 2004; Perel, 1998). For example, ACC and forward collision warning (FCW) may help prevent failures in perceiving and responding to hazards in a timely manner due to declines in attention or other cognitive abilities.

To realize the purported benefits of safety and mobility, advanced systems must be designed and developed considering older drivers' declines in driving abilities, as well as an understanding of their perception or attitudes of those technologies. Compared to younger adults, older adults seem more reluctant and sometimes resistant to adopting innovative technologies (Tacken, Marcellini, Mollenkopf, Ruoppila, & Szeman, 2005).

Older drivers may simply leave advanced features deactivated when driving (Flannagan et al., 2016; Reagan, Cicchino, Kerfoot, & Weast, 2018; Reagan & McCartt, 2016). As a result, some features may not be as beneficial as intended. Thus, older drivers' perception of ADAS is worthy of investigation.

Following sections provide background information on older adults' age-related functioning declines and potential assistance from ADAS (Section 1.2), ADAS and driving automation (Section 1.3), older adults' mobility restriction (Section 1.4), older adults' perceptions of ADAS (Section 1.5), safety measures for older drivers (Section 1.6) and potential safety benefits of ADAS (Section 1.7).

1.2 Older adults' age-related functioning declines and potential assistive ADAS

The aging process is often accompanied by declines in one or more physical, vision, and/or cognitive abilities that may impact driving safety (Anstey et al., 2005; Ball, Owsley, Sloane, Roenker, & Bruni, 1993; Huisingh et al., 2017; Owsley et al., 1998). Table 1-1 summarizes the aging-related declines, the associated driving safety implications, and potential assistive ADAS features as presented by Suen & Mitchell (1998) and later updated by Young et al. (2017).

Table 1-1. ADAS mitigating driving problems associated with age-related decline (adopted from Eby, 1998; Suen et al., 1998; Young, Koppel, & Charlton, 2016)

Domain	Examples of age-related decline or deficit	Associated driving problems	Potential assistance from ADAS
Visual/ Perception	Anatomical changes (e.g., presbyopia, neural changes) in visual system that negatively affect visual perception and function (Corso, 1981); declines in saccadic (Warabi, Kase, & Kato, 1984) and pursuit eye movement ability (Sharpe & Sylvester, 1978); and reduced maximum extent of gaze	Difficulty seeing nearby objects, like reading the dashboard, for older adults with presbyopia.	Traffic sign automatic recognition; In-vehicle signs (e.g., speed limits) and warnings; Night

	with head movement (Chamberlain, 1971)		vision enhancement technologies; BSA
	Slower dark adaptation (e.g., Domey, McFarland, & Chadwick)	Difficulty driving at night or in poor lighting.	
	Decreased sensitivity to light at night (Birren & Shock, 1950; Domey et al., 1960)		
	Increased glare recovery time (Brancato, 1969) and greater debilitating effects after being glared (Wolf, 1960)		
	Declines in static (Owsley & Sloane, 1990) and dynamic visual acuity (Burg, 1966)	Difficulty reading road signs from a distance. Difficulty reading road signs while driving.	
	Declines in contrast sensitivity for high frequency gratings (e.g., Owsley, Sekuler, & Siemsen, 1983)	Difficulty reading road signs or observing objects through the windshield.	
	Shrinkage in the size of useful field of view (UFOV) and declines in peripheral vision (e.g., Ball & Owsley, 1993)).	Difficulty noticing an object or pedestrian appearing in the peripheral vision, for example overlooking other road users while merging or changing lanes.	
	Deficient perception of depth (stereopsis) (Hoffman, Lee, & Hayes, 2003; Hofstetter & Bertsch, 1976; Jani, 1966)	Reduced ability to estimate the distance to the lead vehicle or following distance in traffic.	FCW; ACC;
	Reduced sensitivity of perceiving motion (Ball & Sekuler, 1986)		
Cognitive	Declined both divided attention (Ponds, Brouwer, & Van Wolffelaar, 1988) and selective attention (Parasuraman & Nestor, 1991)	Difficulty in multi-tasking. Overlook traffic signs and signals. Difficulty driving in complex scenarios, like intersections or congested traffic.	FCW; ACC; In-vehicle signs (e.g., speed limits) and warnings;
	Shorter working memory (Schonfield, 1969) and longer term of processing time for the short-term memory (Kausler, 2012)	Slow perceive or react to hazards, especially in complex traffic environment.	Navigation assistance/Route guidance (e.g., GPS); Driver condition

		Recalling traffic rules or complying with signs takes longer.	monitoring; ACC; LDW;
Physical	Arthritis is common among older adults (Centers for Disease Control and Prevention, 2021)	Seating in the vehicle is uncomfortable for long drives.	BSA, Rear collision warning, LDW, Lane change assist/merge warning system; FCW; ACC;
	Increased simple reaction time (Marottoli & Drickamer, 1993) and choice reaction time (Mihal & Barrett, 1976)	Slow responding to a signal or hazard.	
	Decreased flexibility, limited range of motion, and less accuracy in movement (Anshel, 1978; P. H. Marshall, Elias, & Wright, 1985; Szafran, 1953; Welford, 1984)	Having difficulty of turning head to scan the blind spot.	

1.3 Advanced Driver Assistance Systems and driving automation

Advanced driver assistance systems (ADAS) are technologies that are designed to enhance the safety of vehicle operation. ADAS uses advanced technologies, such as various electronic systems (e.g., radar, cameras, LiDAR and multiple sensors) to sense the surrounding environment and detect obstacles or driver errors, and then promptly provides the driver with either early warnings or take control of the vehicle.

ADAS can enable various levels of driving automation. Society of Automotive Engineers (SAE) International developed a taxonomy (SAE J3016_201806) to define and standardize the levels of driving automation systems (SAE International, 2018). The six SAE Levels range from no driving automation (Level 0) to full driving automation (Level 5). SAE International (2018) defines each level of automation and the human role during driving with automation. Level 0 systems have no control over the vehicle and are limited to providing warnings and momentary assistance, for example, BSA, LDW, night vision enhancement technologies, traffic-sign recognition, and forward-collision warning (FCW). Level 1 systems can take control over one functionality relevant to control either lateral or longitudinal directions (e.g., steering or accelerating/braking). Level 2 can simultaneously take control both lateral and longitudinal directions (e.g., steering and accelerating/braking).

Level 3 systems can perform actual driving in certain circumstances without any driver engagement. The Honda Legend claims to be the first production vehicle with the Level 3 automation but is only available for leasing in Japan limited to only 100 vehicles (Beresford, 2021). To date, Level 2 is the highest level of automation available in most commercial vehicles. For most mainstream car manufacturers, Level 2 autonomy is generally realized with ACC with LKA operating simultaneously as available in the Tesla's Autopilot, GM's Super Cruise, Nissan's ProPilot, Volvo (XC90), Audi (A6, A8), Mercedes Benz (E-Class).

This dissertation focuses on the following ADAS features which are situated between SAE Level 0 and 2:

Adaptive Cruise Control (ACC) helps drivers with longitudinal control based on headway distance and desired speed set by the users. ACC detects traffic in front of the vehicle, calculates the current headway, and modifies the vehicle's speed accordingly (Fancher, 1998; Hoedemaeker & Brookhuis, 1998). An ACC system typically includes a ranging sensor (e.g., millimeter-wave radar), an optical sensor, electronic torque control, and electronic braking (Reif, 2014; Tsugawa, 2006). The main area of application for ACC is on expressways and multilane roads with light to relatively heavy traffic densities (Reif, 2014). The primary purpose of ACC systems is to make driving easier, and as such, they are considered comfort and convenient features. Vehicle manufacturers refer to ACC by some alternative names: e.g., pilot assist (2020 Volvo S60), "propilot" assist (2020 Nissan Altima), smart cruise control (2019 Kia Soul), etc.

Blind spot alert (BSA) helps drivers to safely change lanes and prevent lane-change-related crashes by monitoring traffic or obstacles in the vehicle's blind spot and warning drivers of these obstacles (Jermakian, 2011). The warning can be visual (e.g., an icon appearing/flashing on the side mirror), auditory (e.g., a beep), or haptic (e.g., a vibration on the steering wheel) (see e.g., Guo, Wotring, & Antin, 2010). Vehicle manufacturers sometimes refer BSA systems as side-view assist, blind spot monitor, blind spot warning, etc.

Lane keeping assist (LKA): helps drivers with maintaining their vehicles within the current travel lane. LKA typically uses forward-facing cameras and machine vision to detect lane markings on the road (Tsugawa, 2006). If any unintentional lane deviations are detected, the LKA system will automatically steer to prevent the vehicle from departing from the current lane. LKA systems are also named by vehicle manufacturers as lane assist (Volkswagen), lane keeping aid (Volvo), lane departure prevention (Infiniti), lane keeping system (Ford), etc.

Lane departure warning (LDW): helps drivers to warn about lane departure that can cause accidents. LDW utilizes cameras and machine vision to locate lane markings relative to the vehicle (LeBlanc, 2006). When the vehicle drifts too close to the lane markings without an active turn-signal, LDW gives the driver a visual (e.g., flashing icon), auditory (e.g., beep), and/or haptic (e.g., vibration) warning. Compared to LKA, LDW only sends alerts to the driver, and does not take control to keep the vehicle center of the lane. LDW systems are also named by vehicle manufacturers as lane departure alert (Toyota), intelligent lane intervention (Nissan), etc.

1.4 Aging and mobility restriction

Older adults' declines in cognitive, visual, and physical functioning not only undermine their driving safety but are also associated with the changes in their driving habits. The findings from several studies indicated that older adults tend to drive less frequently and shorter distances (e.g., Benekohal, Michaels, Shim, & Resende, 1994; Charlton et al., 2006; Marottoli et al., 1993), or avoid driving in challenging situations, such as at night, in bad weather, in unfamiliar areas, or in heavy traffic/rush hour (e.g., Baldock et al., 2006; Benekohal et al., 1994; Charlton et al., 2006; Kostyniuk & Molnar, 2005; Ruechel & Mann, 2005). As older adults in the United States heavily rely on driving their private vehicles to complete daily tasks, these changes in driving habits result in self-imposed mobility restrictions and even lead to driving cessation, which frequently leads to many adverse consequences such as increased social isolation (Liddle, McKenna, & Broome, 2004; Ragland, Satariano, & MacLeod, 2004), increased depressive symptoms(e.g., Ragland, Satariano, & MacLeod, 2005), and health declines (Edwards, Lunsman, Perkins, Rebok, & Roth, 2009).

For developing efficient intervention for older adults' mobility maintenance, we need to have a sound understanding of the reasons of mobility restriction. Many studies examined the factors causing the change of mobility among older adults. Research has found several dominating factors associated with self-restricted driving, including age, gender, living status, health, vision, physical and cognitive abilities (Ackerman, Edwards, Ross, Ball, & Lunsman, 2008; Betz & Lowenstein, 2010; Braitman & Williams, 2011;

Choi, Adams, & Kahana, 2013; Edwards et al., 2008; Festa, Ott, Manning, Davis, & Heindel, 2013; Lotfipour et al., 2010; Rosenbloom & Santos, 2014; Sandlin, McGwin Jr, & Owsley, 2014; Unsworth, Wells, Browning, Thomas, & Kendig, 2007). Refer to **Chapter 2** for a detailed review of each factor. Built upon these factors collectively, some researchers also modeled older adults' driving mobility to study how those factors interact to impact their mobility (e.g., Labbe, Vance, Wadley, & Novack, 2014; Vance et al., 2006; Wong, Smith, & Sullivan, 2018). For example, Vance et al. (2006) built a casual model examining the effect of age, gender, health, physical, and cognitive functioning on older adults' driving mobility in terms of driving exposure and driving avoidance. Their modeling results indicate that age, gender, health, and cognitive functioning are associated with both driving exposure and avoidance, and the magnitude of the relationship is larger in cognitive functioning than in health. Vance et al. (2006)'s model has implications for early predicting mobility reduction in older drivers and developing effective intervention and remediation programs.

Current modeling works on older adults' driving mobility can be improved by taking into account two limitations. First, the models missing factors depicting important declining cognitive and physical functions that are essential for driving tasks. For example, Vance et al. (2006)'s model lacks visual functioning, which plays a critical role in driving (Owsley, 1994). The model would not be able to explain the changes in mobility well if these factors are not included. Second, driving exposure and avoidance in most older drivers' mobility studies were measured using self-reported data collected from questionnaires. Under-reporting driving exposure and avoidance were discovered in several validation studies that compared self-reported data to actual driving data (e.g., Blanchard, Myers, & Porter, 2010; Molnar et al., 2013). Though the self-reported and objective driving data generally do correspond fairly well (Molnar et al., 2013), the discrepancies still raise some validity concerns warranting research investigation.

1.5 Older adults' perception of ADAS

Despite the potential safety and mobility benefits to older adults, ADAS cannot produce any tangible benefits if they are not purchased, accepted, or used in a sustainable and appropriate manner by older drivers. Therefore, it is necessary to study drivers' perception (or attitudes) of ADAS on acceptance, safety, reliability, trust, and comfort levels. "Perception" in the dissertation refers to *"what they think about the technology"* (Eby et al., 2015, p 1) covering drivers' attitudes, acceptance, trust, and expectations about the technologies.

Many studies have examined older adults' opinions, feelings, and attitudes toward ADAS via questionnaires, surveys, interviews, and focus groups. Researchers in Australia surveyed 1,070 older drivers online and conducted eight in-depth interviews to investigate older drivers' perceptions and acceptance of ADAS (Davern, Spiteri, & Glivar, 2015). The study also investigated factors affecting older adults' purchasing decisions, perception of the safety of ADAS, and awareness of safety technologies. Generally, older drivers displayed positive attitudes toward ADAS but lacked awareness of current automated technologies, such as ACC, LKA, BSA, and LDW. When given the opportunity to elaborate on the contribution of ADAS to safety, older adults most commonly mentioned traditional and standard equipment, such as anti-lock brakes and airbags. Researchers also found that older drivers prefer to rely upon their personal experience or that of close friends in forming opinions about ADAS (Davern et al., 2015).

A literature review and focus groups revealed that the ADAS perceived by older adults as most beneficial to safety based on two criteria: the ability to reduce hazards by compensating for the effects of aging and drivers' acceptance of ADAS (Marshall, Chrysler, & Smith, 2014). The study indicated that ADAS features providing alerts only (e.g., BSA) had the highest acceptance rating from older adults, whereas features that intervene with vehicle controls (e.g., LKA) had the lowest acceptance rating.

The Hartford and the MIT AgeLab recruited 302 drivers aged 50-69 to examine their willingness to accept ADAS (The Hartford, 2015a). A video was played for participants to introduce ADAS. Consistent with the findings from (Marshall, Chrysler, & Smith, 2014), participants expressed the greatest willingness to use blind-spot warning and backup cameras, both of which can be categorized as in-vehicle alerts or information systems. Participants recognized the safety benefits but remained concerned about over-reliance upon the technologies.

In a recent study, 35 older drivers who owned a vehicle with at least two ADAS features were interviewed (Gish, Vrkljan, Grenier, & Van Miltenburg, 2017). The interviews elicited participants' motivation for purchasing the vehicle and explored their perceptions of ADAS. The study showed that awareness of age-related decline is not a major motivation for older adults in purchasing vehicles with ADAS. However, older participants who have used ADAS did value the technologies for improving safety as well as considering them "convenient devices" that improve their driving experience.

Many studies had examined older adults' perceptions of ADAS but do not carefully consider or control for exposure and experience with ADAS. For the studies not requiring experience with or ownership of vehicles with ADAS, participant responses may be influenced by the information received from media or their imaginations. Without the hands-on experience with the systems in the naturalistic driving conditions, the older drivers cannot be expected to be accurate in reporting the ease of use, interaction, or misuse of the systems. Further, these studies do not control exposure time to ADAS and thus cannot illustrate how new users learn and adapt to ADAS that are relevant for developing training plans.

1.6 Safety measures for older drivers

Crash risk is the most direct indicator of driving safety; however, relying on the occurrence of crashes to estimate crash risk is impractical due to their rarity, which, from a transportation safety research perspective, imposes infeasibly large sample sizes or long follow-up periods to attain sufficient statistical power. Kinematic data (e.g., velocity, acceleration, or jerk) collected by advancing in-vehicle data acquisition technology provides a novel source of risk predictors. Elevated kinematic events, also known as high g-force events, are instances when acceleration or deceleration in specific directions exceeds a pre-defined threshold. High g-force events reveal sudden vehicle maneuvers, including hard braking, aggressive acceleration, and sharp turning. These events themselves can be dangerous as they increase the likelihood of leaving drivers and other road users with limited time to react to hazards (Bagdadi & Várhelyi, 2011; Elvik, 2006). Furthermore, high g-force events not only reflect risk taking driving style, but also reflect poor judgment of various driving decisions such as how rapidly to accelerate or turn (McDonald et al., 2015). For example, impaired visual or cognitive capabilities hinder the timely detection and response to objects on the road, resulting in late and sudden maneuvers. Other risk factors, such as driving with strong emotions, can also lead to increased acceleration, deceleration, and speeds (Roidl, Frehse, & Höger, 2014). Thus, high g-force events can be used to assess the safety-related impacts of driving behavior, habits, capabilities, and other risk factors.

Previous studies investigating appropriate thresholds for high g-force events had participant samples heavily skewed towards younger or middle-aged drivers. Older drivers generally have low risk-taking tendencies with, e.g., the lowest percentage of crashes involving alcohol (NHTSA, 2002), the highest rate of seatbelt use compared to other age groups (Glassbrenner, 2004). However, older drivers often have declined or imparied functionngs that are critical to driving safety (Ryan, Legge, & Rosman, 1998). To compensate for these declines, older drivers self-regulate or self-restrict their driving to avoid challenging situations, such as driving at night, in bad weather, in busy traffic, and on the freeway (e.g., Ball, Owsley, Beth, & Roenker, 1998; Liang, Lau, & Antin, 2022; Molnar & Eby, 2008; Owsley, McGwin Jr, Phillips, McNeal, & Stalvey, 2004). Self-regulation may also include the tactical adjustments while driving, such as avoiding secondary tasks, avoiding overtaking, lengthening headways, driving at slower speed, and making few lane changes (e.g., Charlton, Catchlove, Scully, Koppel, & Newstead, 2013; LeBlanc, Bao, Sayer, & Bogard, 2013; Reimer et al., 2013; Siren & Meng, 2013; Trick, Toxopeus, & Wilson, 2010). Given potential age-related impairments and self-regulatory practices, older adults may have substantially different driving capabilities, habits, and driving styles compared to other age groups. These could influence their exposure to traffic conditions, driving habits, and thus kinematic driving pattern. For these reasons, high g-force events may not be interpreted in the same manner across age groups. Specifically, thresholds selection for high g-force events can affect the degree of association with crash risks, and thus the sensitivity, precision, and validity of using these events to assess driving or driver risk. However, investigation into high g-force events to assess driving and driver risk has not specifically targeted older drivers and the relationship between the high g-force events and crash risk for older population has yet to be firmly established.

1.7 Safety benefits of ADAS

The potential of ADAS to improve transportation safety is widely acknowledged by researchers. Driving simulator, test track, and on-road studies have been conducted to assess the impacts of single or combined ADAS features on driving safety. ACC is the most investigated longitudinal control feature. A simulator study observed that participants' (including older drivers) decreased workload and stress during the routes where ACC was activated (Stanton & Young, 2005). Another simulator study investigated how ACC impacted driving performance for two groups of participants: "older drivers" over 60 and "younger drivers" aged 60 and under. The study found that using ACC improved older adults' speed management in various simulated driving scenarios, including open road conditions, urban areas, and zones with lower speed limits (Guo, Blythe, Edwards, Pavkova, & Brennan, 2015). Negative effects have also been reported during ACC usage by younger and middle-aged drivers, such as driving faster, shorter minimum headways, harder braking (Hoedemaeker & Brookhuis, 1998), hitting the stopped vehicle more often (Piccinini, Rodrigues, Leitão, & Simões, 2015), braking later and harder (Fancher, 1998), and deviating further in lane position (Rudin-Brown & Parker, 2004). In those studies, only were included, except in Fancher (1998)'s study, where approximately 1/3 of the participants were older adults. With the exception for Fancher (1998)' s study that tested ACC under naturalistic driving conditions with a third of the participants being older adults, the study environments are either driving simulators or test tracks (Guo et al., 2015; Hoedemaeker & Brookhuis, 1998; Piccinini et al., 2015; Rudin-Brown & Parker, 2004),

As to lateral control features, using LDW was found to have better lane-keeping performance while conducting a secondary task (Blaschke, Breyer, Färber, Freyer, & Limbacher, 2009), exhibited fewer lane deviation incidents and lane excursions, driving closer to the center of the lane, using turn signal more often before changing lanes or making a turn, smaller variation in lane (LeBlanc, 2006; Son & Park, 2012) With BSA being activated, drivers were found to react more quickly to a lateral crash threat (Fitch, Bowman, & Llaneras, 2014) and increase the frequency of mirror checking before changing lanes (Kiefer & Hankey, 2008). These findings were either based on middle-aged drivers (Blaschke et al., 2009; Fitch et al., 2014), or mixed-aged participants (Kiefer & Hankey, 2008; D. LeBlanc, 2006; Son & Park, 2012). The study environments include on-road (Son & Park, 2012), field study (Blaschke et al., 2009), test tracks (Fitch et al., 2014), and naturalistic conditions (LeBlanc, 2006).

Both positive and adverse effects impacts have been reported while using ADAS, however, whether and how ADAS could benefit older drivers is still unclear due to two limitations. First, studies are lacking the focus on older populations, which, in general, have different driving habits, technology acceptance, and functioning capabilities than middle-aged and younger drivers. Second, many previous studies were either conducted on driving simulators or highly controlled road conditions that may not reflect behaviors in naturalistic driving.

1.8 Summary and research gaps

ADAS holds promise for improving older drivers' safety on the road as well as maintaining their mobility. However, research is still limited in: (1) how some critical aging-related factors influence older adults' driving mobility measured by objective driving records; (2) how older drivers perceive ADAS based on hands-on experience in naturalistic driving; (3) what thresholds for high g-force events appropriate for older drivers and how they assess driving risk and driver risk of older drivers in naturalistic driving; (4) how ADAS presence impact safety of older drivers.

For older adults' driving mobility, various factors including demographic, sociodemographic, health, and functioning capabilities, have been investigated and are shown to be associated with the changes in older adults' driving habits. Researchers also modeled older drivers' mobility considering the effects of these factors collectively and their interaction. The current research on modeling the changes in mobility of older drivers has two limitations: (1) several critical functions essential to driving are missing; (2) objective driving records are missing to reflect actual driving habit.

As to older adults' perception of ADAS, previous survey, interview, or focus group studies omitted hands-on experience of ADAS in the real world; thus, current findings may not reflect the ease of use, adoption, misuse, or overuse of ADAS by older drivers. Older adults' perception of ADAS after significant exposure to the technology in a naturalistic condition has not been investigated.

High g-force events has been examined as the safety measures in NDS for assessing driving risk and driver risk but prior studies only contained a handful of participants from the older population. Considering the special characteristics of older adults, including less risk-taking behavior, declines in functioning, and self-regulation practices, research needs to address how g-force events specifically reflect safety in this age group.

Previous studies revealed that ADAS affects driving safety in both positive and negative ways. Most of the findings in these studies were based on younger, middle-aged, or mixed-age drivers without explicit focus on older drivers. Further, many previous studies were conducted either on driving simulators or under controlled conditions. The safety-related impacts of ADAS on older drivers in naturalistic driving have been under investigated.

1.9 Objective

This dissertation focuses on older drivers and ADAS. The overall objective is to improve the safety and mobility of older adults with respect to design and deployment of ADAS. The dissertation examines older adults' mobility to indicate their need for greater support for their driving and how ADAS could potentially improve its perception and the road safety of older drivers (Figure 1-1). To address this overall objective, this dissertation contains four studies.

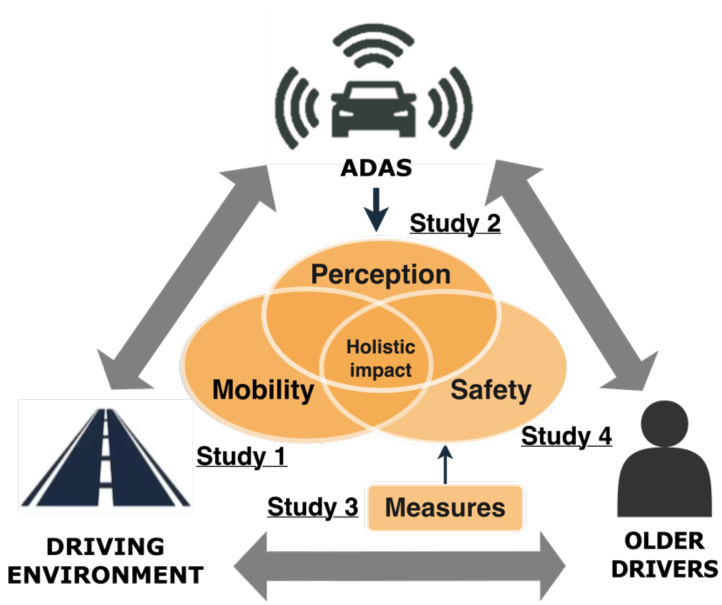

Figure 1-1. The organization of studies in the dissertation

1.9.1 Study 1 objective

Study 1 addresses the limitations of Vance et al. (2006)'s model: (1) not including visual ability, and (2) measuring driving habits using self-reported data. Specifically, study 1 presents a causal model to examine the influences of health, visual, cognitive, and physical functioning on driving exposure and avoidance data collected from a naturalistic driving study. Driving exposure in the model is measured by actual driving data, and driving avoidance is measured by actual driving data as well as self-reported data. Further, sociodemographic variables of age, gender, and living status are included in the model as exogenous variables to examine their direct influences on older adults' driving exposure and avoidance. The modeling results advance the understanding of older adults' mobility restrictions.

1.9.2 Study 2 objective

Study 2 addresses the research limitation on the lacking controls for exposure and experience with ADAS when investigating older drivers' perception of ADAS. This study examines the underlying factors affecting changes in older drivers' perception of ADAS after sufficient exposure under a naturalistic setting. Specifically, the study recruited 18 older drivers aged 70–79 to drive vehicles equipped with ADAS for 6 weeks in their own environments. Afterwards, each participant was enrolled in one of three focus group sessions to discuss their changes in attitude towards ADAS based on their driving experiences. The findings from analyzing the focus group discussion advance the understanding of older drivers' perceptions of ADAS.

1.9.3 Study 3 objective

Study 3 addresses the paucity of research on high g-force events for assessing crash risk specific to older adults. The study investigates a set of thresholds for high g-force events that are most appropriate to older drivers, followed by an examination of how high g-force events at these thresholds are associated with crash risk, and predictive of near-future crashes and high crash-risk drivers.

1.9.4 Study 4 objective

Study 4 addresses the lack of research on safety-related impacts of ADAS on older drivers in a naturalistic environment. The study compares kinematic events experienced by older drivers operating vehicles equipped with and without ADAS to infer safety safety-related impact. Further, this study examines how exposure to ADAS over time affects the number of kinematic events.

1.10 Overview of the Dissertation

The remainder of the dissertation presents the four studies in separate chapters followed by a conclusion chapter. **Chapter 2** presents a study on older adults' mobility through modeling driving habits with respect to age, gender, living status, health, and functioning capabilities. **Chapter 3** presents a study examining the attitudes towards ADAS from older drivers given sufficient hands-on experience of driving vehicles equipped with ADAS in a naturalistic environment. **Chapter 4** presents a study on threshold selection for high g-force events specific to older drivers for predicting and classifying their crash risks. **Chapter 5** presents a study examining whether and how ADAS produces any safety-related impacts on older adults based on analysis of two naturalistic driving study datasets. The final chapter collectively discusses the contribution of the four studies.

2 Study 1 – Modeling of Older Adults' Driving Exposure and Avoidance Using Objective Driving Data in A Naturalistic Driving Study

The first study examines older adults' mobility through modeling their driving habits with respect to age, gender, living status, health, and functioning capabilities. Having a sound understanding of how and what factors affecting mobility restriction is important to evaluate and developing effective interventions to prevent loss of mobility among older drivers. ADAS could be an effective intervention promoting older adults' mobility by compensating for the aging-related declines in abilities needed for safe driving. Thus, this study is an important study for evaluating the effectiveness of ADAS on promoting the mobility of older drivers.

2.1 Introduction

The U.S. population aged over 65 is predicted to reach 83.7 million by 2050 (Ortman, Velkoff, & Hogan, 2014) and the percentage of older adults' licensed to drive is on the rise (U.S. Department of Transportation., 2017). The ability to drive is essential to independent living and quality of life for senior citizens in the US, where the 75% of the population resides in rural and suburban areas (Carp, 1988; Kaplan, 1995; Rosenbloom & Herbel, 2009). Older adults in the US rely heavily on driving their own vehicles to commute to work, shop for groceries or access public services. Musselwhite and Haddad, (2010) and (2018) formulated a hierarchical mobility model to illustrate that mobility is important to satisfy primary/practical, secondary/social or affective, and tertiary/aesthetic needs. Driving reduction or cessation for older adults was associated with reduced activity outside of the home, increased dependency on others for transportation, decreased independence, loss of self-identity, reduced life satisfaction, and emergence of more depression symptoms spanning the entire mobility hierarchy (Chihuri et al., 2016; Harrison & Ragland, 2003).

Aging commonly leads to declines in visual, cognitive, and physical functioning in addition to more health issues that could hinder their driving abilities and increase crash risks (Lombardi, Horrey, & Courtney, 2017; Pitta et al., 2021). Age-related declines or impairments not only undermine their safety on the road but is also linked to reduced mobility and can even cause them to cease driving. As older adults become more aware of their age-related declines, they tend to drive less frequently and shorter distances, avoid driving in challenging situations, such as nighttime, bad weather, unfamiliar areas, and rush hour/heavy traffic (Baldock, Mathias, McLean, & Berndt, 2006; Charlton et al., 2006; Gwyther & Holland, 2012; Stalvey, Owsley, Stalvey, & Owsley, 2000).

Age is a strong predictor of reduced driving due to correlation with general health. A longitudinal interview study between 1994 and 2000 involving multiple followed ups of 752 participants aged 65 years and older living in Australia found that aging increases self-regulatory behaviors, such as, limiting driving to local areas during daylight, and "aged 75 and older" was one of the best predictors for the onset of driving behavioral modification (Unsworth et al., 2007).

Older drivers cite health or medical problems as the most common reasons to stop driving (Brayne et al., 2000; M. K. Campbell, Bush, & Hale, 1993) while research confirms health status as a strong predictor of driving reduction (Haustein & Siren, 2014). Medical problems can exacerbate functioning declines that hinder driving (Anstey, Wood, Lord, & Walker, 2005). Though the relationship between the medical conditions and driving capabilities is complex, a cross-sectional study of a large cohort of older women found that individual medical conditions and comorbidity have a significant impact on driving frequency, driving cessation, decreased driving mileages and trips longer than 100 miles (Forrest, Bunker, Songer, Coben, & Cauley, 1997). From two national surveys conducted in the United States, respondents carrying medical conditions and taking medications often reduce their daily driving and restrict their driving hours to daytime (Rosenbloom & Santos, 2014). Further, the results showed that older adults over aged 65 with medical conditions reported fewer driving trips. The use of medications by older adults was also associated with fewer driving days per week and less nighttime driving. Thus, number of medical problems and medications use are both good indicators of health with respect to predicting avoidance and exposure of driving (Forrest et al., 1997; Vance et al., 2006). Older adults who have ceased driving or showed greater self-restriction on driving commonly have a higher numbers of medical conditions (Campbell et al., 1993; Marottoli & Drickamer, 1993). In addition, some studies found the association between older adults' self-rated health status and driving habits (Barrett, Gumber, & Douglas, 2018; Campbell et al., 1993; Marottoli & Drickamer, 1993; Sargent-Cox et al., 2011; Xize Wang, 2022). For example, Wang (2022) conducted a logistic regression on survey data on 16049 individuals over age 65 indicating that individuals self-rated themselves with "poor health" exhibited an odd ratio 0.306 for driving in the past month compared to those self-rated "excellent health".

Driving strongly depends on vision to gather the information on the road (Lijarcio, Useche, Llamazares, & Montoro, 2020; Owsley & McGwin Jr, 2010); however, the visual functioning decline with aging due to some anatomical changes (see e.g., Owsley & Ball, 1993; Owsley & Sloane, 1990). Decreased size of pupil, ocular structure change, and loss of lens transparency, result in markedly less amount of light reaching the retina. Coupled with photoreceptors loss on retina, older drivers face difficulty in nighttime driving. Declined ability to perceive motion in depth makes left turns without traffic lights or merging more challenging for older drivers. Presbyopia can be noticeable as early as aged forty (Melvin, 2020) affecting the ability to monitor the instrument panel while driving. Visual impairments or declines could result changes in self-imposed driving limitation or cessation of driving. In an observational study, both the modified version of Visual Function (mVF-14) and the Snellen Visual Acuity test scores were found to be significantly correlated with the composite scores of self-reported driving restriction measures (Lotfipour et al., 2010). Vivoda et al. (2020) examined how declines in sensory (hearing and visual) affect the objectively measured driving patterns in four challenging situations. They used visual acuity as the measurement of vision and found that older drivers who had worse vision drove less percentage of trips over 15 miles. Almost half of older adults with cataracts avoided at least one type of challenging situations (e.g., nighttime, freeway, raining, and parallel parking), and those who self-regulate have significantly lower contrast sensitivity in their worse eye than those who do not (Fraser, Meuleners, Ng, & Morlet, 2013). However, the association of driving avoidance with visual declines might only be modest as poor contrast sensitivity but not acuity was associated with reduced driving exposure (Sandlin et al., 2014). Aside from visual acuity and contrast sensitivity, peripheral vision visual field is associated with driving cessation. In a study that followed 2,520 older adults for eight years with four data collection rounds, those experiencing 2-year losses in lower peripheral visual fields were more likely to stop driving. (Freeman, Munoz, Turano, & West, 2005). Poor depth perception has also been found to significantly correlate with self-restriction (C. G. West et al., 2003).

Physical strength and movement decline with age affecting the control of the vehicle (e.g., Anstey et al., 2005). Physical declines were associated with older adults restricting their driving or avoiding challenged situations (K. A. Braitman & Williams, 2011). In a longitudinal study, higher scores on Rapid Pace Walk tasks (higher scores means worse physical status with using longer time to complete the task) were correlated with more strategic self-regulation in driving (Molnar et al., 2014). Older adults who have ceased driving were more likely to report some physical difficulties (M. K. Campbell et al., 1993; Jette & Branch, 1992; Marottoli et al., 1993). Crowe et al. (2019) found that older adults with lower physical functioning, based on the Short Physical Performance Battery, had higher likelihood of being low-mileage drivers (less than 3,000 miles per year).

Aging also related to declines for almost all cognitive functions, such as attention, memory, cognition (Deary et al., 2009; Hedden & Gabrieli, 2004; Wilson et al., 2002; Zaninotto, Batty, Allerhand, & Deary, 2018). These functions play a critical role in perceiving hazards in the road, processing visual cues (e.g., traffic lights, road signs), focusing on driving tasks, predicting other road users' actions, and making quick decisions (Anstey et al., 2005; Breen, Breen, Moore, Breen, & O'Neill, 2007; Horswill et al., 2008; Martin, Marottoli, & O'neill, 2013; Ott et al., 2008; Withaar, Brouwer, & Van Zomeren, 2000). Increased self-restriction or cessation of driving is associated with drivers diagnosed with mild cognitive impairment (MCI) (Davis & Owens, 2021; Feng et al., 2020; Pyun et al., 2018) or early-stage cognitive disorders, such as Alzheimer's disease (Festa et al., 2013; Paire-Ficout et al., 2018) and dementia (Adler, 2010; Drachman, Swearer, & Group, 1993; Ross et al., 2009). This association between cognitive abilities and driving also applies to healthy older adults without diagnosed cognitive impairments. Based on a five-year prospective cohort study of 928 older adults from seven U.S. cities, cognitive performance on the Trail Making part A and part B tests as well as Montreal Cognitive Assessment was correlated with level of driving restrictions (Rapoport et al., 2013). In particular, longer Trail Making A and B completion times were modestly associated with less driving exposure and greater avoidance of those driving scenarios perceived to be difficult or risky, though none of the associations were strong. According to Vivoda et al. (2020)'s study (reviewed before), cognitive function was assessed by Trail Making B, and the lower test scores were associated with lower percentage of trip driven at night, on freeways, and in rush hours. Similar association were also found between worse Useful Field of View (UFOV) scores and more driving avoidance behaviors (i.e., driving exposure and location familiarity) in a five-year longitudinal study (Ross et al., 2009). Slower cognitive speed of processing as measured by UFOV has been found to be a predictor of more restrictive driving habits after controlling for other factors such as vision, age, and health (Ackerman et al., 2008; Edwards et al., 2008).

Besides functioning declines, gender is a strong and consistent predictor of driving habit. In the large longitudinal study (reviewed earlier), women relinquished driving three times more likely than men (Unsworth et al., 2007). Compared to older man, older women had lower average daily driving time (Shen et al., 2017) and were more likely to adopt more avoidance behavior, such as avoiding high speed roads or driving at night (Choi et al., 2013; D'Ambrosio, Donorfio, Coughlin, Mohyde, & Meyer, 2008). In addition, women tend to give up driving all together at an earlier age than men do (Marie Dit Asse, Fabrigoule, Helmer, Laumon, & Lafont, 2014).

The gender difference in changes of driving habits could be explained by health and psychosocial factors. Women generally have worse health than men across a variety of health indicators, for instance, more cognitive, vision, and hearing problems, more decline in functional abilities, and more chronic, potentially disabling conditions, all of which show consistent associations with more self-restriction on driving (Carmel, Rechavi, & Ben-Moshe, 2014; Charlton et al., 2006; Choi et al., 2013; Choi, Mezuk, Lohman, Edwards, & Rebok, 2012; Molnar et al., 2014; Vance et al., 2006). Aside from health status, men tend to keep on driving as long as their health allow them to, while women tend to give up driving for various, less pressing reasons (Hakamies-Blomqvist & Wahlström, 1998). In terms of psychosocial factors, men in most of households are the principal drivers, which was found to have less likely to report self-regulatory avoidance behaviors (Charlton et al., 2006). Besides, men viewed driving a car more as a necessity than women did (Hakamies-Blomqvist & Wahlström, 1998). Compared to men, women reported more traffic-related anxiety as in driving in busy and speeding traffic (Hakamies-Blomqvist & Wahlström, 1998), higher levels of resilience (Louis et al., 2020), and perceived lower confidence in driving (Kostyniuk, Molnar, & Eby, 2009; McNamara, Chen, George, Walker, & Ratcliffe, 2013; Meng & Siren, 2015; Molnar et al., 2014). Confidence has been found to be an important meditating factor of restricting driving (Charlton et al., 2006; Myers, Paradis, & Blanchard, 2008). Further, women were more likely than men to receive transportation support (e.g., rides from family members and friends (Choi et al., 2013; Shen et al., 2017), which facilitate their transition to cessation of driving (Barrett et al., 2018).

Living status also plays a role in changes in driving behaviors. A national level random-digit-dial telephone survey in the United States found that older adults living alone reported being more than twice as likely to engage in self-regulatory behaviors, such as avoiding bad weather, nighttime, traffic congestion, long trips, highways, and high-speed roads than younger respondents (Betz & Lowenstein, 2010). Choi et al. (2013) also found that older adults living alone self-reported higher likelihood of regulating their driving behaviors.

Various health, abilities, and social factors have all been individually shown to be significant contributors to driving mobility of older adults; however, associations between one single factor and driving mobility could present an incomplete picture due co-dependence between the factors. For explaining or predicting older adults' mobility, analysis should strive to examine all contributing factors simultaneously. Causal models have been developed to account for multiple factors to study driving behaviors (e.g., Labbe, Vance, Wadley, & Novack, 2014; Vance et al., 2006; Wong, Smith, & Sullivan, 2018). For example, Vance et al. (2006) presented a structural equation model (SEM) based on self-reported data to study the influence of age, gender, physical, cognitive, and health status on driving habits in terms of avoidance and exposure (Figure 2-1). Their study investigated 815 relatively healthy older adults aged 55 and over and found that both health and cognitive measures were predictive of self-reported driving exposure and avoidance, and the magnitude of this relationship is stronger for the cognitive than health factor. Age and gender were found to have direct influence on older adults' driving habits. However, physical functioning was associated with neither driving avoidance nor exposure in their model.

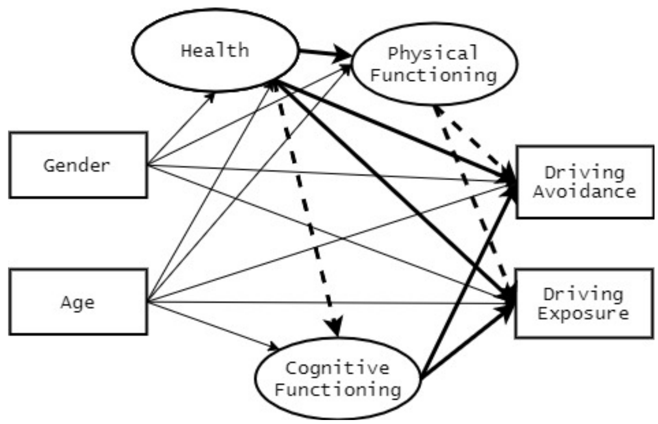

Figure 2-1. The trimmed causal model of driving exposure and driving avoidance presented by Vance et al. (2016). All solid lines represent significant effects; bold lines represent paths of study interest; and broken lines represent non-significant paths (investigated in the research study).

Vance et al. (2006) contributed to the understanding of how different factors associated aging could limit driving of older adults. In particular, their model suggests that maintaining physical health and cognitive abilities would reduce driving avoidance of older adults. However, Vance et al.'s model lacked the factor of visual ability, which plays a critical role in driving and has been shown to be associated with changes in older adults' driving habits. Thus, the model might not present as complete and accurate of a picture of how mobility of older adults is influenced by various types of declines.

Moreover, Vance et al.'s model and most of older adults' mobility studies used questionnaires to collect self-reported data on driving exposure and avoidance. Self-estimations of driving distance may be inaccurate and inconsistent. Under-reporting driving exposure was reported in several validation studies that compared self-reported data to actual driving data (Blanchard, Myers, & Porter, 2010; Molnar et al., 2013). The correspondence between self-reported and actual data was influenced by multiple factors, such as females being more accurate than males (Molnar et al., 2018). Though the self-reported and objective driving data generally do correspond fairly well (Molnar et al., 2018; Molnar et al., 2013; Molnar, Eby, Bogard, LeBlanc, & Zakrajsek, 2018), the discrepancies still raise some validity concerns warranting research investigation.

In-vehicle data acquisition systems (DAS) or GPS records can provide actual vehicle trip data including the dates, duration, speed, and other information (Marshall et al., 2007), enabling the use of objective driving records as the measurements of older adults' mobility. Measuring driving habits solely by looking at actual trip data poses some interpretation challenges. In the case of measuring overall driving exposure, actual driving data is more accurate and thus preferable to self-reported mileage data. However, for driving avoidance, specific driving patterns, such as less frequent nighttime driving or fewer long-distance trips, could mean that the older drivers either intentionally avoid or do not need to drive in such situations (e.g., less driving due to retirement). Therefore, using both self-reported and objective data is best for understanding driving habits (Molnar et al., 2015).

The objective of the study is to address the research gaps discussed above, and advance the knowledge in older adults' driving mobility by building a causal model to examine the influences of health, visual, cognitive, and physical functioning on driving exposure and avoidance data collected from a naturalistic driving study. This model represents a unique contribution because driving exposure was measured by actual driving data, and driving avoidance was measured by actual driving in challenging situations that the participants self-reported to avoid in addition to the self-reported data. In other words, this model includes objective data on the driving habits that the literature commonly cites older drivers tend to avoid. Further, sociodemographic variables of age, gender, and living status were included in the model as exogenous variables to examine their direct influences on older adults' driving exposure and avoidance. Figure 2-2 presents the proposed model with the following characteristics based on literature reviewed earlier:

1. Declining visual, cognitive, physical, and health/medical conditions are associated with driving exposure, self-reported driving avoidance and actual driving in corresponding challenging situations;
2. Declining visual, cognitive, physical, and health/medical conditions are *indirectly associated* with actual driving in challenging situations via self-reported driving avoidance; and
3. Self-reported driving avoidance is correlated with the actual driving in challenging situations.

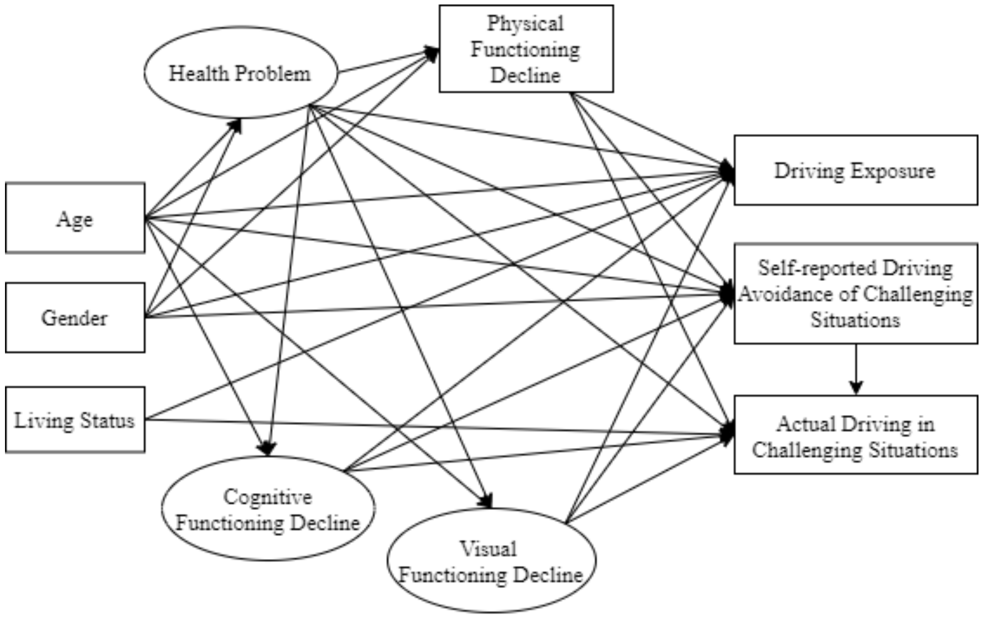

Figure 2-2. Proposed full structural model. Observed variables are shown in rectangles, latent variables are shown in ovals, the solid arrows indicate that there is relationship between the two connected variables.

2.2 Methods

2.2.1 Data acquisition

The data for this modeling study were collected in the Second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study (NDS), which is currently the largest ever full scale NDS containing comprehensive NDS data on drivers, road environment, and trip data. Antin et al. (2019) and Dingus et al. (2015) presented details on the SHRP 2 purpose, study design, eligibility for participation, enrollment procedures, participants recruitment, training, driver assessment equipment and data acquisition system (DAS). The SHRP 2 project completed data collection on 3,541 participants aged from 16 to 98 years, and most of them stayed in the study between one and three years.

At the beginning of the study[1], participants were assessed for their cognitive, physical, and visual abilities, and they completed a wide range of questionnaires regarding their demographic characteristics, personality traits, current health status, medications, risk perception, risky taking behaviors, sensation seeking, and driving behavior. For this study we initially included all trips made by participants aged 55 and over. The analysis also incorporated their demographic information, self-reported health conditions and medications currently in use, results from various tests of their cognitive, physical, and visual abilities. The initial pre-processed trip dataset included 1,804,716 trips and 1,166 participants.

The study protocol was approved by the Virginia Tech Institutional Review Board (**Appendix D**).

2.2.2 Data processing

Trips with moving durations of "null" and means speeds zero were removed from the dataset. Then, trips with moving distance less than 0.5km (i.e., around 0.31miles, such as moving a vehicle in a parking lot) were also deemed inappropriate and removed from the data set for the purpose of the study. These two steps resulted in 1,411,803 trips and 1,166 participants (aged 55 and over). We further eliminated all participants who reported using their vehicles for business purpose. The dataset was further narrowed down to those aged 65 and older to minimize work commutes dictated by the need to earn a living rather than personal desire. The final dataset included 794 participants of 367 women (46.22%) and 427 men (53.78%). Of all participants, 23.55% were between aged 65-69, 20.40%

[1] As a result of a variety of factors that could not be predicted before the study, a small number of participants took some of the assessments at the end of their participation.

between aged 70-74, 29.97% between aged 75-79, 18.26% between aged 80-84, 6.80% between aged 85-89, and 1% aged 90 and over.

Table 2-1 outlines the variables in the model and their measurements.

Table 2-1. Variables in model, definitions of variables and their measurements

Variable	Measurement		Objective/ self-reported
Visual functioning decline	Visual acuity	Visual acuity is the ability of how well you discern the shapes and details of the object from a specific distance. Binocular visual acuity test was administered using the Optec 6500p and assessed under photopic and distance settings. During the test, participants were asked to read all letters in the row on Snellen chart. The last line (smallest letters) the participant could read was recorded as a Snellen fraction and transformed to log mini angle resolvable (logMAR) for better analysis. For this measure, zero indicates average acuity and higher values represent poorer vision. The range in the sample is from -0.2 (good vision) to 0.8 (bad vision).	Objective
	Contrast sensitivity	Contrast sensitivity is a visual ability to tell the difference between an object and the background. Also using Optec 6500p, contrast sensitivity was tested individually for each eye under photopic conditions (85 cd/m) for a 6 cycles per degree grating. Participants started read from the top of the chart until they can no longer see any letters. The last patch the participant correctly identified before missing two consecutive patches was recorded as the test result and converted to log for the purpose of analysis. Noted that a score of 0.78 was assigned to the individuals who were unable to see the target even at the highest contrast level (1.08 log contrast sensitivity) for purpose of analysis. The range is 0.78 (cannot see) to 2.1 (good vision).	Objective
	Depth perception	Depth perception is a visual ability to perceive objects in three dimensions and the distance of the object. Depth perception was assessed for both eyes under photopic and far settings. This measure ranged from 1 (cannot see) to 10 (good vision).	Objective
	Peripheral vision	Peripheral vision is a visual ability to see objects and movement outside the point of fixation without the need of turning head or moving the eye. Using Optec	Objective

		6500p, peripheral vision was assessed by the test that asked the participant to detect the target appearing nasally at 45 degree and at 55, 70, 85 degree. The target at the most extreme degree that the participant can see was coded for analysis. The range for this measure is from "nasal" (coded as 1) up to 85 degree (coded as 4). The larger score represents the better peripheral vision.	
Cognitive functioning decline	UFOV- subtest 2 (ms)	UFOV subset 2 is designed to measure processing speed under divided attention. Participants were asked to identify an object (a car or truck) appear in the center of the screen for varying lengths of time and localize a simultaneously presented target displayed in the periphery of the screen. Test scores are the display duration.	Objective
	Trail making test A (min)	Trail Making Tests assesses the cognitive domains of processing speed that incorporates sequencing, mental flexibility and visual-motor skills (Bowie & Harvey, 2006). In part A, participants were asked to start with the number one and draw lines connecting all encircled numbers in numerical order. The time (min) the participant taken to complete the task was recorded as the test result.	Objective
	Trail making test B (min)	The part B task is similar to part A, the difference is that part A uses only numbers while the part B use letters and numbers. Participants were asked alternate between numbers and letters (e.g., 1, A, 2, B, 3, C…). The time (min) the participant taken to complete the task was recorded as his test result.	Objective
	Visualizing missing information (VMI) test (No. of incorrect)	Spatial ability was measured by VMI test. The total number of errors in the test was recorded as the test result ranged from 0 -11. Lower scores (fewer incorrect answer) indicate better functional performance.	Objective
Health problem	Number of health conditions	The total number of medical conditions selected by participants. One listed condition chosen, or "other", is worth one point. The possible range for this measure is 0-16.	Objective
	Number of medications	The total number of medications were presently taken as self-reported by participants. (Supplements, such as vitamins, fish oil, were not counted as medications.)	Objective

Physical functioning decline	Rapid pace walk test (s)	The time took for the participant to complete a 20-ft rapid pace walk was recorded as the test result. Taking less time to complete the test indicates better physical functioning.	Objective
Living status		Participants' household status was used to indicate whether or not they lived alone. The response "living alone" was coded 1. Other responses "one parent household" and "two parent household" were both coded 0.	Self-reported
Actual driving in challenging situations composite score (z-score)	Percentage of trips at night	Percent of all trips taken during nighttime (local time 9pm-5am).	Objective
	Percentage of trips on freeways	Percent of trips driven at least 80% on freeways (rural freeway, rural freeway < 4 lanes, urban freeway, urban freeway < 4 lanes).	Objective
	Percentage of trips during rush hour	Percentage of trips taken during rush hours on weekdays (local time 6am - 10am or 3pm -7pm from Monday to Friday). Used as a proxy for high traffic volumes.	Objective
	Percentage of trips with low frequency destination	Percentage of trips with destination being classified as a "low frequency", which occurred in less than 5% of the given participants' trips. Used as a proxy for driving in unfamiliar areas.	Objective
Driving exposure composite score (z-score)	Trips per week	Total number of trips taken divided by total number of weeks participated in study.	Objective
	Driving days per week	Total number of days with at least one trip taken divided by total number of weeks participated in study.	Objective
	Distance driven in kilometer per week	Total distance in kilometers driven divided by total number of weeks participated in study.	Objective
	Distance in kilometer per trip	Total distance in kilometers driven divided by total number of trips driven during study participation.	Objective
Self-reported driving avoidance of challenging situations (number of situations self-reported being avoided)		Driving avoidance was based on the total number of situations that the participants selected being avoided. The given situations were at night, highway or interstate travel, high traffic volumes, unfamiliar areas, and other. One condition chosen, or "other" that was not being listed, is worth one point. The possible range is 0-5. (*Note.* The selection "left turn" was dropped from the analysis.)	Self-reported

2.2.3 Data analysis

2.2.3.1 Missing Data

Missing data can affect the model fitting and parameter estimation (Vaske, 2019). Within the 794 participants, 74 participants did not respond to the questions on health status, and their data were missing one or all the visual, cognitive, and physical tests. The 74 participants with missing data did not differ from the remaining 720 participants in gender (χ^2 (1, n=718) = 0.18, p=0.67>0.05) but differ in age group (F (1, 718) = 6.55, p=0.01 <0.05) given that the older groups were more likely to have missing data. Of the 720 participants, 224 cases have between one and three missing values for the measurements of the various variables in Table 1, 496 had complete data. For these 224 cases, I imputed their missing data using multiple imputation (MI) method (Rubin, 1988), After imputation, the final sample size for analysis is 720 participants, which can be analyzed using SEM based on the recommendation of at least 20 responses per variable in the model (Schumacker & Lomax, 2004). The model has three latent variables and 17 observed variables, thus the sample size 720 satisfied the criterion established by Schumacker and Lomax.

2.2.3.2 Test for Normality

A Multivariate Royston test (H=1682.68, p < 0.001) indicated the presence of multivariate non-normality. Besides, the sample dataset includes both categorical and continuous variables. The two issues both influence the model fitting and parameter estimation. Thus, diagonally weighted least squares (DWLS) was selected as the estimation method. Compared to the default estimator, maximum likelihood estimation (MLE), DWLS provides more accurate parameter estimates and more robust model fit against departures from scale types of the variables and normality (Hart & Conn, 1992; Hoyle, 1995; Mindrila, 2010).

2.2.3.3 Analysis

SEM was used to examine the proposed causal model (Figure 2-2). SEM is a multivariate quantitative technique to depict the relationships among observed variables, which can be measured directly by existing data, and latent variables, which cannot be measured directly but are modeled on the basis of the observed variables. The present study followed the two-stage approach recommended by Anderson & Gerbing (1988). First, the measurement models were specified and tested to assess the validity and reliability of the constructs. Second, the proposed model was tested by data. The final trimmed model was constructed by eliminating the non-significant paths from the full model. The analysis mainly used R ("Lavaan" package for model fitting (Rosseel, 2012), "mice" package for multiple imputation Buuren & Groothuis-Oudshoorn (2010). The following model fit indices were computed: Chi-square test, Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR).

2.3 Results

2.3.1 Sample statistics

The descriptive statistics of 720 drivers are presented in Table 2-2.

Table 2-2. Descriptive statistics (N = 720)

	N	%	Range	Mean	SD	Skew	Kurtosis
Age group							
65-69	162	22.50					
70-75	141	19.58					
76-79	222	30.83					
80-84	137	19.03					

84-90	51	7.08					
Over 90	7	0.97					
Gender							
Female	325	45.14					
Male	395	54.86					
Living status							
Living alone	290	40.28					
Not living alone	430	59.72					
Rapid pace walk time (s)			3.06 -15.69	6.28	1.84	1.76	5.00
No. of health problems			0 -16	4.72	2.67	0.72	0.70
No. of meds			0 -17	3.81	2.99	1.49	2.77
Visual acuity under day and far conditions, logMAR (both eyes)			-0.20 - 0.80	0.08	0.15	0.79	1.21
Depth perception			1-10	4.68	2.72	0.38	-0.95
Peripheral vision (worse eye)							
1	12	1.67					
2	51	7.08					
3	108	15.00					
4	549	76.25					
Contrast sensitivity under day condition, log sensitivity (worse eye)			0.78 - 2.11	1.46	0.37	-0.64	-0.55
Trials A (min)			0.23 - 5.44	0.69	0.32	5.61	68.01
Trails B (min)			0.61 - 5.98	1.73	0.69	2.03	7.23
VMI test (No. of incorrect)			0 -10	2.55	2.06	1.45	2.23
UFOV subset2 (ms)			100-500	210.88	121.65	0.51	-0.96
Self-reported driving avoidance of challenging situations			0-5	0.79	0.95	1.40	1.94
Actual driving in challenging situations (composite z-score)			-6.56 - 5.63	-0.37	1.82	0.06	0.04
Driving exposure (composite z-score)			-6.31 - 9.29	0.007	2.65	0.29	-0.01

2.3.2 Measurement models

The measurement model was examined first to assess the fitness of the latent variables of health (number of health problems, number of medications), cognition (Trails A, Trails B, VMI, and UFOV), and vision (visual acuity, contrast sensitivity, depth perception, and peripheral vision). This step aimed to reduce measurement error by only retaining significant indicators. Items with factor loadings below 0.3 were removed from subsequent model development for parsimony (Kline, 2005).

The fitting indices in Table 2-3 indicate a general good fit between the proposed measurement model and the sample data. However, for visual functioning decline latent variable, peripheral vision has low factor loading (0.15 < 0.3) and thus removed from the subsequent model development (Kline, 2005). The re-specified model, without variable of peripheral vision, has improved fit performance compared with the initial one (see Table 2-3).

Table 2-3. Measurement model

		Initial Model (χ^2 (df) = 50.78 (32), p-value = 0.02, CFI= 0.99, RMSEA= 0.03, SRMR= 0.04, GFI=1.00, NNFI= 0.99, AGFI=1.00**)**				**Re-specified Model** (χ^2 (df) = 22.38 (24), p-value= 0.56, CFI=1.00, RMSEA= 0, SRMR=0.03, GFI=0.99, NNFI=1.00, AGFI=1.00**)**			
Statistics		**B**	**SE**	**Z (p>|Z|)**	**Beta**	**B**	**SE**	**Z (p>|Z|)**	**Beta**
Health problem	No. of health conditions	1	-	-	0.37	1			0.37
	No. of meds	3.59	0.31	11.69 (0.00)	1.20	3.55	0.40	9.04 (0.00)	1.19
Cognitive functioning decline	Trials A	0.14	0.01	14.33 (0.00)	0.44	0.14	0.02	8.92 (0.00)	0.43
	Trails B	0.39	0.04	11.22 (0.00)	0.57	0.39	0.04	10.79 (0.00)	0.56
	VMI test	0.65	0.06	11.32 (0.00)	0.32	0.69	0.08	9.17 (0.00)	0.33
	UFOV subset2	0.64	0.05	14.34 (0.00)	0.53	0.63	0.06	11.50 (0.00)	0.52
Visual functioning decline	Visual acuity	0.09	0.01	16.25 (0.00)	0.64	0.09	0.01	15.43 (0.00)	0.61
	Contrast sensitivity	-0.23	0.02	-14.93 (0.00)	-0.63	-0.25	0.02	-16.08 (0.00)	-0.67
	Depth perception	-1.81	0.11	-15.91 (0.00)	-0.67	-1.88	0.12	-16.29 (0.00)	-0.69
	Peripheral vision	-0.15	0.04	-3.88 (0.00)	-0.15	-	-	-	-

Note: CFI: Comparative fit index; GFI: Goodness-of-fit index; SRMR: Standardized Root Mean Squared Residual; RMSEA: Root mean square error of approximation; AGFI: Adjust GFI; NNFI: Non-Normed Fit

Index Criteria of acceptable fit: CFI, GFI, AGFI, NNFI ≥ 0.90; RMSEA, SRMR ≤ 0.08 (Hu & Bentler, 1999; Schermelleh-Engel, Moosbrugger, & Müller, 2003; Wan, 2002)

2.3.3 Structural equation model

The hypothesized model (Figure 2-2) was then tested with a number of goodness of fit indices to identify non-significant paths (Table 2-4). A trimmed model was then created by removing the least significant path one at a time (based on least z value) and recalculating model fit. The process iterated until only statistically significant paths ($p<0.05$) remained in the model.

Table 2-4. Goodness-of-fit for full and trimmed model

Goodness-of-fit Measures	Full model	Trimmed model
χ^2 (df)	180. 56 (79)	185.81 (88)
p-value χ^2	0.00	0.00
RMSEA	0.04	0.04
SRMR	0.04	0.04
CFI	0.95	0.95
TLI	0.92	0.93
NNFI	0.92	0.93
GFI	0.99	0.99
AGFI	0.99	0.99

Note: CFI: Comparative fit index; GFI: Goodness-of-fit index; SRMR: Standardized Root Mean Squared Residual; RMSEA: Root mean square error of approximation; AGFI: Adjust GFI; NNFI: Non-Normed Fit Index Criteria of acceptable fit: CFI, GFI, AGFI, NNFI ≥ 0.90; RMSEA, SRMR ≤ 0.08 (Hu & Bentler, 1999; Schermelleh-Engel et al., 2003; Wan, 2002)

Standardized and unstandardized path coefficients are listed in Table 2-5.

Table 2-5. The estimation results of the trimmed model SEM (All paths are statistically significant with p-value < 0.05)

		Est.	SE	Z-value	Standardized coefficient
Latent Variables					
Health problem ~	No. of health problem	1	-	-	0.37
	No. of meds	3.25	0.38	8.58	1.09
Visual functioning decline ~	Visual acuity	0.08	0.01	15.67	0.65
	Contrast sensitivity	-0.20	0.01	-16.04	-0.66
	Depth perception	-1.51	0.09	-16.03	-0.67
Cognitive functioning decline ~	Trails A	0.10	0.01	8.18	0.40
	Trials B	0.27	0.03	9.18	0.53

	VMI test	0.46	0.06	8.43	0.31
	UFOV subset 2	0.51	0.05	9.91	0.57
Regressions					
Visual functioning decline ~	Age	0.56	0.05	11.52	0.54
	Health problem	0.08	0.03	2.69	0.07
Cognitive functioning decline ~	Age	0.79	0.10	7.83	0.67
	Health problem	0.13	0.05	2.69	0.10
Physical functioning decline ~	Age	0.63	0.05	12.09	0.40
	Gender	-0.43	0.13	-3.21	-0.12
	Health problem	0.33	0.08	4.14	0.18
Driving exposure ~	Age	-0.50	0.08	-6.51	-0.22
	Gender	1.34	0.25	5.43	0.25
	Health problem	-0.24	0.09	-2.67	-0.09
	Living status	0.89	0.28	3.19	0.16
Self-reported driving avoidance of challenging situations ~	Gender	-0.36	0.07	-5.26	-0.19
	Visual functioning decline	0.08	0.03	2.26	0.10
	Cognitive functioning decline	0.07	0.03	2.19	0.11
	Physical functioning decline	0.05	0.03	1.97	0.09
Actual driving in challenging Situations ~	Self-reported driving avoidance of challenging situations	-0.18	0.08	-2.27	-0.09
	Cognitive functioning decline	-0.17	0.06	-2.93	-0.13
	Physical functioning decline	-0.20	0.06	-3.61	-0.20
	Living status	0.28	0.14	1.97	0.08

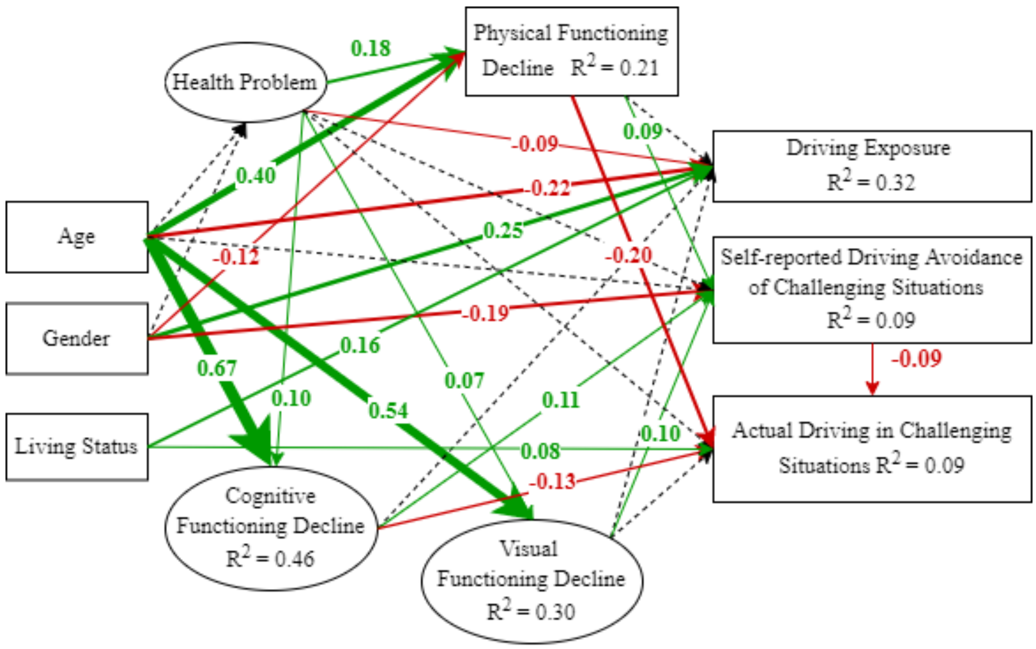

Figure 2-3. Final trimmed causal model (standardized estimates). Solid line = significant effects (p<0.05); broken lines = non-significant proposed paths. Line widths are proportional to coefficient values.

The full model (Figure 2-2) and final trimmed model (Figure 2-3) both showed good fit to the sample data. The final trimmed model (Figure 2-3) shows that *age, gender, health problems,* and *living status* are directly associated with *driving exposure*. *Gender, visual, physical functioning decline* and *living status* can be directly related to *self-reported driving avoidance,* as well as *actual driving in challenging situations. Age* is a predictor of *declines in visual* (standardized coefficient = 0.54), *cognitive* (standardized coefficient = 0.67), *physical functioning* (standardized coefficient = 0.40) and *driving exposure* (standardized coefficient = -0.22). Therefore, older adults tend to have declining visual, cognitive, and physical capabilities, and drive less as they age. *Health problems* have association with older adults' declines in *visual functioning* (standardized coefficient = 0.07), *cognitive functioning* (standardized coefficient = 0.10), and *physical functioning* (standardized coefficient = 0.18). Additionally, *health problems* are predictive of *driving exposure* (standardized coefficient = -0.09). *Genders* exhibit different *physical functioning decline* (standardized coefficient = -0.12), *driving exposure* (standardized coefficient = 0.25), and *self-reported driving avoidance of challenging situations* (standardized coefficient = -0.19). Results showed that older females have worse physical performance, and they are more likely to self-restrict their driving through less exposure and report greater avoidance of challenging situations. Both *cognitive* and *physical functioning declines* were found to be directly related to driving avoidance as reflected by self-reported measurements (standardized model coefficients of 0.11 and 0.09 respectively) and actual driving measurements (standardized model coefficients of -0.13 and -0.20 respectively). Older adults with cognitive and physical functioning declines self-reported to avoid more and exposed less to challenging situations. In addition, *visual functioning decline* is associated with more *self-reported driving avoidance* but is not linked to *actual driving in challenging situations* according to the model. Lastly, *living status* is predictive of *driving exposure* (standardized coefficient = 0.16) and *actual driving in challenging situations* (standardized coefficient = 0.08). Older adults who live alone tend to drive more and expose themselves to challenging situations to a greater extent.

2.4 Discussion

A causal model was built to predict driving exposure and driving avoidance according to age, gender, living status, and functional capabilities. This model includes self-reported as well as actual driving data collected during naturalistic driving observation. Using SEM, the relationship between the factors and driving exposure, self-reported driving avoidance and actual driving in corresponding challenging situations were examined. The final model presents several important findings: (1) poorer health is predictive of less driving exposure; (2) living alone is associated with greater driving exposure in general (i.e., higher mileage) as well as greater exposure to challenging driving situations; (3) self-reported driving avoidance is inversely related to observed exposure to challenging driving situations, and (4) worsening cognitive and physical functioning have a direct association with more driving avoidance as reflected in both self-reported and objective measurements.

The present model revealed a small association between health conditions and observed driving exposure, indicating that older adults with poorer health status tend to drive less. This relationship is logical and consistent with previous studies that relied on self-reported driving exposure (Campbell et al., 1993; Marottoli et al., 1993; Rosenbloom & Santos, 2014; Vance et al., 2006). However, age and gender in the model showed no relationship with health, and no links to driving avoidance. Health measurement in this study may not fully reflect the health status of older adults because quantifying health by merely adding up self-reported diseases without accounting for severity might not reflect practical health status related to driving. Future work ideally should include more measurements or indicators of health status, including health status rated by participating drivers and health professionals in addition to the number of health conditions or medication use.

The model shows that older adults who live alone tend to drive more and engage in more driving in challenging situations. This finding is contrary to previous studies indicating that older adults who reported living alone also reported more restrictions in their own driving (Betz & Lowenstein, 2010; Choi et al., 2013). This discrepancy may be attributed to the fact that previous studies employed self-reported data for measuring driving mobility, while the current study used observed driving data. How much a driver drives or how frequently the individual is exposed to potentially hazardous situations is determined by many factors, such as work status, schedule flexibility, and the environment in which the individual lives. Additionally, living status is a sociodemographic factor intricately tied to transportation support and dependency on others, which can influence older adults' driving behaviors. Older adults living with families can easily access transportation support; however, for those who live alone, even if they may want to restrict their driving as the earlier studies suggested, those intentions might not be easily carried out and develop to the actual behavior due to lack of the alternatives to driving on their own. The access to alternative transportation could be an essential factor in the transition from driving frequently to cessation (Barrett et al., 2018). Hassan, King, and Watt (2015) concluded that relying on a spouse or other family members for transportation facilitated the transition to non-driving, whereas living alone (i.e., no reliance) led to extended driving. In addition to transportation support, older adults living with families are more likely to make decisions about self-regulating behaviors collectively or at least with more inputs or concerns for their safety and well-being (Kostyniuk, Molnar, & Eby, 2009).

The discrepancy or a modest inverse association between self-reported driving avoidance and actual driving in challenging situations is also observed in the model, lending some support to our interpretation of the model result on living status. The discrepancy between self-reported driving avoidance and actual driving in challenging situations is consistent with prior research (Molnar et al., 2013). Self-reported driving avoidance, which was collected from the questionnaire items asking participants which/if they tried to avoid certain driving situations, may reflect drivers' intention to limit their behavior and/or driving thought to have been avoided (i.e., counter factual that is difficult to verify). There are many factors in real life interfering with carrying out the intention or translating it to actual behavior. For example, as I discussed above, the lack of alternative to driving themselves would hinder a transition to not driving. Developing self-regulatory practice is about having the ability to adjust the behavior if one choose to. Baldock et al. (2006) defined self-regulation as an ability to harmonize driving ability and avoidance. The imperfect association in the present model may be best interpreted as how much of the intention matches with, or translates to, the actual behaviors. Future work should examine how certain social, demographic, or environment factors (i.e., population density, public transportation in the area, income…) influence this transition.

Worsening cognitive, physical, and visual functioning are associated with more self-reported driving avoidance. These relationships are consistent with findings from earlier studies with the exception of work by Vance et al. (2006) who did not find a relationship between physical functioning and driving habits. In the present model, the magnitudes of the influences are nearly equivalent for visual, physical, and cognitive functions on self-reported driving avoidance. The magnitude of the direct association between actual driving in challenging situations and physical capability function is slightly greater than between cognitive ability. The reason for this finding may be that cognitive ability is less easily self-monitored compared to physical ability; thus, older adults with mild cognitive declines may not be sensitive to the change or any need of avoiding driving in challenging situations. In a longitudinal study, cognitive function was identified as a better predictor of driving cessation than physical performance (Anstey, Windsor, Luszcz, & Andrews, 2006). However, driving cessation is different from avoidance. Driving cessation could be seen as the final stage of self-restricted driving. Those who gave up driving entirely in Anstey et al.'s study were more likely to have poor health or severe impairment. Participants in the study were active and legally licensed with good cognitive status. A naturalistic study with early-stage dementia participants suggested that driving mobility might not be affected at the early stage of cognitive impairment (Eby, Silverstein, Molnar, LeBlanc, & Adler, 2012). According to an interview study, older drivers with cognitive impairments were aware of the problems but did not feel their driving was affected (Meng, Siren, & Teasdale, 2013). However, research has shown that driving could deteriorate before cognitive impairment can be detected using standard instruments (Roe et al., 2017). There appears to be a lot of nuances in the relationship between cognitive and physical functioning in the contexts of driving avoidance and cessation that need further research to explain these relationships.

This study has four limitations. First, the study has a restricted range of sample in terms of visual, physical, cognitive, and health status, which might explain why those paths/associations that were not statistically significant. Participants in SHRP 2 were required to be active drivers who held valid driver licenses, thus this sampling method inherently favored healthier older adults. Those who had severe illnesses or functional impairments may have been less likely to volunteer (or be considered eligible) for a driving study even though they are still driving.

Second, the measurement of self-reported driving avoidance is incomplete. The present model only accounted for self-ratings (on a six-point scale) of their driving avoidance in four situations[2] - freeway, nighttime, unfamiliar areas, and rush hour. This measurement approach may not have been sufficiently sensitive to subtle changes in the intention of avoiding certain driving situations. Many other situations commonly mentioned in previous studies about older adults' driving mobility were not included in the SHRP 2 questionnaires, such as, inclement weather (e.g., foggy or rainy conditions), and long-distance traveling.

Third, raw data collected by DAS is not able to be directly applied to examine driving patterns in challenging situations. Deriving the measures for studying the patterns from the raw data needs triangulation of various of supporting datasets (e.g., vehicle speed, time of day, location, weather…). For example, precisely defining "nighttime" or "daytime" should consider the local solar angle, as in the Molnar et al. (2013)'s study which characterized "nighttime" as the solar angle greater than 96° and "daytime" less than 90°. However, the dataset does not contain latitude/longitudinal coordinates and GPS time for each trip, which are required to calculate the solar angle. Thus, this study employed the simplification of defining trips between 9pm and 6am as nighttime driving even though the solar angles could be less than 90° after 9pm or greater than 96° after 6 am depending on the seasons. The relatively large dataset should contain sufficient cases either way to render these exceptions having negligible influence on the results. Similarly, the definitions of unfamiliar areas and high traffic volume were also simplification based on distance and time, respectively. Defining driving patterns in

[2] Participants were presented five situations, but the selection of avoiding "left turn" was dropped and not counted for analysis. So, four situations were considered in this study.

simpler, though well-accepted, terms may limit the degree of association between self-reported driving avoidance and actual driving patterns in challenging situations.

Finally, the study assumed that participants' functioning abilities, health, and living status had no significant changes during the period of participation. SHRP 2 administered ability assessment only at the beginning of the study participation. Significant changes (e.g., a sharp decline in vision due to a disease or an accident) could result in overestimating or underestimating the influence of the factors on mobility.

Notwithstanding these limitations, the findings of the study offer several implications for developing early detection and intervention programs to help older adults who are relatively healthy, active, and legally licensed drivers. A major goal of transportation policies and measures are to ensure older adults' safety on the road as well as maintaining their mobility and avoiding unnecessary driving cessation (O'Neill, Walshe, Romer, & Winston, 2019). Routine screenings for cognitive, visual, and physical functioning may be effective in detecting a change in driving habits, especially physical functioning, which has larger association with elders' avoidance driving pattern. The local government should also offer older adults some incentives to encourage them to take the screening tests regularly and advise older adults who are at risk to access alternative transportation methods. Special attention should be given to elders living alone and experiencing physical, cognitive, and visual declines.

The educational intervention had demonstrated effectiveness in promoting self-regulatory practices, though the program examined only visually impaired older adults (Owsley, Stalvey, & Phillips, 2003). The present model supports continuation of program to educate older adults on how to monitor all aspects of their driving function (e.g., vision, health, cognition…) and to appropriately reduce exposure to hazardous situations. Further research is necessary to investigate whether cognitive training could be a potential remedy to delay declines and driving avoidance with older drivers. Speed of processing training has been found to increase responsiveness to road signs in driving simulators and reduce dangerous driving maneuvers in on-road tests (Roenker, Cissell, Ball, Wadley, & Edwards, 2003), and UFOV training has been shown to reduce the risk of driving cessation (Edwards, Delahunt, & Mahncke, 2009). However, other studies have not found such positive effects (Antin, Owens, Foley, Ebe, & Wotring, 2016). A recent literature review suggests an overall effectiveness in training and educating older drivers but discrepancies between studies challenge comparison between techniques and methods (Castellucci, Bravo, Arezes, & Lavallière, 2020). Timely access to medical interventions is effective in improving mobility and reducing crash risk. For example, Agramunt et al. (2018) found that 47.3% of 55 older adults self-reported to regulate their driving behavior while waiting for cataract surgery but the percentage dropped to 29.1% after first eye surgery and further to 18.2% after second eye surgery. The crash rate for those who underwent cataract surgery was half that of those who didn't but needed such operation (Owsley et al., 2002). Advancing vehicle technology might play a role in maintaining mobility and enhancing safety as some researchers have suggested that Advanced Driver Assistance Systems (ADAS) (e.g., ACC, LKA, etc.) have the potential to assist older drivers in compensating for declining abilities (Caird, 2004; Davidse, 2006). Though less accepting of new technology, older adults have also shown some positive attitude towards some advanced technology in supporting their driving and road safety (Liang, Lau, & Antin, 2019; Liang, Lau, Baker, & Antin, 2020) and these technology might affect their driving habits and thus mobility. As the model affirms that multiple factors contribute to driving avoidance, a comprehensive approach involving many techniques and solutions would be necessary to extend mobility while maintaining road safety of senior drivers.

2.5 Conclusion

This study developed a causal model to examine the influences of health, visual, cognitive, physical functioning and sociodemographic factors on older adults' driving exposure and avoidance. The study analyzed both self-reported as well as actual driving data to examine older adults' driving habits. Results indicate that health is a reliable predictor of driving exposure, and cognitive and physical functioning are predictive of their intention and actual driving in challenging situations.

3 Study 2 - Examining Older Drivers' Perception of ADAS after a Naturalistic Exposure

The first study examined the older adults' mobility by modeling their driving habits based on age, gender, living status, health, and functioning capabilities. This study focuses on older drivers' perception of ADAS based on a sufficient hands-on experience of them in a naturalistic setting.

3.1 Introduction

The U.S. Census Bureau (2018) predicts that the population of seniors aged 65 and over will reach 94.7 million by 2060, making up about a quarter of the U.S. population. The number of senior drivers is projected to increase from 42 million (Federal Highway Administration, 2016) to over 60 million by 2030 (AAA Exchange, 2017). More senior drivers on the road could raise road safety concerns. Though not all senior drivers are at high risk of traffic accidents, they do have a higher likelihood of being involved in fatal crashes due to increased fragility (Insurance Institute for Highway Safety, 2013). While seniors may have years of driving experience, they often show mild impairments that could impact driving safety. Examples include poor vision (e.g., Anstey, Wood, Lord, & Walker, 2005; Attebo, Mitchell, & Smith, 1996), declining memory performance (e.g., Perlmutter & Nyquist, 1990; Rabbitt, 2019; West, Crook, & Barron, 1992), divided attention-related failures (e.g., Ponds, Brouwer, & Van Wolffelaar, 1988; Salthouse, Mitchell, Skovronek, & Babcock, 1989), and slower reaction time (Marottoli & Drickamer, 1993).

Emerging Advanced Driver Assistance Systems (ADAS) technologies have the potential to improve safety and mobility for senior drivers by compensating for some of these milder impairments. ADAS is a general term that includes a broad array of features. In the context of this paper, the term ADAS refers to features at the lower three SAE International levels (levels 1–3) of driving automation (SAE International, 2014), excluding those only in highly automated and driverless vehicles. ADAS can sense and provide important driving information, such as vehicles in the blind spot with BSA, and help control the vehicle in very specific conditions, such car following with ACC. The potential safety benefits can be substantial for seniors experiencing mild cognitive or physical declines. For example, seniors with neck rotation difficulties may find a BSA particularly helpful. Researchers have been optimistically anticipating that ADAS will alleviate age-related safety decrements commonly manifested in driving (e.g., Band & Perel, 2007; Caird, 2004; Davidse, 2006; Eby et al., 2016; Meyer, 2014).

Attaining anticipated ADAS benefits is dependent on drivers' acceptance of and adaptation to the capabilities of new technologies and thus a new way of driving. Relative to other age groups, seniors seem more reluctant (Caird, 2004), sometimes even resistant, to adopt innovative technologies (Tacken et al., 2005). Trust in technology also seems to decrease with age (Ho, Kiff, Plocher, & Haigh, 2005) and learning new skills and changing well-established routines become more difficult with age (Craik & Jacoby, 1996). However, seniors have indicated that they may adapt to advanced technologies as readily as younger groups if provided with sufficient training and exposure opportunities (Owens, Antin, Doerzaph, & Willis, 2015). Thus, policy makers and manufacturers must understand the factors influencing senior drivers' attitudes towards and adaptation to using ADAS to alleviate aging-related traffic risks.

Most studies on seniors' attitudes towards ADAS have employed surveys on a large sample of drivers from all age groups and sometimes have held focus groups comprising various user populations. Seniors generally have significantly lower technology utilization and acceptance rates than younger and middle-aged users (Czaja & Sharit, 1998), which is reflected in their lower inclination to use ADAS (Bansal, Kockelman, & Singh, 2016; Munich RE, 2017). Through a focus group study about LDW system, Regan, Mitsopoulos, Haworth, & Young (2002) found that seniors were not willing to pay as much for the feature as young adults were. Other studies also found that, in general, seniors appeared less willing to pay for ADAS, highly automated, or driverless technologies (Abraham et al., 2016; Bansal & Kockelman, 2018; Bansal et al., 2016; Payre, Cestac, & Delhomme, 2014; J.D. Power, 2012). These survey studies illustrate differences in attitudes towards ADAS between seniors and drivers in other age groups.

In comparison to other age groups, seniors may be less willing to accept ADAS, but studies focused specifically on seniors reveal substantial nuances in their perception of advanced vehicle technologies. In terms of awareness, Davern, Spiteri, and Glivar (2015) conducted a two-phase study, in which eight 45-minute in-depth interviews were conducted with eight senior drivers, and then an online survey was administered to 1,070 seniors. Participants were required to be over the age of 60 for both phases. Findings revealed that seniors generally had limited knowledge of the latest vehicle technologies and ranked "features/technologies within the car space" to be the most important factor in their perceptions of car safety.

The Hartford Center for Mature Market Excellence and the MIT AgeLab conducted a series of nationwide surveys on drivers over 50 years of age to assess ADAS and driverless technology acceptance, preference, and system learning. Collectively, the main findings of the studies were that (1) most seniors were willing to purchase a car with at least one ADAS (The Hartford, 2015, 2017), citing safety as their primary reason (The Hartford, 2012b, 2012a, 2015, 2016); (2) seniors were most willing to adopt BSA (in-vehicle alerts warning of objects in blind spots)(The Hartford, 2012a, 2015b, 2016); and (3) seniors first relied on an owner's manual, second on trial and error, and finally on car dealers to learn about the ADAS installed in their own cars (The Hartford, 2012a). One survey highlighted seniors' preference for well-designed driver education programs, such as workshops, online tutorials, and hands-on learning with an instructor driving, to be provided by trusted organizations or dealers (The Hartford, 2017).

Besides surveys, the literature includes interview and focus group studies. An early focus group study investigated the expectations of British senior drivers (aged 52–79) on emergency signaling, navigation systems, fatigue monitoring, and forward collision avoidance systems (Sixsmith, 1990). Seniors expressed skepticism about the warning features, which could take their attention away from driving, but they were receptive to systems providing real-time information on road conditions. Oxley (1996) investigated reactions of seniors aged over 65 to in-vehicle navigation, rear collision warning, an emergency notification ("Mayday") system, and night vision enhancement after they had experience with the systems under examination. Seniors found that navigation systems were distracting but that night vision enhancement was highly acceptable. Generally, participants showed a high willingness to adopt and purchase

ADAS, provided that the benefits were perceived to be real and the design was perceived to suit their needs.

Recently, Marshall, Chrysler, and Smith (2014) conducted a focus group study with 51 participants aged 55–75 to rate their acceptance of four ADAS categories: enhancement, alert, vehicle control, and fully automated/connected vehicle systems. The highest acceptance score was for systems providing alerts as necessary while allowing drivers to remain in control (e.g., forward collision warning systems). Vehicle control systems (e.g., ACC systems) received a relatively low acceptance rating due to issues of trust, distraction, and over-reliance.

Researchers conducted semi-structured interviews with 32 drivers aged 60–80 to explore their experience with and barriers to using ADAS (Trübswetter & Bengler, 2013). Results revealed that the most common reason that seniors avoided using ADAS was that they perceived little in the way of benefits, followed by the beliefs that ADAS provided limited functionality, were high in cost, and were untrustworthy. Gish, Vrkljan, Grenier, and Van Miltenburg (2017) interviewed 35 seniors who had at least two ADAS in their vehicles about their perception of and motivation for using the technology. The interviews revealed that ADAS were perceived to counteract age-related declines but were not the motivating factor in purchasing decisions. Hence, participants who were exposed to ADAS valued the safety benefits as well as the convenience and comfort.

In short, while the literature contains surveys, interviews, and focus group studies on seniors' perception, acceptance, and preferences in regard to ADAS, these studies do not carefully consider or control for exposure and experience with ADAS. Thus, how seniors perceive, accept, and actually use ADAS requires further investigation, especially as these technologies are rapidly proliferating into the existing vehicle fleet. The objective of this study is to examine the underlying factors affecting changes in senior drivers' perceptions and attitudes towards ADAS after substantial driving exposure.

3.2 Method

3.2.1 Data collection

Eighteen seniors (nine men and nine women) were recruited to participate in a driving study in the New River Valley area of Southwest Virginia. Participants were recruited from a list of individuals who had previously indicated an interest in serving as a participant in Virginia Tech Transportation Institute research efforts. Eligibility criteria included age (70–79), ADAS experience (never owned an ADAS-equipped vehicle), driving regularity (at least two days per week), a valid driver’s license, and insurance coverage. The needs and preferences of the individual were considered when assigning the vehicles. For example, if a participant preferred a Volvo based on current or prior ownership, the team tried the best to allocate a Volvo to that individual. If there were no special needs or preferences, we randomly assigned study vehicle models to individual participants. The study began with an intake session during which potential participants showed their driver’s license and proof of liability insurance. After providing informed consent, participants were given questionnaires to collect demographics, driving habits, and history, as well as their pre-exposure attitudes towards ADAS. Each participant was then assigned to one of the four vehicle models (2017 Audi Q7, 2016 Mercedes E350, 2016 Volvo XC90, 2015 Infiniti Q90). Each of these vehicles was equipped with at least the following four ADAS: BSA, LKA, LDW, and ACC. The Supplementary Material section includes further details about the implementation of these four ADAS for each of the four vehicle makes-models used in this study.

After being assigned to a study vehicle, participants received a three-part training session. The first part was performed in the parked vehicle while an experimenter explained the basic vehicle features (e.g., windshield wipers, gear shift selector, etc.) and how the four ADAS functioned. The second part was an on-road drive in which the experimenter drove the vehicle and demonstrated how to use the four ADAS common to all the vehicles used in this study. The experimenter also briefly mentioned the scenarios or environments in which the participants should try to avoid using ADAS given the technology limitations. In the third part, the participant drove the vehicle, using or experiencing each of the four common ADAS, based on the experimenter's verbal guidance. The on-road drive was designed to provide training on the proper use of ADAS under practical conditions on highways in the New River Valley area. The entire training session lasted 1.5–3 hours.

After training, participants were asked to drive the study vehicle as they normally would for a six-week period. Weekly phone surveys were conducted to collect data on participants' attitudes about and usage of the vehicles and each ADAS. Upon return of the vehicles, the same questionnaire used at the beginning of the study was re-administered to collect participants' post-exposure attitudes towards the ADAS.

Within two weeks of returning the study vehicle, each participant took part in a 90-minute focus group session. Three focus groups were conducted, each of which included six participants. During the focus groups, participants shared their opinions about and perspectives on the ADAS through the following series of specific guiding questions:

- What one word describes how you felt about the advanced features in your vehicle when you began the study?
- What one word describes how you felt about the advanced features in your vehicle at the end of the study?
- What caused your feelings change or remain the same?
- What would make you feel more comfortable with these features?
- What is one thing you liked best about these features?
- What is one thing you liked least about the features?
- Suppose a friend is considering purchasing a car with these features and they ask you if you think if they improve driving safety or not. What would you say?

The guide questions were all open-ended and designed to address the main research question of seniors' attitudes towards the ADAS controlling for exposure (i.e., seniors' attitudes towards ADAS, how they liked or disliked certain systems, and their perceptions regarding the safety benefits of the ADAS).

A skilled moderator facilitated the focus group sessions, guiding discussions to ensure responses were being provided by all participants and asking probing questions as necessary. Two other researchers also attended each session to take notes and monitor the recording equipment. Three researchers transcribed the focus group recordings verbatim. The study protocol was approved by the Virginia Tech Institutional Review Board (**Appendix E**).

3.2.2 Data analysis

Topic modeling is an unsupervised text analysis method that recognizes, classifies, and extracts information by clustering words frequently appearing together across a collection of documents to identify different and prevalent topics (Blei, 2012). This computer-assisted text analytical method has multiple advantages over the standard practice of using a human subjective coding procedure in focus group analysis. Benefits of topic modeling including avoiding the issue of observer dependency bias, greater speed in processing large volumes of text, and consistent treatment of all documents (Grimmer & King, 2011; Hillard, Purpura, & Wilkerson, 2008; Lowe & Benoit, 2013). The collection of documents consisted of the transcripts from all three focus groups. Each document was composed of text transcriptions of the discussion (i.e., all verbal exchanges from all participants and the moderator) on one guiding question in one of the three focus groups. Thus, the complete collection comprises 24 documents, given that there were seven guiding questions and an open discussion section in each of the three focus group sessions.

Based on a latent Dirichlet allocation algorithm (Blei, 2012; Blei, Ng, & Jordan, 2003), structural topic modeling (STM) (Roberts, Stewart, Tingley, & Airoldi, 2013; Roberts, et al., 2014) was selected to obtain the following results: (1) a set of topics, (2) a set of keywords to represent each topic, (3) prevalence/expected proportion of each topic in the collection, (4) per-document-per-topic (gamma) probabilities. All data processing and analysis was conducted with an STM package in R (Roberts, Stewart, & Tingley, 2014).

3.2.3 Data pre-processing

In order to apply STM, the transcripts were pre-processed as follows:

1) Remove introduction and greetings at the beginning of each focus group as well as the introductory sentences under each guide question.
2) Convert different word phrases representing the same ADAS feature to one acronym such as "ACC" for "adaptive cruise control," "ACC," and "cruise control."[3] BSA was used for blind spot alert, LKA for lane keeping assist, and LA for lane alert.
3) Remove all common stop words, such as "a," "the," and "we," which have limited semantic value.
4) Remove customized stop words, such as "car," "vehicle," and "driving."
5) Consolidate words with different tenses or forms to their word stem, such as, "experienc" for "experiencing," "experienced," and "experience."

3.2.4 Number of topics

The number of topics must also be pre-set by the analyst in order to apply STM. Typically, the number of topics is determined by exploring the dataset to compute four metrics: held-out likelihood, sematic coherence, residual, and lower bound. To find the model that produces the most semantically coherent and distinct topics, the four metrics were computed for a range of 3–10 topics, based on recommendations by Benoit (2018). The five-topic model was selected for its relatively high semantic coherence and held-out

[3] In the analysis, "cruise control" was converted to ACC only when participants were discussing ACC specifically. Three instances of "cruise control" were converted to CC when participants discussed traditional cruise control.

likelihood while maintaining a relatively low residual and lower bound (Figure 3-1) (Blei et al., 2003). Semantic coherence measures the co-occurrence of words within the documents to ensure selected keywords belong to a single concept, thus preserving the interpretability or quality of the topic (Mimno, Wallach, Talley, Leenders, & McCallum, 2011). Held-out likelihood estimates the probability of key words appearing in documents (excluded or held-out of the training) to indicate the generalization capability of the topic model (Wallach, Murray, Salakhutdinov, & Mimno, 2009).

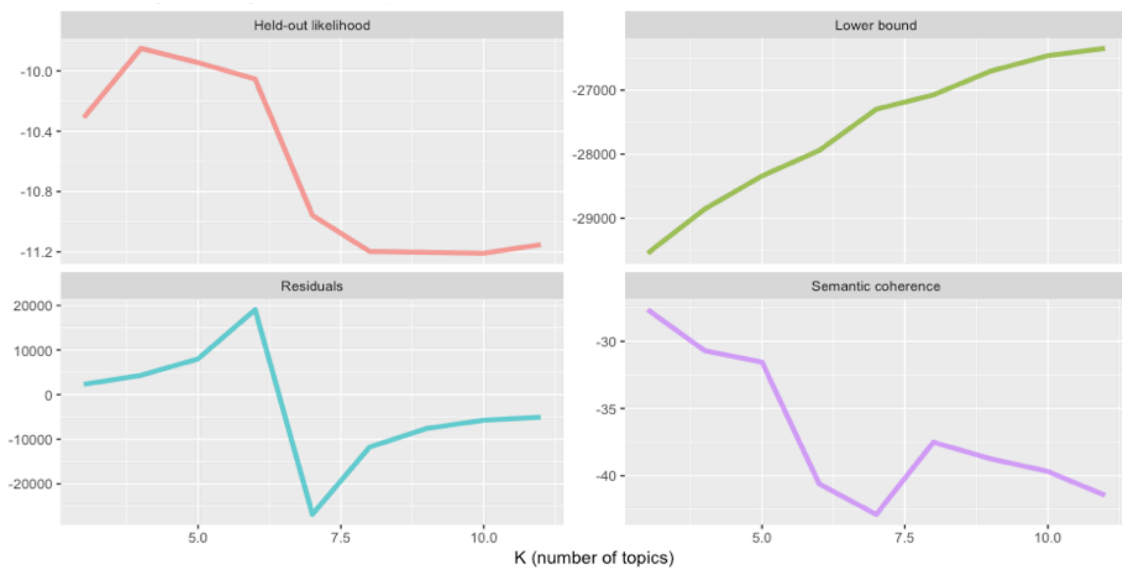

Figure 3-1. Held out likelihood, lower bound, residuals, and semantic coherence scores for models with 3–10 topics.

3.3 Results and Discussion

3.3.1 Topic and prevalence

Table 3-1 presents the prevalence and the most representative words based on *Prob* and *FREX* metrics for each topic. *Prob* is the probability of occurrence of a term within a given topic, whereas *FREX* ("FRequency and EXclusivity") is calculated based on the frequency of the word and its degree of exclusivity to a particular topic (Airoldi &

Bischof, 2016; Bischof & Airoldi, 2012). Researchers assigned a label to each topic based on inspection of its content. The first four topics pertain to the primary interests of this study, while the responses associated with topic 5 mainly contain vehicle components that are not related to ADAS. We display the content for all five topics in the following section, but there is no further discussion on topic 5.

Table 3-1. Topic Label, Keywords, and Topic Proportion

No. Topic Label	Metric	Keywords	Topic Proportion
1. Safety	Prob	safeti*, control, improv*, lane, chang*, set, bsa	0.25
	FREX	improv*, headlight, rain, safeti*, friend, bright, construct*	
2. Confidence concerning ADAS	Prob	confid*, lane, control, acc, chang*, experi*, manual	0.22
	FREX	pleas*, confid*, equip*, lane, center, convinc*, stai*	
3. ADAS functionality	Prob	acc, seat, bsa, set, light, slow, comfort*	0.22
	FREX	seat, head, bsa, spot, advanc*, miss, slow	
4. User Interface/ Usability	Prob	heat, figur*, button, trainer, confus*, learn, nervou*	0.17
	FREX	intuit*, heat, train, press, sound, figur*, confus*	
5. Non-ADAS related features	Prob	wheel, steer*, light, stop, signal, brake, acc*	0.14
	FREX	stop, hang, signal, placement, son, technologi*, rear	

Note: Asterisks indicate stemming. For example, the term "confid*" refers to both "confidence" and "confident." Translations are best approximations based on readings of representative quotes.

3.3.2 Per-document-per-topic Probabilities

Table 3-2 presents the per-document-per-topic (gamma) probabilities for the three focus groups (Silge & Robinson, 2017). The gamma probabilities indicate how much individual documents contribute to each topic. All three focus groups discussed the three most prevalent topics (i.e., safety, confidence concerning ADAS, and ADAS functionality). However, focus group 1 had virtually no discussion on topic 5 (non-ADAS related features), nor did focus group 3 have any substantive discussion on topic 4 (user interface/usability). However, in general, the three focus groups shared the same discussion topics, especially those that were most prevalent.

Table 3-2. Per-document-per-topic (gamma) Probabilities; The Numbers in Bold Highlight the Major Contributions of Individual Documents to a Topic

Group	Document No. (Section)	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Group 1	1. Pre Attitude	0.0019	0.0073	0.0018	**0.9869**	0.0021
	2. Post Attitude	0.0004	**0.9976**	0.0008	0.0005	0.0007
	3. What Makes Change	0.0021	**0.9870**	0.0041	0.0028	0.0040
	4. Perception	0.0007	0.0009	0.0007	**0.9969**	0.0007
	5. Like Most	0.0032	0.0042	**0.9900**	0.0012	0.0014
	6. Like Least	**0.9951**	0.0012	0.0014	0.0012	0.0011
	7. Safety	**0.9954**	0.0009	0.0019	0.0009	0.0009
	8. Open Discussion	**0.9965**	0.0008	0.0011	0.0007	0.0009
Group 2	9. Pre Attitude	0.0016	0.0020	0.0016	**0.9931**	0.0016
	10. Post Attitude	0.0017	**0.9923**	0.0026	0.0013	0.0021
	11. What Makes Change	0.0062	**0.5796**	0.0049	0.0046	**0.4047**
	12. Perception	0.0008	0.0008	0.0007	**0.9970**	0.0007
	13. Like Most	0.0014	0.0019	**0.9950**	0.0007	0.0009
	14. Like Least	**0.9951**	0.0013	0.0013	0.0010	0.0013
	15. Safety	**0.9973**	0.0006	0.0009	0.0006	0.0006
	16. Open Discussion	0.0011	0.0015	**0.9958**	0.0009	0.0008
Group 3	17. Pre Attitude	0.0009	0.0016	0.0009	0.0008	**0.9960**
	18. Post Attitude	0.0011	**0.7097**	0.2842	0.0009	0.0041
	19. What Makes Change	0.0015	**0.9906**	0.0049	0.0017	0.0033
	20. Perception	0.0008	0.0013	0.0008	0.0006	**0.9966**
	21. Like Most	0.0012	0.0017	**0.9955**	0.0007	0.0009
	22. Like Least	0.0012	0.0017	**0.9952**	0.0008	0.0011
	23. Safety	**0.9958**	0.0012	0.0012	0.0007	0.0011
	24. Open Discussion	0.0016	0.0021	0.0016	0.0011	**0.9937**

Topic 1: Safety ranked as the most prevalent topic (0.25). These entries emphasized two aspects of safety-related discussions. On one hand, seniors appreciated the safety benefits associated with using certain aspects of the ADAS—BSA and adaptive headlights, specifically. On the other hand, limited capability and false alerts when

driving through a construction area or in inclement weather conditions resulted in safety-related concerns. Representative quotes regarding this topic are outlined in Table 3-3 (quotes 1–6).

Topic 2: Confidence Concerning ADAS ranked as the second most prevalent topic (0.22). This topic expresses two aspects of confidence. First is confidence in ADAS functioning effectively on the road. Practice with ADAS and seeing the systems working well changed participants' attitudes towards ADAS from apprehensive to confident. Second is the self-confidence in using ADAS appropriately. Experience and reading the vehicle manual appear to be the two methods that promote seniors' self-confidence in using ADAS. Though some had negative comments on readability and a lack of sufficient detail, participants agreed that the vehicle owner's manual plays an important role in building both aspects of confidence noted above during the early adoption period. Participants gained familiarity with and learned some of the limitations of the ADAS from the manual. Representative quotes regarding this topic are outlined in Table 3-3 (quotes 7–14).

Topic 3: ADAS Functionality tied for second in topic prevalence (0.22), highlights the particular ADAS technologies that made the biggest impression on seniors—BSA and ACC. This topic overlaps with Topic 1 regarding perceived safety benefits. BSA helps seniors with neck problems manage the blind spot without turning their heads, and thus is specifically associated with helping counter the effects of aging. Participants perceived BSA to counteract limitations in neck flexibility and rotation. ACC was also frequently discussed. Some participants showed appreciation for the capability of automatically keeping the vehicle at a comfortable distance from a leading vehicle.

However, other participants disliked being slowed down by the ACC and expressed sometimes preferring to disengage the technology and pass the slower leading vehicle. Representative quotes regarding this topic are outlined in Table 3-3 (quotes 15–21).

Topic 4: Usability/user interface ranked fourth in topic prevalence (0.17)., concerns usability issues. Some participants were confused about the location of the appropriate ADAS controls or about how to operate the function that they intended to use. The user interfaces were not intuitive to them. Accompanying complaints about usability were requests for in-depth training, going through how to turn on/off all functions, including those not related to ADAS. Representative quotes regarding this topic are outlined in Table 3-3 (quotes 22–27).

Topic 5: Non-ADAS related features, the least prevalent topic (0.14), surrounded issues that were not directly related to participants' ADAS experience. Participants discussed car interior designs and components, such as car seats, steering wheel, handicap tag hanger, and various luxury features. Representative quotes regarding this topic are outlined in Table 3-3 (quotes 28–31).

Table 3-3. Representative responses by induced topics

Topic	Representative Responses
1. Safety	1. It improves safety as long as you're still in control 2. Yes, improves safety. And, you will love the blind spot alert 3. There were all kinds of things I liked about the car, not the car itself, but they weren't in these safety features [ADAS] we were supposed to be concentrating on. I liked not having to turn on my headlights. They were on all the time and they did adjust really well to a brightness or any time when I was driving in the bright daylight and then it started to rain and I noticed that they headlights went brighter. 4. I LOVED and it is not one of these, the fact that if you're driving the Volvo at night, maybe yours didn't, it adjusts the lights too. I think that's fantastic.

Topic	Representative Responses
	You know, if you're in the dark and you're going around a curve, it will brighten it for you. Yeah, that was really neat. 5. The lane changing. One of the things about the lane changing at least because I was on 460 all the time, is particularly in construction areas. You know when the roads are divided by the white lines and part of it's the road and part of it is the construction. It doesn't seem to quite know it's vibrating in the wrong place. 6. Uh, if, if the wind is blowing, it doesn't work. If it's raining, it told me it wasn't working, you know, all these situations and, and at night and I'm like well I'm a senior driver and I need help in these situations more than when I, when it works.
2. Confidence concerning ADAS	7. By using the system, I became more confident and also by testing various things. 8. I felt confident with the systems. I had done enough to know that within its limitations it did what it was supposed to do. And then I also felt confident that I knew that there was some parts of it that I couldn't, I couldn't rely on in certain situations. 9. Experiencing the features. At first I was wondering if they were going to be effective, if I could actually use them to my benefit. And after experiencing them, you know, it convinced me that it was a good thing. 10. Confident. Oh, well, I, um, I used the car as much as I possibly could. So I think practice, you know, made the awkwardness go away. Wasn't long before I knew where each little control was without having to look for it. You know, I could feel where it was and everything. So I also felt confident about the fact that I gave it a fair trial. That I tried every little thing I could think of to see how it behaved and how it worked and I felt good about that. 11. Just experience and time to play with it. Trying it, you know like trying to see if I could get onto 460 and put on the lane control, see if I could drive out to Lowes without using my hands, did not work. 12. Well, the owner's manual is four inches thick and it's not well written. In the sense that where you go to find, how do I do this? It'll say push the something button, but then it doesn't tell you where the something button is and I just found it really hard to learn. 13. Well, from reading the manual and trying things, you know, figuring out how it worked by the time I brought the car back, I knew where the functions were and how to use them and so forth. 14. In the manual I have, it outlined the limitations very clearly. So all of that made me feel how much, you know, really better about the whole system.

Topic	Representative Responses
3. ADAS functionality	15. I like blind spot also, even though it was there I was in the habit of turning my head away, but it alerts me to turn my head to double check that there is nothing there. 16. "BSA is an enhanced safety for me... as the arthritis sets in more and more in my neck and spine, turning around is not easy" 17. After I brought the car back and I was driving my car again, then I missed some of the features. I, you know, I catch myself looking for the light [BSA] that blinks and the light wasn't there. 18. I'm not somebody who likes cruise control, but I fell in love with the adaptive cruise control. 19. The ability to along with that adaptive cruise control, the ability to set the comfortable distance for yourself because people drive differently. 20. I felt safer. Cause our mind wanders when we're driving, and it did happen to me twice, I made notes, that I wasn't paying attention, and it all of a sudden, I said, why am I slowing down? and there was a car in front of me! 21. Well, let's say, the ACC, I use ACC all the time if I'm on the interstate or open road, but whenever that thing kicks in and slowed me down, because the car in front of me, I hit the brake knock it out and can sneak on up there and get around.
4. User interface/ Usability	22. I was just nervous about using it and not being able to... At first it was hard to find some. For example, the ACC and the signal light switches are real close together and, if you're not familiar with them, you hit the wrong things. Well I'd be wanting to hit the signal light and I'd hit the cruise and speed up you know, so I was a little nervous about using them. And to this day I haven't figured out how to set the radio. 23. I think the controls could be … I didn't find them very intuitive as far as their location. And so I think that the controls should be relocated, maybe to a panel where they're isolated these special safety features all in one panel maybe instead of trying to remember is it on this stalk or that stalk or this little button under here. I just think it could be more intuitive as far as the controls are concerned. 24. I couldn't figure out how to turn the heat off and get the AC on. 25. You just pushed a button to turn on the features but you couldn't decide which features to be on. 26. I had to read the book [manual] to figure out what where that was, now it was under climate I found, but I didn't know that right away. 27. So some in-depth training on how to turn things on, when to use them, when you want them on …

Topic	Representative Responses
5. Non-ADAS related features	28. Now, the seat did not move but it was the steering wheel and I really liked that. 29. It wasn't comfort with the features, it was comfort with the seats. 30. What I mentioned before, the, the, the driver's seat, which is way back. You can't, can't even put your foot on the accelerator when you get in the car and then you have to start the car and, and it moves the seat up about a foot and a half and it was just annoying. It's a, you don't need that. 31. If you have a handicap tag, there's no place to hang your handicap tag.

Note: The selected quotes are from the representative answers by topic, based on a qualitative assessment of their responsibility.

3.4 Discussion

This is the first naturalistic driving study investigating seniors' attitudes toward and experience in using ADAS based on significant driving exposure. Focus groups were conducted after participation in the driving portion of the study. STM performed on the focus group transcripts revealed five prevailing topics or factors of importance to participants.

These five topics, in order of prevalence as revealed by the STM, are: (1) safety, (2) confidence concerning ADAS, (3) ADAS functionality, (4) user interface/usability, and (5) non-ADAS related features.

The safety implications of ADAS were foremost in the minds of study participants, which is consistent with the finding that seniors consider the safety of a vehicle as a primary criterion in their purchase decisions (Davern et al., 2015). Similarly, in a survey asking about purchasing a self-driving vehicle, results showed that mature drivers (aged 50 and over) would consider such a purchase if the self-driving vehicle was proven to be as safe as if the participants were driving the vehicle themselves (The

Hartford, 2016). Participant impressions in this study were mixed in that ADAS elicited both positive feelings about safety improvements as well as concerns regarding false alerts and a limited range of effective operations. Terms such as “safety” and “improved” frequently co-occurred in the focus group sessions, indicating that participants believed ADAS brought safety improvements. Similar positive findings of the perceived ADAS safety benefits can be found in previous studies (Davern et al., 2015; Gish et al., 2017; The Hartford, 2015a). However, the false alerts that occurred during particular situations (e.g., construction zones) were a concern to participants. Concerns about ADAS are also apparent in the literature, particularly regarding false BSA alerts and LKA and ACC malfunctions in certain driving conditions (Strand, Nilsson, Karlsson, & Nilsson, 2011). In other words, many current LKA and ACC systems are not sufficiently robust for the full range of road conditions, making training an important remedial solution to support drivers in learning about appropriate use of ADAS as well as their inherent limitations.

Seniors indicated that both confidence in the ADAS as well as their self-confidence in using them grew along with their knowledge derived from driving experience and reading the owner’s manual. This topic mirrored the findings by comparing questionnaires collected pre- and post-6-weeks’ exposure to ADAS. Participants reported positive attitude changes towards ADAS, especially in regard to familiarity, lower concern about false alerts, and trust in the effectiveness of the systems regarding safety (Liang, Antin, et al., 2019). The focus group discussion adds to the finding that the positive attitude change in the survey results can be attributed to the driving experience as well as reading the manual. The Hartford (2012a, 2012b) also found similar results on increased confidence in driving with ADAS and seniors’ preferred learning methods. Similarly, Koustanaï, Cavallo, Delhomme and Mas' (2012) also found that training and experience were essential for drivers to learn about capabilities, benefits, and limitations of a forward collision warning system. Interaction with and first-hand demonstration of ADAS can improve seniors' perception and understanding of these systems (Davern et al., 2015). Llaneras (2006) indicated that seniors were more likely to learn ACC through the owner's manual than were other age groups, which is consistent with the findings in this study that seniors used the owner's manual to gain system knowledge.

Taken together, topics 1 and 2 indicate that a training program is an essential aspect of promoting sufficient knowledge and calibrated trust that will eventually translate to adoption of an ADAS. However, most current ADAS still need improvement in robust operations across a wide range of driving situations. An imperfect or unreliable system can negatively influence driver trust in the system (Beggiato, Pereira, Petzoldt, & Krems, 2015; Llaneras, 2006). In this study, participants showed signs of ADAS mistrust via expressing concerns about false alerts from LKA in construction zones. On one hand, competency across driving conditions is essential in helping drivers trust ADAS, as effective operation in a very narrow range of conditions is impractical, if not unsafe, in real-world driving. On the other hand, drivers must also understand and appreciate operational constraints, which exist even in the best technology, in order to avoid mistrust and misuse of ADAS and maximize the system's expected benefits. Safe cooperation with technology depends on system knowledge, which influences an individual's attitude (Beller, Heesen, & Vollrath, 2013) and calibrated trust (Chavaillaz, Wastell and Sauer, 2016; Lee & See, 2004; Sexton & Geffen, 1979). Since seniors have been found to have less ADAS knowledge (Davern et al., 2015), they are more prone to mistrust or use ADAS in inappropriate driving conditions compared to other age groups. As technological improvements of ADAS take time, effective training for seniors must be available and have two key components. First, practical, hands-on experience to provide real-time operational knowledge and familiarity with ADAS is essential for seniors to remain “in-to-the-loop” and avoid automation surprises (Louw & Merat, 2017). Further, familiarity is a good predictor of senior ADAS adoption (Souders, Best, & Charness, 2017). Second, well-written documentation can augment driving experience on real roads given seniors’ greater willingness to read owner’s manuals for ADAS basic knowledge and limitations.

Among the investigated ADAS technologies, BSA and ACC made the biggest impression on seniors in terms of their safety benefits. The positive comments on BSA confirmed the results of multiple survey studies about the willingness to purchase and adopt ADAS (The Hartford, 2012a, 2015 and 2016). Seniors appeared most receptive to ADAS that provided alerts only (Marshall et al., 2014); they felt positive, safe, and less stressed with BSA (Braitman, McCartt, Zuby, & Singer, 2010) and were found to value the BSA functionality almost twice as much as younger drivers (Souders et al., 2017). The participants in this study indicated that turning their heads to check blind spots to be a challenging driving task and found BSA to be helpful in mitigating this difficulty, supporting the findings from Gish et al. (2017) about how seniors’ perceptions of ADAS were shaped with respect to their aging bodies.

Interestingly, several participants in the focus group sessions reported that they found themselves still looking for the BSA in their own vehicles, which were not equipped with this feature. BSA has been shown to promote the frequency of mirror checking (Kiefer & Hankey, 2008). Though seemingly promoting safety, this finding leads to an important set of questions not directly addressed in the current study regarding the implications for ADAS trust, usage, and safety when seniors (all drivers, in fact) switch back and forth between ADAS and non-ADAS equipped vehicles.

Participants also extensively discussed ACC, reporting that it made them feel more comfortable behind the wheel. Stanton and Young (2005) showed that using ACC was associated with decreased workload and stress in addition to the safety benefits. Vision-related factors during night driving were found to be a significant predictor of seniors' willingness to use ACC (Souders et al., 2017). Given that night vision declines with age, seniors might find ACC comparatively beneficial and thus be willing to yield control to this technology. However, previous studies also found negative impacts on safety associated with decreased situational awareness (De Winter, Happee, Martens, & Stanton, 2014) and over-reliance on ADAS (Rajaonah, Anceaux, & Vienne, 2006). Collectively, from the literature and the present study results, senior drivers were found to have positive perceptions of BSA and ACC. This stands in contrast to the participants of the present study's impression of LKA, which was not perceived to perform effectively under many driving and road conditions. Therefore, some ADAS features appear ready for adoption to promote safety when users are provided sufficient training and instruction. Participants identified usability as an area of concern, as they had difficulty locating and operating particular ADAS functions. As seniors tend to have difficulty changing their well-established routines (Craik & Jacoby, 1996), learning to use the latest in-vehicle technologies may require a longer period of adjustment. Prior research has demonstrated that seniors desire more in-depth training on vehicle technology from dealers or other instructors (The Hartford, 2017). Any such in-depth training should include hands-on experience operating the advanced features in a real driving environment, which has been found to be crucial for understanding and trusting the technology (Li, Blythe, Guo, & Namdeo, 2019). Further, the user interface design for new ADAS or future vehicle automation systems deserves further attention, especially with considerations of seniors' preferences and limitations (Guo et al., 2015).

This study had some limitations in the data collection and data analysis methods. Like all focus group studies, the findings of current study have limited generalizability to a larger population and there was no way to rule out alternative explanations of findings, such as participants behaving in ways to meet experimenter expectations. In addition, the implementations of the ADAS differed across four car models, so the participants did not have an identical ADAS experience. Nevertheless, the focus group discussion did not reveal any model-specific issues but rather common limitations of some ADAS technology (e.g., false LKA alerts). As to the analysis method, the results produced by STM, which are the keywords identified in each topic, still need domain expertise to interpret and assign a meaningful label. In addition, STM may omit important but infrequently occurring details in the discussion, such as a unique response from one participant that may yield major design insights.

3.5 Conclusion

This study used focus groups to examine senior drivers' attitudes towards ADAS based on their real-world driving experience with these systems. The findings indicate that safety is seniors' main ADAS-related consideration. To promote ADAS adoption, user interfaces should be designed to accommodate seniors' preferences and limitations, which would typically also accommodate most non-seniors. In-depth training programs would be helpful for senior drivers in learning proper ADAS operations as well as in promoting the crucial understanding of system limitations or constraints. The findings of this study should encourage car manufacturers and policy makers to direct their efforts in vehicle design and training to aid seniors in adopting ADAS so as to enhance their mobility and safety.

4 Study 3 - High G-force Events to Indicate Safety-related Impacts on Driving of Old Adults

Study 1 and study 2 addressed mobility and perception of older drivers, respectively. To assess safety-related impacts, it is necessary to identify appropriate measures or indicators of safety-related impacts. This study identified the appropriate high g-force events for assessing safety-related impacts for older adults.

4.1 Introduction

Average age across most countries continues to increase (United Nations, 2022), and more individuals are retaining their driver licenses well into older adulthood (Sivak & Schoettle, 2012). The rates of injury and fatal crashes per kilometer driven in the US were shown to decline with age up to about 70 years-old, then rise to the highest rate for those over 80 (Tefft, 2017). As people age, the visual, cognitive, and physical abilities necessary for safe driving tend to decline, sometimes to the point of hindering driving safety. Age-related declines partly explain why the oldest drivers form the group with the second highest crash rate, right after teenagers (Tefft, 2017). These young drivers lack driving experience and more often engage in risky and distracted driving behaviors (e.g., Seacrist et al., 2018; Yellman et al., 2020). Given the demographic shifts, road safety of older drivers thus deserves increasing research attention.

Crash risk is the most direct indicator of driving safety; however, relying on the occurrence of crashes to estimate crash risk is impractical due to their rarity, which, from a transportation safety research perspective, imposes infeasibly large sample sizes or long follow-up periods to attain sufficient statistical power. Kinematic data (e.g., velocity, acceleration, or jerk) collected by advancing in-vehicle data acquisition technology provides a novel source of risk predictors. Elevated kinematic events, also known as high g-force events[4], are instances when acceleration or deceleration in specific directions exceeds a pre-defined threshold. High g-force events reveal sudden vehicle maneuvers, including hard braking, aggressive acceleration, and sharp turning. These events themselves can be dangerous as they increase the likelihood of leaving drivers and other road users with limited time to react to hazards (Bagdadi & Várhelyi, 2011; Elvik, 2006). Furthermore, high g-force events may not only reflect risk taking driving style, but also result from delayed perception and reaction due to poor hazard perception, which may mandate subsequent evasive maneuvers to avoid crashes (McDonald et al., 2015). For example, impaired visual or cognitive capabilities hinder the timely detection and response to objects on the road, resulting in late and sudden maneuvers. Other risk factors, such as driving with strong emotions, can also lead to increased acceleration, deceleration, and speeds (Roidl et al., 2014). Thus, high g-force events can be used to assess the safety impacts of driving behavior, habits, capabilities, and other risk factors.

Numerous studies have investigated the association between crash risk and high g-force events, including elevated longitudinal acceleration and deceleration, lateral acceleration, and yaw rate (refer to Table 4-1). Based on the vehicle and crash data collected from 42 newly licensed teenagers driving study vehicles for 18 months (Simons-Morton et al., 2009, 2012, 2015), Simons-Morton et al. (2012) found that *at-fault* crash and near-crashes (CNCs) had correlations with longitudinal acceleration greater than 0.35g (Spearman's $\rho = 0.28$), longitudinal deceleration greater than 0.45g

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[4] Yaw rate is angular velocity (deg/s) instead of acceleration (g), "high g-force events" referred in this study includes yaw rate exceeding specific thresholds just for maintaining a concise expression.

(Spearman's ρ = 0.76), leftward lateral acceleration greater than 0.5g (Spearman's ρ = 0.53), rightward lateral acceleration greater than 0.5g (Spearman's ρ = 0.62), yaw rate greater than 6 degrees in 3 seconds (Spearman's ρ = 0.46). The rate of all elevated kinematic events from the above five categories (termed "kinematic risky driving (KRD)") was also correlated with at-fault CNC rates (Spearman's ρ = 0.60). Further, Simons-Morton et al. (2012) provided evidence of the predictive performance of KRD rate, reaching about 76% predicative accuracy of a near-future crash. Based on this result, Simons-Morton et al. (2012) concluded that KRD can be used to assess driving risks. However, this study only used the data from novice teenage drivers, thus may limit the generalization of the findings to other age groups.

Other investigations focused on longitudinal high g-force events with respect to crash involvment. Using smartphone GPS data of 4000 drivers and four-year historical crash data in Quebec city, Canada, Stipancic et al. (2018) examined the correlation between crash frequency and longitudinal acceleration and deceleration events at the thresholds of 0.204g, 0.306g, and 0.408g, respectively. All three high g-force events at the corresponding thresholds exhibited positive significant correlation with crash frequency, and the threshold of 0.204g yielded the strongest correlation across almost all road types. From the driving data and crash records of 176 male bus drivers, Khorram et al. (2020) examined the correlation between rates of crashes and longitudinal deceleration events at thresholds of 0.204g, 0.306g, 0.408g, 0.510g, and 0.611g. The threshold of 0.306g for longitudinal deceleration yielded the strongest correlation with crash rate (Pearson's r = 0.244). Instead of defining high g-force events by predefined fixed thresholds, Zhu et al. (2017) built a Bayesian network model from GPS data of 521 drivers and found different longitudinal acceleration and deceleration freeway driving events to be positively associated with self-reported crash rate after accounting for various contextual driving behaviors (e.g., relative speed).

Two studies looked specifically into attributing longitudinal deceleration to rear-end crash risk. Kim et al. (2016) found that the number of seconds and fraction of time drivers braking harder than 0.408g had the strongest correlation (coefficient[5] = 0.39) with rear-end crash rate compared to 0.306g and 0.611g. Palat et al. (2019) utilized the threshold of crash surrogate from the 100-Car naturalistic driving study (NDS) (Dingus et al., 2006) and the Second Strategic Highway Research Program (SHRP 2) NDS to reveal that driver groups with high frequency of longitudinal deceleration exceeding 0.65g also had more characteristics of risky drivers, self-reported crashes, and demerit points on their driver licenses.

Table 4-1. Major NDSs on association between road safety and kinematic events (ACCEL: Longitudinal acceleration; DECEL: Longitudinal deceleration; LAT: Lateral acceleration)

	ACCEL (g)	DECEL (g)	LAT (g)	Yaw rate	Participant sample	Crash related data	Statistical analysis methods
Simons-Morton et al.(2015)	≥.35	≥.45	≥ .50 or ≤-.50	≥ 6 or ≤ -6°/3s	42 teen novice drivers (mean age = 16.4) for 18 months	At-fault CNCs observed in the study	Spearman's correlation, logistic regression with GEE
Kim et al., (2016)	-	≥.408 (suggested)	-	-	A 63-mile section of interstate I-40 between Exits 266 and 328 in North Carolina. A fleet of 20 vehicles from 4/1 to 6/30 in	1311 rear-end crash records in four years (2010–2013) extracted from Traffic Engineering Accident Analysis System.	Correlation

[5] Their paper does not provide details about the type of correlation analysis used in their study.

					2014, total of 43 hours driving, 224 trips.		
Zhu et al. (2017)	No predefined value. Conditional on drivers' behavior and road type.		-	-	521 drivers (mean age = 37.29), 307,204 trips and 2,611,838 miles traveled	Self-reported historical crash data	Bayesian network model
Stipancic et al., (2018)	≥ .204g (suggested)		-	-	Over 4000 drivers and 21,939 trips in Quebec City	Crash data for from the Ministry of Transportation from 2006 to 2010 in Quebec City	Spearman's correlation
Palat et al., (2019)	-	≤-.65g	-	-	131 aged 23-77 (mean age = 39.7), 24 aged 50+, 2015/03 - 2016/12	Self-report critical safety events	Hierarchical clustering, regression
Khorram et al. (2020)		≤-.306g (suggested)	-	-	176 bus drivers, all males, aged 35-58, mean age = 45.24)	Self-reported crashes in two years before the study	Pearson correlation, negative binominal regression

Ample empirical evidence on the association between crashes or related critical safety events from NDSs supports the use of high g-force events as indicators of safety. However, thresholds adopted for identifying high g-force events varied significantly across studies (refer to Table 4-1). In other words, there is a lack of consensus on threshold selection, yet the performance of employing high g-force events to detect safety critical events within NDSs can be influenced by the thresholds (Perez et al., 2017). Further, threshold selection directly impacts the number of events deemed safety-relevant, affecting statistical power, validity of study results, and crash risk prediction accuracy (Mao, Guo, Deng, & Doerzaph, 2021). For example, Chevalier et al. (2017) and Keay et al. (2013) examined the relationship between rapid longitudinal deceleration and functional abilities in older drivers, and reported opposite findings. Chevalier et al. (2017)

found that older drivers with poorer contrast sensitivity had higher rates of longitudinal deceleration ≥ 0.75g, while Keay et al. (2013) found that those with poorer visual, cognitive, and psychomotor functions exhibited lower rates of longitudinal deceleration ≥ 0.35g. Eby et al. (2019) posited an explanation for these opposite findings to be the use of different thresholds and recommended checking a range of thresholds as a critical step in future studies to understand the implications of longitudinal deceleration as a suitable safety indicator.

There is also a paucity of research on high g-force events in the lateral direction and yaw rates that are relevant to lane changing, negotiating curves, or making turns, and potentially indicative of accidents. Combining lateral acceleration or yaw rates with DEC would be beneficial in enhancing the performance of assessing crash risk or identifying risky drivers, particularly for older drivers. Their age-related declines can interfere with driving, particularly in stressful or challenging driving situations that could involve turning left, merging, or lane changing. NHTSA (2012) summarized older drivers' top five overrepresented types of crashes, all of which involved the lateral or yaw maneuvers. The top three were all about turning left or right at intersection, the remaining two were lane merging and lane changing maneuvers. The strong correlation between elevated lateral and yaw rate events and *at-fault* crashes revealed in (Simons-Morton et al., 2012), highlighting the potential of lateral and yaw acceleration events as an indicator for assessing risk; however, their analyses for predicting near-future crashes utilized the composite measure, lacking information on how each type of high g-force event was associated with crash risks. More detailed investigation into these lateral and yaw acceleration events is necessary.

Finally, previous studies had participant samples heavily skewed towards younger or middle-aged drivers (refer to Table 4-1). Older drivers generally have low risk-taking tendencies with, e.g., the lowest percentage of crashes involving alcohol (NHTSA, 2002), the highest rate of seatbelt use compared to other age groups (Glassbrenner, 2004). However, older drivers often have declined or imparied functionngs that are critical to driving safety (Ryan et al., 1998). For compensating for these declines, older drivers develop practices of self-regulating or self-restricting their driving exposure and driving habits by avoiding situations that are challenging to them, such as driving at night, in bad weather, in busy traffic, and on the freeway (e.g., Ball, Owsley, Beth, & Roenker, 1998; Liang, Lau, & Antin, 2022; Molnar & Eby, 2008; Owsley, McGwin Jr, Phillips, McNeal, & Stalvey, 2004). Besides to these strategic practices, self-regulation may include the tactical adjustments while driving, such as avoiding secondary tasks, avoiding overtaking, lengthening headways, driving at slower speed, and making few lane changes (e.g., Charlton, Catchlove, Scully, Koppel, & Newstead, 2013; LeBlanc, Bao, Sayer, & Bogard, 2013; Reimer et al., 2013; Siren & Meng, 2013; Trick, Toxopeus, & Wilson, 2010). Given potentially impaired functioning and associated self-regulatory practices, older adults may have substantially different driving capabilities, habits, and driving styles compared to other age groups. These could influence their exposure to driving, driving habits, and kinematic driving pattern, older drivers and other younger groups, high g-force events may demonstrate different performance of assessing risk, crash prediction, or risky driver identification. As mentioned earlier, thresholds selection has a direct impact on high g-force events, the magnitude of their association with crash risks, and the sensitivity, precision, and validity of using these events to assess driving risk and driver risk. Therefore, further research is necessary to identify appropriate threshold values and investigate the relationship between the high g-force events and crash risk for older population.

This study aims to address the paucity of research on high g-force events specific to older adults by: (1) identifying a set of thresholds for high g-force events that are most appropriate to older drivers, (2) examining how the high g-force events are associated with historical crash risk and predictive of near-future crashes, (3) examining how individual driver rates of high g-force events are associated with their risk of being involved in crash for classifying older drivers of high crash-risk.

4.2 Method

4.2.1 Study participants

The SHRP 2 NDS was a large-scale observational study with more than 3500 licensed participants aged 16 to 98 recruited from six sites across the United States (Tampa, FL; Bloomington, IN; Durham, NC; Buffalo, NY; State College; PA; Seattle, WA) (Antin et al., 2019). The study collected drivers' behavior, driving environment, vehicle kinematic data (e.g., velocity and acceleration), and operation information under real driving situations without experimenter effects (Antin et al., 2019). The current study included all participants aged from 70 to 79-year-old (N = 406; average age = 75.4), with 177 females and 229 males. Most of these drivers participated in the SHRP 2 NDS for one to two years. The study protocol was approved by the Virginia Tech Institutional Review Board (**Appendix F**).

4.2.2 Vehicle instrumentation

Participants' own vehicles were equipped with a data acquisition system (DAS), which included a radar, GPS, three dimensional accelerometers, multiple cameras, and other equipment (Campbell, 2012). The DAS collected sensor data and videos automatically and continuously whenever the vehicle ignition was on. The kinematic driving data collected by accelerometers at 10HZ.

4.2.3 Crashes and near-Crashes

To identify crash events, the time-series kinematic data collected and synchronized from three dimensional accelerometers, GPS, and vehicle network were first screened using an automated algorithm to identify potentially crash-involved driving segments. Then, trained data reductionists at Virginia Tech Transportation Institute manually examined these segments via watching the video clips to confirm whether a crash had actually occurred (Hankey, Perez, & McClafferty, 2016).

Our study also included near-crashes as crash surrogates because the number of actual crashes observed was limited. Near-crashes were defined in the SHRP 2 NDS as "*any circumstance that requires, but is not limited to, a rapid, evasive maneuver by the subject vehicle, or any other vehicle, pedestrian, cyclist, or animal to avoid a crash*" (Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006, p.xv). Near-crash events in SHRP 2 were encoded by the trained data analysts via watching the video footage (Hankey et al., 2016). When actual crash data is scarce, using combined crash and near-crash data provides definite benefits by enhancing the precision of risk estimation, although the risk of contributing may be underestimated (Guo, Klauer, Hankey, & Dingus, 2010).

4.2.4 High g-force events

Longitudinal and lateral acceleration/deceleration were measured in gravity of Earth g ($1g = 9.8 \text{ m/s}^2$). The yaw rate is the angular velocity of the vehicle rotation, or rate of change of the heading angle when vehicle is horizontal. It was measured in degrees per second. High g-force events were the events involving acceleration or angular velocity exceeding a given threshold.

Four categories of high g-force events were counted – (i) longitudinal acceleration (ACCEL), (ii) deceleration (DECEL), (iii) lateral acceleration (LAT), (iv) yaw rate (refer to Table 4-2). The range of thresholds investigated for each direction started from the minimum of 0.3g or 4 deg/s for yaw to ensure the majority of rapid evasive maneuvers were included. The maximum thresholds for the range were set to g-force that yield less than a dozen events.

Table 4-2. Thresholds being tested for four categories of high g-force events

Category	Description	Unit	Related rapid, evasive maneuver	Thresholds tested
(i) Longitudinal acceleration (ACCEL)	Vehicle acceleration in longitudinal direction versus time. Vehicle is moving forward from accelerator sensor position.	g	Rapid starts, rapid acceleration	0.30, 0.35, 0.40, 0.45, 0.50
(ii) Longitudinal deceleration[6] (DECEL)	Vehicle deceleration in longitudinal direction versus time. Vehicle is moving backward from sensor position.	g	Hard stops, rapid deceleration	0.30, 0.35, 0.40, 0.45, 0.50, 0.55, 0.60, 0.65, 0.70, 0.75, 0.80
(iii) Lateral acceleration (LAT)	Vehicle acceleration in lateral direction versus time. Vehicle is moving rightward or leftward from the sensor position, and both directions are considered equally when counting the event.	g	Hard turns or lane changes	0.30, 0.35, 0.40, 0.45, 0.50, 0.55, 0.60, 0.65

[6] Vehicle speed changes in the longitudinal direction were recorded using a single accelerator. Negative values indicate longitudinal deceleration, positive values represent longitudinal acceleration. To simplify the presentation of results, both deceleration and acceleration were represented using positive values. The same applied to lateral and yaw movements as well.

(iv) Yaw rate	Vehicle angular velocity around the vertical axis. Vehicle is swerving towards right or left (in right-hand coordinate SAE J760), and both directions are considered equally when counting the event.	deg/s	Hard turns, swerve, loss of control, extreme maneuvers	4, 5, 6, 7, 8, 9, 10

4.3 Statistical Analysis

4.3.1 Identifying the thresholds for high g-force events

The Spearman's Rank correlation coefficients, or Spearman's rho (ρ), were computed to indicate the strength of dependency between two ranked variables as this coefficient is commonly used for quantifying the correlation between event-based indicators and CNCs. Spearman correlation is a nonparametric method that does not assume any specific data distribution and is commonly used when the data are not normally distributed or the relationship between the variables is non-linear (Spearman, 1987). Spearman correlation has been applied to many studies for deciding the thresholds (e.g., Simons-Morton et al., 2011; Stipancic et al., 2018). The thresholds resulting in the highest ρ and thus strongest association with CNC rates for older drivers are adopted for defining high g-force events for subsequent analysis.

4.3.2 High g-force events and driving risk

A logistic regression model was used to examine the association between the occurrence of CNCs in a 1000km drive with the number of high g-force events in the proceeding 1000km of drive, along with other factors specific to the older population. The factors included night trips, night driving distance, number of trips, number of driving days, number of trips to low-frequency destination, number of trips over 100km, and maximum speed in the same 1000km duration as the high g-force event counts. Generalized estimating equations (GEE) were used to account for the within-subject correlation among trips driven (excluding CNC data for each driver's first 1000km driven in the study). The GEE used exchangeable correlation structure, considering that older drivers have extensive driving experience and establish stable driving patterns, resulting in constant correlation. GEE is a statistical method commonly used for analyzing longitudinal or clustered data to handle correlated observations within clusters or repeated measurements over time (Wang, 2014).

The full logistic regression model incorporated all four types of high g-force events as the predictors – ACCEL, DECEL, LAT, and yaw rate, which were identified using the thresholds adopted from the correlation analysis (0.40g, 0.60g, 0.40g, and 9 deg/s, respectively) and all other factors. Backward selection was performed to eliminate non-significant variables until all predictors in the model are significant and reach the highest predictive performance. The predictive ability of the model was assessed by the receiver operating characteristic (ROC) curve (Hanley, 1989). The ROC curve is a plot of true positive rate (i.e, sensitivity) versus false positive rate (i.e., 1-specificity) corresponding to different cutoff values for a continuous predictor. Area under the curve (AUC) represents the predictive capability of the predictor to the outcome measure (i.e., CNCs) and the value of 0.5 and lower value indicates a useless predictor and 1.0 indicates a perfect predictor.

4.3.3 Other modeling considerations

Modeling CNC occurrences involved extensive exploratory analysis based on major three types of considerations. First, a composite measure of four types of high g-force event (total number of all four types of high g-force events) was considered to replace the four separate types of high g-force events. However, this approach was abandoned because the composite measure had low internal consistency (Cronbach' $\alpha < 0.30$). Second, when predicting the occurrence of CNCs in the near-future, different periods for calculating the high g-force events and CNCs events were considered: 1 month, 2 months, 3 months, and 100km, 500km, 1000km, 2000km. Using 1000km as the period demonstrated the best predictive performance. Third, relying solely on high g-force events for predicting CNC occurrences while driving may be challenging due to the significant variations among trips, e.g., road design, weather, traffic density, and traveling purposes, all of which may contribute to crash risk. To improve prediction performance, additional factors were considered for modeling. Specifically, several factors were selected for control to account for exposure to challenging situations that older drivers have the tendency to avoid, including night driving, unfamiliar areas, long-distance trips, driving at high speeds, and overall driving exposure.

4.3.4 High g-force events and driver risk

A logistic regression model was used to associate older drivers' rates of high g-force events with their risks of being high crash-risk drivers. Prior to modeling, K-means clustering was performed to categorize the 406 participants into two groups based on their rates of CNCs per 1000km. Drivers in the group with the higher mean of CNCs rate was labeled as high crash-risk drivers, drivers in the other group with lower means of CNCs rate was labeled as low crash-risk drivers.

Following the driver classification, the modeling process started with a full logistic regression model including drivers' rates of all four types of high g-force events as predictors. Backward selection was then performed to eliminate nonsignificant factors one-by-one until all factors in the model were statistically significant and reached the highest predictive performance. The AUC of the ROC was used to quantitatively assess the prediction performance of the final model.

4.4 Results

4.4.1 Descriptive statistics

The 406 participants generated a total of 633,269 trip records, which was reduced to 554,708 after removing invalid trips (i.e., those where the vehicle did not move). The total distance of the 554,708 trips was 5,162,881 kilometers.

High g-force events concurrent with CNCs (i.e., any overlaps between start and end times for two types of events) were excluded from analysis to minimize crash-induced high g-force events that could inflate correlation statistics of certain thresholds. Across accelerations across lateral, longitudinal, yaw directions, 323 high g-force events were identified and removed prior to analysis.

presents the number of ACCEL, DECEL, LAT, and yaw rate by different thresholds. The number of high g-force events varied substantially with respect to different thresholds, from millions of events to a few ones.

Figure 4-1 depicts the distribution of the number of CNCs experienced by the driver. The study included 385 near crashes and 43 crashes (a total of 428 CNCs). Over three quarters of drivers had only 0 to 1 CNCs during their SHRP 2 participation, and only four participants had over 5 CNCs. .

Figure 4-1. Number of high g-force events by a series of thresholds (left). Number of drivers for number of CNC (right).

Table 4-3 presents the descriptive statistics on the trips, participants, and high g-force events per 1000km by different thresholds and CNCs per 1000k.

Table 4-3. Descriptive statistics of number of trips, distance driven, age, CNCs rate, and high g-force events rates for the SHRP 2 NDS drivers (N = 406; Female=177, Male=229)

	Mean	**SD**	**Median**	**Skew**	**Kurtosis**
Number of trips per participant	1366.276	929.382	1166.000	1.327	2.360

Distance driven (km) per participant	12716.455	10267.363	10287.976	1.707	4.036
Age	75.054	2.986	76.000	-0.420	-1.152
Individual event rate (per 1000 km)					
CNCs	0.093	0.214	0	8.904	118.289
Longitudinal acceleration (ACCEL)					
ACCEL ≥.30g	24.819	38.437	9.801	3.164	13.209
ACCEL ≥.35g	3.875	10.535	0.704	6.218	49.937
ACCEL ≥.40g	0.470	2.154	0.000	8.812	91.219
ACCEL ≥.45g	0.029	0.141	0.000	6.595	48.438
ACCEL ≥.50g	0.002	0.036	0.000	18.586	357.995
Longitudinal deceleration (DECEL)					
DECEL ≥.30g	66.747	64.174	47.687	2.487	9.096
DECEL ≥.35g	20.053	23.692	13.175	3.331	14.984
DECEL ≥.40g	6.239	7.937	4.005	3.563	16.661
DECEL ≥.45g	2.058	2.660	1.302	3.191	12.841
DECEL ≥.50g	0.714	1.012	0.407	3.085	12.014
DECEL ≥.55g	0.265	0.440	0.101	3.664	21.884
DECEL ≥.60g	0.100	0.215	0.000	3.824	20.427
DECEL ≥.65g	0.036	0.104	0.000	4.520	24.905
DECEL ≥.70g	0.012	0.045	0.000	5.304	32.654
DECEL ≥.75g	0.005	0.034	0.000	8.717	82.943
DECEL ≥.80g	0.002	0.021	0.000	17.482	326.481
Lateral acceleration (LAT)					
LAT ≥.30g	100.822	92.380	73.348	1.893	4.959
LAT ≥.35g	31.502	43.816	16.926	3.269	15.222
LAT ≥.40g	8.466	18.459	2.217	5.429	39.324
LAT ≥.45g	2.054	6.016	0.256	6.566	52.697
LAT ≥.50g	0.463	1.713	0.000	7.535	69.465
LAT ≥.55g	0.104	0.434	0.000	8.180	87.163
LAT ≥.60g	0.017	0.089	0.000	10.034	129.288
LAT ≥.65g	0.003	0.021	0.000	9.071	92.464
Yaw rate					
Yaw ≥ 4°/s	17.393	51.060	9.698	12.012	156.027

Yaw ≥ 5º/s	6.696	34.005	2.105	12.773	179.185
Yaw ≥ 6º/s	3.942	25.893	0.711	13.919	219.341
Yaw ≥ 7º/s	2.726	21.550	0.293	14.468	233.741
Yaw ≥ 8º/s	2.062	18.463	0.115	14.348	225.872
Yaw ≥ 9º/s	1.684	16.056	0.031	13.790	206.123
Yaw ≥ 10º/s	1.433	14.129	0.000	13.308	189.907

4.4.2 Correlation analysis

Table 4-4 presents the Spearman's rho correlation coefficients between participants' rates of high g-force events at different thresholds and their rates of CNCs. Most correlations are positive and statistically significant (p-value < 0.05). The thresholds yielding the highest correlations with CNC rates are 0.4g for ACCEL, ρ (404) = 0.223, p <0.001; 0.6g for DECEL, ρ (404) = 0.335, p <0.001; 0.4g for LAT, ρ (404) = 0.238, p <0.001; and 9º/s for yaw rate (ρ (404) = 0.243, p <0.001). These threshold values were selected for identifying high g-force events in subsequent analysis for modeling CNCs occurrence and high crash-risk drivers' identification.

Table 4-4. Spearman's ρ correlation coefficients between participants' CNC rate and high g-force event rates.

Category	EVENT TYPE ≥. threshold	Number of events	Correlation with CNC rate ρ (404)
Longitudinal acceleration (ACCEL)	ACCEL ≥ .30g	104,933	0.174***
	ACCEL ≥ .35g	17,127	0.200***
	ACCEL ≥ .40g	**2,136**	**0.223*** **
	ACCEL ≥ .45g	117	0.077*
	ACCEL ≥ .50g	5	-0.057**
Longitudinal deceleration (DECEL)	DECEL ≥ .30g	289,956	0.257**
	DECEL ≥ .35g	86,302	0.295*
	DECEL ≥ .40g	27,165	0.317***
	DECEL ≥ .45g	9,319	0.310***
	DECEL ≥ .50g	3,423	0.321**
	DECEL ≥ .55g	1,308	0.273***
	DECEL ≥ .60g	**513**	**0.335***
	DECEL ≥ .65g	199	0.279**
	DECEL ≥ .70g	76	0.179*
	DECEL ≥ .75g	29	0.061
	DECEL ≥ .80g	11	-0.018

Lateral acceleration (LAT) (towards right or left from the sensor position)	LAT ≥ .30g	4,785,151	0.217**
	LAT ≥ .35g	151,265	0.229***
	LAT ≥ .40g	40,557	0.238***
	LAT ≥ .45g	9,673	0.236***
	LAT ≥ .50g	2,205	0.206**
	LAT ≥ .55g	93	0.154*
	LAT ≥ .60g	17	0.128
	LAT ≥ .65g	2	0.065
Yaw rate (right or left, in right-hand coordinate system SAE J760)	Yaw ≥ 4º/s	74,624	0.168***
	Yaw ≥ 5º/s	29,129	0.198***
	Yaw ≥ 6º/s	17,913	0.199***
	Yaw ≥ 7º/s	13,009	0.233**
	Yaw ≥ 8º/s	10,242	0.220**
	Yaw ≥ 9º/s	**8,472**	**0.243****
	Yaw ≥ 10º/s	7,220	0.211**

p-value <0.05, **<0.01, *<0.001*

4.4.3 Modeling the relationship of high g-force events in 1000km drive with CNC occurrence in the subsequent 1000km of drive.

The final logistic regression model using GEE includes the number of DECEL, LAT, max speed, number of trips longer than 100km, and number of trips to low frequency destinations. Table 4-5 summarized the results of fitting this model. DECEL and LAT both exhibited positive associations with CNCs risk. Specifically, holding other variables constant, an additional DECEL and LAT observed in a 1000km drive was associated with 46.8% and 1% increase in the risk of at least one CNC occurring in subsequent 1000km drive, respectively (DECEL: RR = 1.468, 95% CI = [1.059, 2.035]; LAT: RR = 1.010, 95% CI = [1.006, 1.015]). Further, a CNC is more likely to occur as older adults drive at higher maximum speeds and take more trips to low frequency destinations. CNC is less likely to occur if they have more trips over 100km.

Figure 4-2 shows the ROC curve for evaluating the prediction performance of the final model, and the AUC was 0.642, indicating an acceptable prediction performance.

Table 4-5. Logistic Regression with GEE for predicting CNC occurrence in a 1000km driven – final model

	Est.	Rate Ratio (95% CI)	SE	Wald	p-value
DECEL ≥ 0.60g	0.384	1.468 (1.059, 2.035)	0.002	19.28	0.021 *
LAT ≥ 0.40g	0.010	1.010 (1.006, 1.015)	0.166	5.32	<0.001 ***
Max speed – proxy of driving on freeway	0.017	1.018 (1.007, 1.028)	0.005	11.16	<0.001 ***
Trips ≥ 100km – proxy of long-distance driving	-0.247	0.781 (0.684, 0.893)	0.068	13.10	<0.001 ***
Trips to low frequency destinations – proxy of driving in unfamiliar areas	0.009	1.011 (1.006, 1.013)	0.002	34.34	<0.001 ***

p-value <0.05, **<0.01, *<0.001*

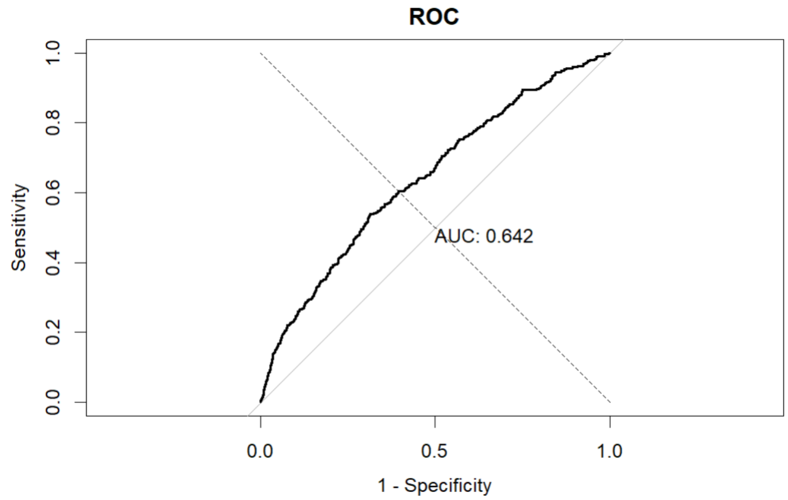


Figure 4-2. ROC curve for accessing prediction performance of the final model

4.4.4 Modeling the relationship of individual high g-force events rates with being high crash-risk driver

Based on drivers' CNC rates, K-means clustering grouped 374 drivers into one cluster with a mean of CNC rate of 0.052, and 32 drivers into another cluster with a mean CNC rate of 0.567 (Table 4-6). Thus, the 32 drivers in the cluster with the higher CNC rate were labeled as high crash-risk, while the ones in the other cluster were labeled as low crash-risk. The clustering results aligned with the fact that the majority of drivers were relatively safe, and a small percentage of drivers were responsible for a significant portion of the CNCs.

Table 4-6. K-means cluster for labeling low crash-risk and high crash-risk drivers

Cluster	Number of drivers	Mean of CNC rate	Within cluster sum of squares (SS)
Low crash-risk group	374	0.052	2.04
High crash-risk group	32	0.567	8.94
Between SS / Total SS = 41.6 %			

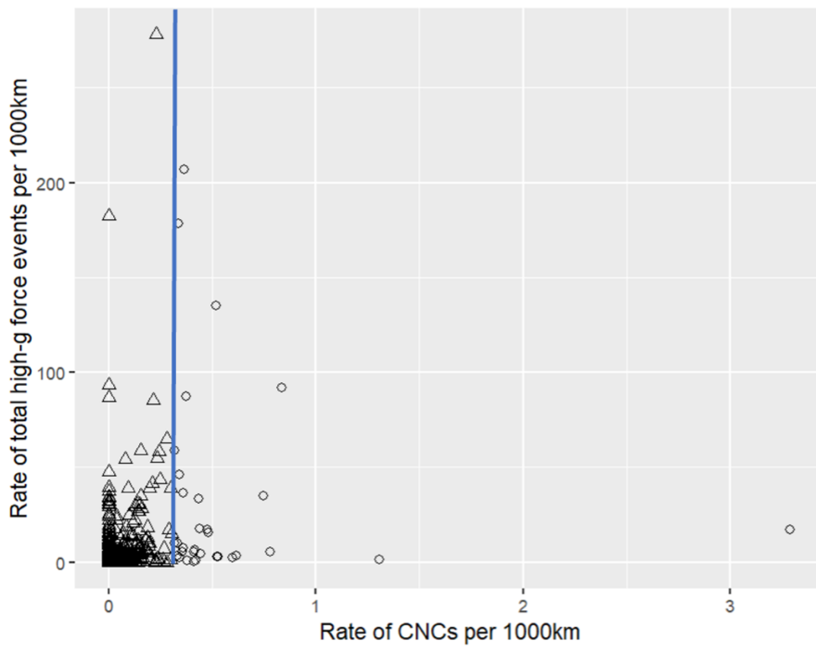


Figure 4-3. K-means clustering results (△: low crash-risk driver ○: high crash-risk driver)

The final logistic regression model included the rates of DECEL and LAT as significant predictors of crash-risk group of older drivers (Table 4-7). Older drivers who had higher rates of the two types of events had an increased risk of being classified into the high crash-risk group. Specifically, holding rate of LAT constant, for every one unit increased for DEC rate, the risk of being classified as high crash-risk drivers increased by 1905.9% (RR = 20.059, 95%CI = [5.723, 79.778]). Holding rate of DECEL, for every one unit increased for LAT rate, the risk increased by 2.4% (RR = 0.023, 95%CI = [1.010, 1.040]). Figure 4-4 illustrates the ROC curve used to evaluate the prediction performance of the final model. The AUC was 0.803, indicating a strong predictive capability. Drivers' rates of longitudinal deceleration and lateral acceleration are highly predictive of the risk of being high crash-risk drivers.

Table 4-7. Logistic Regression for predicting high crash-risk drivers – final model

	Estimate	Rate Ratio (CI 90%)	SE	Z-value	p-value
Intercept					
Rate of DEC ≥ 0.60g	2.9987	20.059 (5.723, 79.778)	0.6698	4.48	<0.001***
Rate of LAT ≥ 0.40g	0.0234	1.024 (1.010, 1.040)	0.0075	3.13	0.0017*

p-value <0.05, **<0.01, *<0.001*

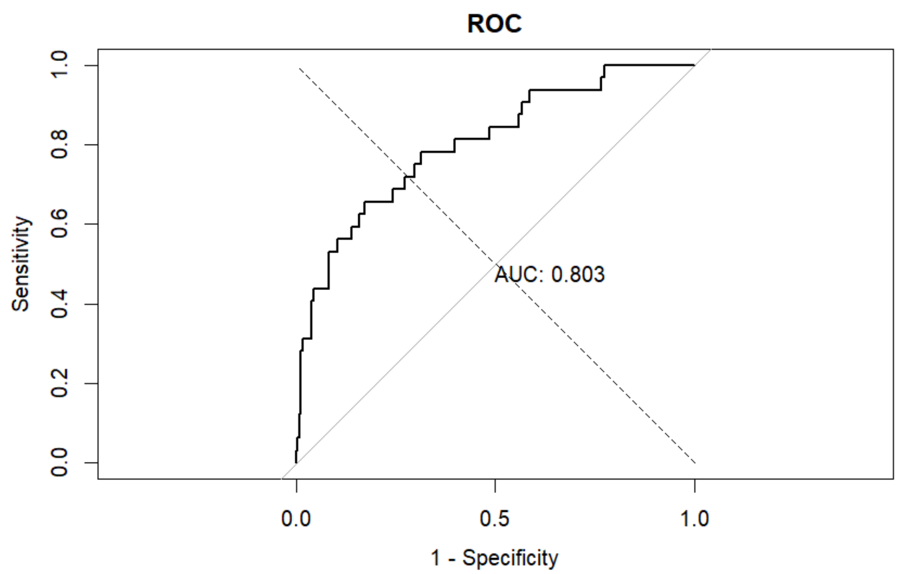


Figure 4-4. ROC curve for prediction performance of the final model

4.5 Discussion

4.5.1 Predicting CNC occurrence for older drivers

DECEL and LAT events were significantly associated with CNCs risk of older drivers. DEC had a stronger association with CNCs risk than LAT. Accounting for the factors of overall driving exposure, driving in unfamiliar areas, long-distance trips, and at high speed, DECEL and LAT events in a 1000km driver are predictive of the risk of at least one CNC occurring in subsequent 1000km drive. The ROC curve indicated an acceptable model prediction performance with AUC of 0.642. In other words, DECEL and LAT events showed acceptable predictive accuracy in near-future CNCs of older drivers and thus meaningful indicators of safety-related impacts of older drivers.

The model performance can be further improved by incorporating more factors that contribute to crash risk, like environmental characteristics, roadway conditions, and advanced vehicles technologies. Older drivers appear to be influenced more by environmental characteristics than the general population, as suggested by the rate of fatal crashes in darkness for older drivers to much less than drivers under age of 25 but greater overall than age 25 to 64 (Mortimer & Fell, 1989).

4.5.2 Predicting high crash-risk older drivers

Individual LAT and DECEL event rates are significantly associated with CNC risk of individual older drivers. DEC event rate had a stronger association with risk of individual drivers than LAT rates. The ROC curve also indicated that the model predictive accuracy is a high with the AUC of 0.803.

This provides strong evidence that drivers' t DECEL and LAT rates can assess their crash risk and identify high crash-risk older adults. By identifying high crash-risk drivers with older population, we can implement targeted safety strategies to enhance road safety effectively. According to Habtemichael & de Picado-Santos (2013), limiting the risk-taking behavior of 4% to 12% of high-risk drivers can reduce crashes by 9% to 27% in different traffic conditions.

4.5.3 Safety indictors for older drivers: DECEL ≥ 0.60g and LAT ≥ 0.40g

DECEL ≥ 0.60g and LAT ≥ 0.40g were significantly associated with driving risk and driver risk. DECEL ≥ 0.60g is more indicative of the risk of CNCs than LAT ≥ 0.40g, exhibiting a significantly larger magnitude of association. Especially for identifying high crash-risk drivers, the association of DECEL was 1000 times stronger than LAT while ACCEL and Yaw rate did not show significant association with either driving risk or driver risk.

It is not surprising to observe that different types of high g-force events exhibited a substantial difference in magnitude of association with CNCs. First, in SHRP 2, about 92% of maneuvers immediately before CNCs involved braking (see **Appendix A**), which most likely induces a DECEL event. In contrast, about 30% of CNCs involved prior turning maneuvers, which most likely involve LAT or yaw events. Thus, the difference in magnitude of association to CNCs is expected given how CNCs occurred in the SHRP 2 dataset and likely normal driving. Second, majority of driving time is spent on moving straight, which demands longitudinal control (e.g., managing speed and headway), while longitudinal impacted crashes (e.g., rear-end and head-on crashes) are much more common than lateral impacted crashes (NHTSA, 2020). Thus, rapid braking is more intrinsically and strongly associated with CNC involvements. Third, it aligns with the extant research that DECEL, often referred to as "rapid deceleration (RDE)" (e.g., Chevalier et al., 2016, 2017; Keay et al., 2013), is the most frequently examined or applied type of high g-force event, whereas high g-force events in other directions have been neglected. Finally, for older drivers, this finding is consistent with many studies that have revealed correlation between more hard braking and declining health and functioning, such as lower contrast sensitivity (Chevalier et al., 2017), mild cognitive impairment (Di et al., 2021), diabetes mellites (Liu et al., 2022), and medication misuse (Xue et al., 2021).

4.5.4 Low thresholds bias for assessing crash risk for older drivers: less risky or more conservative?

The appropriate thresholds identified in this study for older drivers are generally higher than Simons-Morton et al. (2012)'s thresholds that were examined using novice teen drivers' data, and 0.5g for DECEL events suggested by Dingus et al. (2006) for general population.

Compared to other age groups, teen and younger drivers are more likely engaged in risk-taking behaviors, which are considered as most common cause of their crashes (NHTSA, 2014). These risk-taking behaviors often result in events with acceleration larger than regular driving but fall within a relatively low acceleration range. Thus, the thresholds for high g-force events that are most indicative of teen and younger drivers' crash risk might be relatively low (e.g., Simons' g-force thresholds for kinematic risky driving). Thus, high g-force events at lower range of thresholds appear more appropriate for assessing risk for younger population.

However, older drivers often have low risk-taking and self-regulation tendencies, as well as stable driving styles given the years of experience. These may result in proportionally fewer high g-force events at lower thresholds and less variation in their vehicle control. As a compensatory measure for the late hazard perception due to aging-related physical, cognitive, or visual impairments, older adults may engage in occasional evasive actions of braking harder or turning sharply to avoid potential CNCs. Chevalier et al. (2017) found that older drivers' declined contrast sensitivity was associated with more frequent longitudinal deceleration events that were identified by a high threshold of 0.75g. Though unrelated to older adults, some studies found that drivers aged over 30 tended to decelerate quicker than younger drivers (Kusano, Chen, Montgomery, & Gabler, 2015; Montgomery, Kusano, & Gabler, 2014; Porter & Whitton, 2002). Given these factors, the high g-force events mostly indicative of older drivers' crash risk may fall in the higher threshold range. G-force events set at low thresholds may lead too many noise events that mask the g-force events actually associated with CNC risk and thus become insensitive for assessing risk for older drivers.

The research results may help explain the opposite findings between Keay et al. (2013)'s and Chevalier et al. (2017)'s findings. In Keay et al. (2013)'s study, older participants with lower contrast sensitivity had fewer DECEL over 0.35g, which is may be too low to reflect safety-related impacts compared to the appropriate threshold of 0.60g identified in this study. The fewer DECEL events over 0.35g observed in their study may likely reflect less risk-taking driving behavior or, for older drivers, a more appropriate interpretation is "more conservative" or "more cautious" driving patterns due to increased self-regulation associated with their declined functioning. In contrast, Chevalier et al. (2017) observed more DECEL events over 0.75g, which is closer to the 0.60g threshold identified in this study. Contrast sensitivity decline may contribute to more driving situations that require response with g-force events at high threshold, given that numerous studies have provided evidence linking declined contrast sensitivity to increased crash risk (e.g., Guo, Fang, & Antin, 2015; Jones et al., 2022; Owsley, Swain, Liu, McGwin, & Kwon, 2020). Therefore, threshold selection for g-force events could affect interpretation of results. A decreased rate of high g-force events may be misinterpreted as lower risk or a low-risk drivers when, in fact, it could reflect a tendency in self-restriction in driving habbits in response to functioning declines. These self-restrictions or adaptations may mask the true risk of impairment and give a false impression of their safety. Further research is necessary to investigate the relationship between high g-force events at lower thresholds (e.g., Simons' selection for kinematic risky driving or lower) and the tendency of self-regulation among older drivers. Assessing driving risk or identifying risky drivers by driving behavior, it is crucial to consider the underlying reasons for observed changes in driving behavior. Researchers should carefully select the appropriate thresholds to prevent misinterpretations and ensure a more nuanced understanding of the risk they may pose while driving.

4.5.5 Correlation magnitude

Comparing our correlation results with Simons-Morton et al. (2012)'s study's, the high g-force event rates exhibited lower correlation with CNC rates for older than teen drivers. In this study, the correlation of CNC rates with 0.4g longitudinal acceleration is .22; 0.6g longitudinal deceleration is .41; 0.4g lateral acceleration is .23; and 9°/s yaw rate is .24; whereas, Simons-Morton et al. (2012) reported higher correlations: 0.28 for longitudinal acceleration, 0.76 for longitudinal deceleration, 0.62 for lateral acceleration to the right, 0.53 for lateral acceleration to the left, and 0.46 for yaw rate.

It is important to note that the novice teenage drivers in Simons-Morton et al. (2012)'s study is a very unique group. Teenagers exhibit more risk-taking driving behavior, and notable large variability (Simons-Morton, Hartos, Leaf, & Preusser, 2006; Simons-Morton, Hartos, Leaf, & Preusser, 2006). Thus, high g-force events rates are considerably higher and more variable among teen drivers than adults drivers (McDonald et al., 2015; Simons-Morton, Cheon, Guo, & Albert, 2013; Simons-Morton et al., 2011). These were reflected in Simons-Morton et al. (2012)'s study, where their participants had KRD rates five times higher than experienced adults' rates (Simons-Morton et al., 2019). Besides, KRD rates declined for the novice participants within the first six months of licensure (Simons-Morton et al., 2019, 2012), indicating large variation in data. More frequent high g-force events and larger variation amongst teenage participants in Simons-Morton et al. (2012)'s study are two major factors contributing to the larger observed correlation coefficients (Goodwin & Leech, 2006). Thus, direct comparison in the magnitudes of correlation between two studies must be taken with caution because the observed correlation between high g-force event rates and CNCs rates can simply be a result of the sample size and the variation in the unique sample from a small portion of driving population (i.e., only 5.11% licensed drivers are aged 19 (FHWA, 2022b)).

Compared with studies examining the general population, the correlation magnitudes between crashes and high g-force events were similar. For instance, the correlation of longitudinal acceleration and deceleration events with crash records was about 0.4 in the Stipancic et al., (2018)'s study, and longitudinal deceleration with rear-end crash records was 0.39 in the Kim et al., (2016)'s study.

4.5.6 Practical considerations on thresholds for high g-force events

While 0.60g for DECEL and 0.40g for LAT yielded the highest predictive performance using the data from a large-scale NDS, these thresholds may not necessarily be the optimal choice for other studies which have their unique properties. That is, empirically-determine thresholds for high g-force events are sensitive to the properties of the dataset governed by study design and idiosyncrasies of the data collection. The 0.60g threshold for DECEL is relatively high that inherently requires a large study-scale to accumulate sufficient events for meaningful analysis. When applied to small-scale studies, like the SMX study, high thresholds may become impractical due to insufficient number of events to assess driving risk. In such cases, lowering the thresholds to increase the number of events is a reasonable approach for assessing risk or achieving other modeling outcomes specific to the study. However, lowering thresholds for identifying high g-force events can introduce more noise events reflecting only regular driving behaviors. The noise events can weaken the association with crash risk, potentially impacting the validity of the measurement. In other words, there can be trade-off between overall sample size and proportion of noise events, especially for small scale studies. For smaller-scale studies or those with limited trips, other kinematic measures could be considered, e.g., the maximum acceleration/deceleration value within the trip to represent the tendency of rapid acceleration/deceleration, or the median acceleration/deceleration value within a trip to summarize the average driving patterns. In essence, careful consideration must be taken when determining the thresholds for high g-force events for assessing crash risk in each individual study.

4.5.7 Limitations

The study has several limitations. Firstly, older participants in SHRP 2 NDS were relatively active, healthy, and high functioning so they may not be representative of the general older driver population in the U.S. (Antin et al., 2019; Antin, Stulce, Eichelberger, & Hankey, 2015). Secondly, as with any cohort study, the study results only illustrate the general patterns of acceleration and deceleration events associated with frequency of CNCs and cannot indicate which specific high g-force events associating a crash or near-crash event. Investigating individual CNC events would yield deeper qualitative insights into the findings. Thirdly, the selection of environmental factors incorporated into the model was limited by data availability. Future studies could incorporate more context parameters that affect driving behavior and crash risk, such as, speed, road environment, travel information. Contextual driving parameters are particularly important for older drivers who commonly exhibit self-regulatory driving patterns to compensate for self-perceived age-related declines (Ball et al., 1998; Charlton, Oxley, Fildes, Oxley, & Newstead, 2003; Green, 1998; Liang et al., 2022).

4.5.8 Conclusion

This study utilized the SHRP 2 NDS data to investigate the appropriate thresholds for high-g force events to assess crash risk while driving and individual crash risk for older drivers. The strongest correlations of CNCs rates were revealed for ACCEL at 0.4g, DECEL at 0.6g, LAT at 0.4g, and yaw rate at 9°/s. Further, the study revealed that DECEL ≥ 0.60g and LAT ≥ 0.40g events can be used to assess older adults' driving risk and are predictive of near future CNCs occurrence with acceptable predictive accuracy. The event rates of DECEL ≥ 0.60g and LAT ≥ 0.40g are also useful in classifying older drivers as high or low crash-risk groups with high predictive accuracy.

5 Study 4 - Examining Older Drivers' Safety under Naturalistic Driving Conditions: With and Without the Advanced Driver Assistance Systems Presence

The first study of this dissertation examined the older adults' mobility through modeling driving habits with respect to age, gender, living status, health, and functioning capabilities in their naturalistic driving environment. The second study turned to older drivers' perception of ADAS after six weeks of hands-on driving experience with them also in a naturalistic setting. The third study identified and examined high g-force events for assessing driving risk and driver risk for older drivers. This final study focuses on the impacts of ADAS on older drivers' safety.

5.1 Introduction

Aging presents one of the most significant social transformations and challenges to our society in this century, impacting housing, health care, and transportation. Americans are projected to have a life expectancy of 85.6 in 2060 up from 79.7 in 2017, resulting in both a higher number and proportion of adults aged 65 and over. People aged 65 and over is expected to reach 94.7 million and nearly one quarter (23.41%) of the U.S. population by 2060 (Medina et al., 2020). The number of licensed drivers aged 70 and over has already reached 31 million in 2020, representing 13.6% of drivers (FHWA, 2022a), and is expected to increase over the next few decades (Sivak & Schoettle, 2012). Further, older drivers are expected to drive more than ever before (Buehler & Nobis, 2010; Santos et al., 2011).

Older drivers have higher crash rate per mile driven than the middle-aged drivers (Cox & Cicchino, 2021). Unlike teen drivers, whose high crash risk is mostly attributed to their risk-taking tendency (Doherty, Andrey, & MacGregor, 1998; Jaccard, Blanton, &

Dodge, 2005; Jonah, 1990; McCartt, Shabanova, & Leaf, 2003; M. Zhu, Chu, & Li, 2009), the elevated crash rate of older drivers are attributed to their declines or impairments in cognitive, sensory, and physical capabilities due to aging (Anstey et al., 2005; Owsley et al., 1991). Besides, fatal crash involvement increases drastically after the age of 69 (Cox & Cicchino, 2021; Insurance Institute for Highway Safety, 2020). This is largely due to their physical vulnerabilities and poorer health status with aging that limits their capacity to recover from injuries from car accidents (Clegg, Young, Iliffe, Rikkert, & Rockwood, 2013). Given to the aging demographics, which indicates an increasing number of older drivers on the road, it is projected that fatal crash involving older population aged 65 and over will make up approximately 25% of all crashes by 2030 (Lyman, Ferguson, Braver, & Williams, 2002). Thus, the road safety of older drivers warrants significant attention from governments, vehicle manufacturers, and the drivers themselves.

Advanced Driver Assistance Systems (ADAS) is technologies designed initially for comfort and convenience but found to potentially improve safety through features like early warnings and automated functionalities. Early warnings or signals in the form of sounds and vibration can alert drivers about encroaching vehicles or lane drifting through features like blind spot assist (BSA) and lane departure warning (LDW). Forward collision warnings (FCW) can alert drivers to brake to avoid imminent crashes. The vehicle-maneuvering features have some limited automatic control of the vehicle to intervene and ease with routine driving tasks, such as adaptive cruise control (ACC) for driving forward and car following, and lane keeping assistant (LKA) for staying on center of lane. Both could reduce the likelihood of the vehicles entering into dangerous driving situations.

In theory, older adults who often suffer from age-related deficits are likely to find more benefits from ADAS, as these functions are expected to compensate for their deficits. For example, BSA helps older drivers in checking the blind spot that can be difficult due to declining range of motion for the neck, thereby reducing the crash risk related to merging or changing lanes. ACC and FCW monitor the environment and alert the driver when frontal collision is imminent, mitigating some failures in perceiving and responding to hazards due to declines in cognition and vision that are critical to hazard perception. ACC and LKA can relieve drivers from moderate longitudinal and lateral vehicle control, respectively, potentially reducing fatigue and crash risk in long-distance trips.

While ADAS has been suggested to benefit older drivers (Classen et al., 2019; Eby et al., 2016; Rhiu, Kwon, Bahn, Yun, & Yu, 2015), empirical evidence is still lacking to establish the relationship between ADAS and safety benefits for older drivers (Classen et al., 2019). One primary contention is that age-related declines, particularly in executive functions, can hinder older drivers in multi-tasking that are necessary to managing ADAS as well as the normal driving task. In a recent study examining the age-related differences in handling takeover request in highly automated vehicles, younger group (aged below 35), had significantly more stable lateral maneuvering than older drivers (aged 65+) who might be experiencing declines in executive function in cognition (Peng, Wu, Qie, & Iwaki, 2022). Older adults often performed more poorly than younger drivers at multi-tasking, such as driving while responding to multiple simultaneous alerts from ADAS (Fisk, Charness, Czaja, Rogers, & Sharit, 2004). Older drivers have slower response time, taking approximately 170 milliseconds longer to accelerate or brake in response to auditory warnings (Kim, Lee, & Son, 2010). Aging-related characteristics add complexity to estimating the benefits of ADAS features for older drivers based on extant research. Lack of use negates potential benefits of ADAS, while misuse or non-compliance can even introduce additional risks for older drivers.

ACC has been most investigated ADAS feature because it tends to intervene driving tasks much more often than other ADAS features (Classen et al., 2019; Furlan et al., 2020). When driving in a longitudinal direction, ACC maintains speed and manages headway that are central to forward collision. Researchers consider ACC to have well achieved its design purpose of comfort and convenience (Eby et al., 2015; Stanton & Young, 2005). For safety, using ACC was found to using ACC improved older adults' speed management in various simulated driving scenarios, including open roads, urban areas, and zones with lower speed limits (Guo, Blythe, Edwards, Pavkova, & Brennan, 2015). However, researchers also reported safety-related concerns (e.g., De Winter, Happee, Martens, & Stanton, 2014; Hoedemaeker & Brookhuis, 1998; Piccinini, Rodrigues, Leitão, & Simões, 2015). A simulator study of 38 participants between age 25 and 60 found that ACC resulted in driving faster, braking harder, and having smaller minimum headways (Hoedemaeker & Brookhuis, 1998). Another simulator study found that both experienced and inexperienced ACC users between 33 and 61 years old showed higher risk of hitting the stopped vehicle than not using ACC (Piccinini et al., 2015). Late and hard braking was also investigated in a test-track study, which found that using ACC increased response time to hazard as well as lane deviation; however, this study only recruited young drivers aged between 21 to 34 (Rudin-Brown & Parker, 2004). In a five-week naturalistic driving study, 108 participants, of which 35% were aged between 60 and 70, exhibited significantly higher deceleration rates while using ACC, suggesting more aggressive maneuvers for preventing collisions (Fancher, 1998).

For the lateral direction, the most critical tasks of driving a vehicle are staying in the lane and making lane changes. Though less common than head-on or rear-end crashes in the longitudinal direction, side-impact crashes related to lane drifting, lane changing, or turning are typically much more severe. Lane keeping related features, including LDW and LKA, are designed to prevent the vehicle from deviating from its lane and related crashes. One simulator study recruiting 128 adults over 64 years old did not find any reduced deviations of lane position for older drivers using LDW than those who did not have any lateral warnings (Souders, Charness, Roque, & Pham, 2020). However, in a field study investigating vibration alerts of lane departure on the steering wheel while driving on the actual road and dialing a phone, 30 participants between 23 and 59 years old showed better lane keeping performance with than without LDW (Blaschke et al., 2009). In a naturalistic study that included 83,000 miles of driving by 78 participants, 26 of which were aged 60-70, LDW was found to reduce lane departure incidents and excursions, deviations from center of the lane, and variation in lane positions for changing lanes or making a turn while elevating the use of turn signal (LeBlanc, 2006). Son & Park (2012) examined the effects of age and gender on effectiveness of LDW using an instrumented vehicle with 26 younger drivers aged 25 to 35 years old and 26 older drivers aged between 55-65 years. Age and the LDW support both significantly affect the standard deviation of lane position, but the interaction effect was not investigated. Regarding gender effect, males performed significantly less lane excursions with than without LDW; however, females had 28% more lane excursions when LDW was on.

BSA warns drivers about the objects in their blind spots to prevent crashes while changing lanes. A high-fidelity simulator study found that sixteen older adults over 65 years old used less turn signals but were more aware of adjacent traffic with BSA being activated than the sixteen younger adults between 16 and 21 years old (Guo et al., 2010). In a test-track study, BSA was found to help middle-aged drivers react more quickly to a lateral crash threat (Fitch et al., 2014), and in an on-road study, BSA helped 32 drivers between 40 and 70 years old, sixteen of which over 60 years old, to increase the frequency of mirror checking before changing lane (Kiefer & Hankey, 2008).

According to a review of 324 studies investigating the driving outcomes of ADAS features, only 3% focused on older drivers and about half of them were mixed-aged drivers but difference in age groups were not always analyzed (Furlan et al., 2020). Most ACC studies included a mix of age groups but some omit older participants altogether (e.g., Hoedemaeker & Brookhuis, 1998; Piccinini et al., 2015). Regarding lane related systems, there is only one study of LDW focusing on older drivers (refer to the review on Souders et al., (2020)'s study), so safety-related impacts of LDW and LKA on older drivers still needs further research. Considering that older drivers have different capabilities and tendencies from the rest of the population, the results from investigating younger and middle-aged drivers, or mixed-aged group may not be applicable. Further, many of these studies rely on simulators to examine driving behaviors and performance (Furlan et al., 2020) that may not be always translated to real-world driving environment, especially for emergency situations (Ljung Aust & Engström, 2011). In summary, there is still a paucity of evidence on the safety-related impacts for older drivers in using ADAS.

The majority of studies have focused on examining the influence of individual ADAS features on drivers. However, the automotive industry often groups the ADAS features into a safety package for the market. The influences of multiple features on the safety of drivers may not be additive but complex and multifaceted. In addition, assessing the influence on older drivers' safety in a holistic perspective should take account of their perception (refer to **Chapter 3**), driving exposure and habits (refer to **Chapter 2**), usage, and environments, along with the interaction of these factors. Studies focusing on a single feature or individual factor could provide formative assessment with valuable insights for designers, but they do not provide any summative assessment of how the ADAS packages and how ADAS benefits older drivers' safety. Thus, there are merits to examining net safety-related impacts of driving actual vehicles equipped with ADAS, including multiple warning and control features, in naturalistic driving environments that account for their perception, driving exposure, habits, and usage. The net safety-related impacts of ADAS could serve as an important reference for governments, policy makers, and car manufacturers on promoting the use of ADAS among older drivers.

Finally, drivers new to ADAS-equipped vehicles may need only a few hours to understand the basic functions; however, learning to use these features effectively in different environments and in a manner compatible with their driving habits may take weeks. Manser, Creaser, & Boyle (2013) introduced three phases of driving exposure to the introduction of a change in the road system: 1. Immediate phase: takes place right after the change in the road system is introduced; 2. Short-term Phase: occurs within hours, days, or weeks after the change; 3. Long-term Phase: extends over months or years following the change. The short-term phase adaptation is the interest of the study, exploring drivers' adaptation of vehicles equipped with ADAS at this phase can provide valuable insights for developing training programs to better facilitate this adaptation phase to these technologies for road safety of older drivers.

This study addresses the aforementioned limitations of previous research by examining the following three objectives in naturalistic driving settings:

Objective 1: What safety-related impacts might emerge when older drivers are provided with vehicles equipped with ADAS?

Objective 2: How does driving with ACC or LKA being engaged affect driving behaviors that are related to safety?

Objective 3: How do exposure time to ADAS equipped vehicle might influence their driving behaviors that are related to safety or crash risk?

5.2 Method

5.2.1 Method overview

5.2.1.1 With versus without presence of ADAS

Safety-related impacts of driving with ADAS equipped vehicles on older drivers were examined through a cross-sectional study by analyzing the kinematic driving data extracted from two NDSs. One NDS involved vehicles equipped with ADAS only - Senior Drivers Adaptation to Mixed Level Automated Vehicles (SMX (Liang, Antin, et al., 2019)), the other NDS was the Second Strategic Highway Research Program (SHRP 2 (Antin et al., 2019; Dingus et al., 2016)). SMX served as an exposure group providing the data from driving vehicles with ADAS equipped, and SHRP 2 served as a baseline providing the data from driving traditional vehicles without advanced features equipped.

The association of ADAS presence with kinematic event rates was examined. The results would reveal the net safety-related impacts from all the ADAS features collectively. To minimize confounding due to the differences between the two NDSs, sampling controls applied on SHRP 2 were conducted by selection of participants, vehicles, and locations to best match with those in the SMX study (i.e., sample matching).

5.2.1.2 ACC and LKA being versus not engaged

The comparison of kinematic event rates between the two NDSs can only indicate net safety-related impacts on older adults that may be difficult to attribute purely to the ADAS features. For this reason, an observational retrospective cohort study with a crossover design (Carlson & Morrison, 2009; Kim & Mooney, 2016) utilizing the SMX data was conducted to examine the safety-related impacts from LKA or ACC being engaged. A crossover design is possible because each SMX participant drove naturally resulting in the exposure trip segments that engaged either LKA or ACC as well as control trip segments that disengaged both LKA and ACC. The exposure trip segments are trip segments when ACC or LKA was active and engaged during driving. The control segments were trip segments when neither ACC nor LKA was active and engaged during driving. ACC and LKA exposure group of trip segments were compared with these baseline trip segments. The segments being compared were drawn from different trips to avoid carryover influence.

5.2.1.3 Adaptation of ADAS over time

Older drivers' adaptation was examined by the changes in kinematic event rates over the exposure time to ADAS in SMX study. The association between the extended exposure time and their kinematic event rate could reveal safety-related impacts on older drivers with practice driving ADAS-equipped vehicles.

5.2.2 Data acquisition

5.2.2.1 SMX NDS with ADAS presence

5.2.2.1.1 Participants

Eighteen older drivers (nine men and nine women) were recruited to participate in New River Valley, VA. Eligibility criteria of participation included: (1) age between 70 and 79, (3) driving at least two days per week, (4) a valid driver's license, and (5) insurance coverage.

5.2.2.1.2 Vehicle fleet and ADAS features

The fleet included four vehicle models: 2017 Audi Q7, 2016 Mercedes E350, 2016 Volvo XC90, 2015 Infiniti Q90. These vehicles were equipped with an ADAS that included at least the following four features: BSA, LDW, LKA, and ACC. All vehicles were instrumented with a miniature data acquisition system (mini-DAS) which collected video and sensor-based naturalistic driving data continuously and automatically while the vehicle is operating.

5.2.2.1.3 Procedure overview

The study began with an intake session during which potential participants showed their driver's license and proof of liability insurance. After providing informed consent, participants were given questionnaires to collect data on demographics, driving habits, and history, as well as their pre-exposure attitudes towards ADAS. Random vehicle assignment to the participant followed.

Afterwards, participants received a three-part training session. The first part was performed in the parked vehicle while an experimenter explained the basic vehicle features (e.g., windshield wipers, gear shift selector, etc.) and how the four ADAS features functioned. The second part was on-road driving in which the experimenter drove the vehicle and demonstrated how to use the four ADAS features available to all the vehicles in SMX. The experimenter also briefly mentioned the scenarios or environments in which the participants should try to avoid using ADAS given the technology limitations. In the third part, the participant drove the vehicle, using each of the four common ADAS features according to the experimenter's verbal guidance. The on-road drive was designed to provide training on the proper use of ADAS under practical conditions on highways in the New River Valley area. The entire training session lasted 1.5–3 hours.

Following the intake session, each participant was free to drive the study vehicle as the individual's personal vehicle for six weeks. Weekly phone surveys were conducted to collect participants' attitudes about and usage of the vehicles and each ADAS.

On the sixth week, the participants returned the vehicle and completed the same questionnaire administered at the beginning of the study to collect post exposure attitudes towards ADAS.

5.2.2.1.4 Data collection

The mini-DAS included multiple cameras recording videos of the forward roadway scene, the driver's foot, drivers' hands on the steering wheel, the right rearview, and the dashboard. The continuously recorded and stored vehicle data included: vehicle controls, such as brakes, turn signals, throttle, speed and lights, GPS location and time of day, acceleration (g-force) along the lateral, longitudinal, and yaw directions.

5.2.2.2 SHRP 2 – NDS without ADAS presence

5.2.2.2.1 Participants

SHRP 2 participants were recruited in six sites across the United States: Buffalo, NY; Tampa, FL; Seattle, WA; Durham, NC; Bloomington, IN; and State College, PA, with each site recruited 150 to 450 participants. The study enrolled 3,541 drivers aged 16 to 98 for a period between one to two years. The inclusion criteria were: (1) driving regularity (at least three days per week), (2) being licensed, (3) owning an eligible vehicle, and (4) planning to keep vehicle for duration of anticipated study participation (i.e., 1-2 years) (Antin et al., 2019; Dingus et al., 2015). This dissertation study only used the data from the participants aged 70-79 across all six recruitment sites.

5.2.2.2.2 Study vehicles

Study vehicles in SHRP 2 were the participants' personal vehicles, with only very small portion of vehicles being reported as "advanced technology vehicles" (Antin et al., 2019; Dingus et al., 2015). Participants' personal vehicles were equipped with a data acquisition system (DAS) that worked like the ones used in SMX. However, the DAS in SHRP 2 included more channels (i.e., sensors) and collected more data (Antin et al., 2019; Dingus et al., 2015). This dissertation study only used the SHRP 2 data from SUVs and sedans that were <u>not</u> reported as "advanced technology vehicles".

5.2.2.2.3 Procedure overview

SHRP 2 recruited participants through call centers, traditional recruitment methods (e.g., flyers, mass mailings, and web-based Craigslist), and internet-based methods. Female and male drivers were supposed to be balanced across the age groups. Young (aged 16-25) and older drivers (aged 66 and over) were intentionally oversampled due to the elevated crash risk of the two groups (Antin et al., 2019; Dingus et al., 2015). At the enrollment session, the participants first completed the informed consent process. Afterwards, their vehicles were inspected for suitability and installed DAS at a contractor facility. While waiting for the DAS installation, the participants completed a variety of questionnaires collecting their basic demographic information, driving knowledge and behavior, personality factors, health and psychological conditions (Antin et al., 2019; Dingus et al., 2015). Their cognitive, visual, and physical abilities were assessed by a battery of tests. These questionnaires and tests usually took 2 to 3 hours.

The participants were instructed to drive their vehicles as they normally would, and most participated in the study between 1 to 2 years (Antin et al., 2019; Dingus et al., 2015). As the end of the study, the participants completed the medical condition and medication questionnaire again and were interviewed about their experience of the study (Antin et al., 2019; Dingus et al., 2015).

5.2.2.2.4 Data collection

The DAS in SHRP 2 included four cameras recording four video views of the forward roadway scene, the driver’s foot, hands on the steering wheel, and the rear view. In contrast to SMX, no dashboard tracking views were recorded. Vehicle data collection includes all SMX collected (e.g., g-force values along the longitudinal, lateral, and yaw directions). SHRP 2 DAS also collected other beyond the scope of this dissertation, such as cell phone, machine vision, passive alcohol sensor, etc. (Antin et al., 2019; Dingus et al., 2015).

The study protocol was approved by the Virginia Tech Institutional Review Board (approval letter in **Appendix E**).

5.2.3 Analysis

5.2.3.1 Measures of Safety-related Impacts

High g-force events, which are acceleration events exceeding given thresholds, has been used to assess driving risk (Bagdadi & Várhelyi, 2013; Hankey et al., 2016). These kinematic events, such as high deceleration, could reflect hazardous traffic conditions or risk-taking driving behavior, such as hard braking, rapid acceleration, and sharp turns. Cognitive and physical declines among older drivers may also be associated with more elevated kinematic events (Chevalier et al., 2017). Many studies have found association between high g-force events and crash risk, confirming that these events can be used to assess driving risk (Simons-Morton et al., 2013, 2012). Besides high g-force events, derivatives of acceleration, e.g., longitudinal and lateral jerk, showed potential in revealing aggressive driving behaviors and predicting crash risk (Bagdadi & Várhelyi, 2011). Other kinematic measures, such as mean speed and volatility, have also been used in assessing risk (af Wåhlberg, 2006; Xin Wang, Khattak, Liu, Masghati-Amoli, & Son, 2015).

Sensors installed in both SMX and SHRP 2 study vehicles collected vehicle acceleration data in longitudinal, lateral, and yaw directions at 10Hz. The rates of *high g-force events* were used to assess safety-related impacts on older drivers with respective to the presence of ADAS (objective 1) and exposure time to ADAS (objective 3). This study used DECEL and LAT events (Table 5-1) to assess the influences of ADAS on driving risk of older adults. This selection was partly based on the findings of Study 3 (**Chapter 4**), which demonstrated that DECEL and LAT events yielded good accuracy in predicting CNC occurrence in the near future for older drivers and thus effective for assessing driving risk for older drivers a good predictive.

For this study, the thresholds were lowered to 0.30g from the 0.60g and 0.40g for DECEL and LAT events, respectively. As mentioned in Section 4.5.6, the properties of a specific study and thus the dataset may pose practical challenge in adopting the thresholds with the highest predictive performance from a large-scale study. The sample size of the study presents another critical factor in selecting thresholds with the highest predictive performance for the specific study. Applying 0.60g for DECEL and 0.40g for LAT in this study would have resulted in insufficient events to assess the impact of ADAS presence and exposure time to ADAS on older drivers' safety or crash risk (This study does not contain any DECEL exceeding 0.60g. Refer to **Appendix B** for the event counts at different thresholds in SMX). Given the constraints of the small sample size, the two thresholds were lowered 0.30g to generate a greater number of events for improving predictive performance. For an evaluation of selecting 0.3g as the in assessing safety-related impacts for older drivers, please refer to **Appendix C.** Briefly, applying the same analysis in the **Study 3 SHRP 2** dataset would reveal significant association of DECEL $\geq$ 0.30g and LAT $\geq$ 0.30g with CNC occurrence in near-future driving, lending empirical support for the threshold selection in this study.

Table 5-1. High g-force events

High g-force events	Thresholds	Associated evasive, or sudden maneuvers
Number of longitudinal deceleration (DECEL) events	≥ 0.30g	Late or hard brake
Lateral Acceleration (LAT) (towards right and left)	≥ 0.30g	Sharp turn, lane drift, or swerve

To assess safety-related impacts of only ACC or LKA being engaged (objective 2), a series of other *kinematic measurements* for trip segments given insufficient high g-force events from a limited number of trip segments. The kinematic measurements were the acceleration and jerk values at 85^{th} (high positive value) and 15^{th} (high negative value) percentile in lateral and longitudinal directions to summarize the elevated kinematic driving behavior for each trip segment. Maximum or minimum values were not selected to avoid inclusion of large spurious values lasting very short period, which were not indicative of driving behaviors (e.g., driving through the bump). Thus, the threshold slightly lower than the maximum values was used for the segment summary for elevated kinematic behaviors. The median values summarize the average or representative kinematic driving behavior in the trip segments.

All measurements applied in the study was summarized in Table 5-2.

Table 5-2. Measurements in the study

	Driving behavior captured	Kinematic measurements	Study objective applied
Longitudinal	Deviation from norm behavior Abnormal, or elevated kinematic driving behavior	DECEL ≥ 0.30g	Objective 1: with vs. without ADAS presence Objective 3: Adaptation
		85^{th} percentile longitudinal acceleration value	Objective 2: ACC and LKA
		85^{th} percentile longitudinal jerk value	
		15^{th} percentile longitudinal deceleration value	

		15^{th} percentile longitudinal deceleration jerk value	
	Central tendency of driving behavior Average, or representative kinematic driving behavior	Median longitudinal acceleration value	
		Median longitudinal deceleration value	
Lateral	Deviation from norm behavior Abnormal, or elevated kinematic driving behavior	LAT ≥ 0.30g	Objective 1: with vs. without ADAS presence Objective 3: Adaptation
		85^{th} percentile lateral acceleration value	Objective 2: ACC and LKA
		85^{th} percentile lateral jerk value	
		15^{th} percentile lateral deceleration value	
		15^{th} percentile lateral deceleration jerk value	
	Central tendency of driving behavior Average, or representative kinematic driving behavior	Median lateral acceleration value	
		Median lateral deceleration value	

5.2.3.2 With versus without ADAS presence

Generalized linear mixed models (GLIMMIX) for recurrent events for Negative Binominal distribution were built to examine the influence of ADAS presence on individual-level LAT and DECEL rates for older drivers. Due to the overdispersion of data for DECEL (dispersion = 3.012, z = 36.868, p-value < 0.0001) and LAT (dispersion= 4.169, z-value= 37.824, p-value < 0.0001), the negative binomial model was applied. ADAS presence was included in the model as the fixed effect. The intercept of random effect was the participant ID nested within Vehicle ID, that were further nested within recruitment sites. Additionally, the natural log of distance driven was included as an offset. Differences in LAT and DECEL rates for the cohort drove without and with ADAS presence were expressed by incidence rate ratios (IRRs) with 95% confidence limits.

SHRP 2 and SMX NDS served as the baseline and exposure groups, providing high g-event data without and with ADAS presence, respectively. In SHRP 2, participants aged 70 to 79, from the recruitment sites *State College, PA, Bloomington, NI, Durham, and NC* driving vehicles of the model released after 2010, and without advanced features were included in the analysis (Table 5-3). The selection of the SHRP 2 data best-matched driver, vehicle, and environmental factors to the SMX study.

Table 5-3. The comparison between the exposure and baseline groups

	Exposure	Baseline
Data source	SMX	SHRP 2
Location	Blacksburg, VA	State College, PA, Bloomington, NI, Durham, NC
Number of participants	18	28
Age	70-79	70-79
Vehicle model year	2014, 2015, 2016	2010, 2011, 2012
Vehicle classification	SUV and car	SUV and car
ADAS	ADAS equipped	No advanced features reported
Number of study vehicles	8	28[7]

5.2.3.3 ACC and LKA versus L0 segments

Three types of trip segments were identified: LKA, ACC, and L0 trip segment. The description of these three types is listed in Table 5-4. Given that the data were not normally distributed, nonparametric Mann-Whitney tests were conducted to compare the

[7] One participant ID linked with two vehicle IDs. To maintain the simple nesting structure, one vehicle was excluded from the analysis.

kinematic measurements of the ACC and LKA trip segments against the L0 segments (i.e., baseline).

Table 5-4. Definition of three types of segments

	Definition
LKA segment	LKA was engaged but ACC was off or deactivated, while other Level 0 warning systems (BSA, LDW) were available but the status of their usage was unknown. The duration ≥ 1 min The minimum speed ≥ 60km/h
ACC segment	ACC was engaged but LKA was off or deactivated, while other Level 0 warning systems (BSA, LDW) were available but the status of their usage was unknown. The duration ≥ 1 min The minimum speed ≥ 60km/h
L0 segment	LKA and ACC both were disengaged while warning systems were available but the status of their usage was unknown. The duration ≥ 1 min The minimum speed ≥ 60km/h

5.2.3.4 Adaptation of ADAS over time

Generalized linear mixed models (GLIMMIX) for recurrent events for Negative Binominal distribution were built to examine individual-level changes on DECEL and LAT event rates over the exposure time to vehicles equipped with ADAS. Due to the overdispersion data of DECEL (dispersion = 5.371, z = 7.99, p-value < 0.0001) and LAT (dispersion= 4.578, z-value= 8.428, p-value < 0.0001), the negative binomial model was applied. *Exposure time* to ADAS was included in the model as a fixed effect. For each participant, exposure time was divided into seven 5-day intervals, ranging from 1 to 6 intervals (1 to 30 days). Starting from the 31st day and continuing up to the 42nd day (full six weeks), some participants began to leave the study (see Table 5-5). This was attributed to the flexibility of the SMX project, which allowed participants to return the study vehicle on their preferred day in the last week. For avoiding potential bias, only six intervals were included for this analysis. The intercept of random effect was the participant ID nested within Vehicle ID. Additionally, the natural log of distance driven was included as an offset. The models were rerun for LAT and DECEL.

Table 5-5. Distance driven, number of trips and drivers for each 5-day interval

Days after exposure	Total kilometers	No. of drivers	No. of trips
1-5	3,368.868	18	294
6-10	2,819.858	18	271
11-15	2,629.518	18	254
16-20	4,979.811	18	270
21-25	5,025.881	18	281
26-30	2,443.265	18	222
31 -	1,648.274	14	135

Differences in LAT and DECEL rates for the cohort over the time intervals (5-day periods) after exposure were expressed by incidence rate ratios (IRRs) with 95% confidence limits. The rates for the first interval after exposure were compared with each subsequent interval. Trips shorter than 1 kilometer were excluded as invalid trips, such as moving the vehicle in a parking lot.

5.3 Results

5.3.1 With versus without ADAS presence

Eighteen participants drove the study vehicles with ADAS package presence generating a total of 22,915.48 kilometers. Twenty-eight participants drove a total of 407,123.63 kilometers without ADAS presence. Table 5-6 presents the incident rates (IRs) for DECEL and LAT, as well as their 95% CLs, for driving with and without ADAS presence.

The Analysis of Deviance (Wald chi-square tests) based on GLIMMIX indicated a statistically significant effect of ADAS presence on rates of DECEL events (χ^2(1, N= 28,626) = 7.4876, p-value = 0.0062). The IRRs and 95%CL in Table 5-7 indicate that DECEL rates with ADAS presence were significantly lower than without ADAS presence (IRR = 0.3431, 95% CL = [0.1594, 0.7382]). No significant effects of ADAS presence reveal on LAT rates (χ^2(1, N=40,757) = 2.1397, p-value = 0.1435 > 0.05)).

Table 5-6. Incidence rates (IRs) and 95%CL for DECEL and LAT without and with ADAS presence

	ADAS presence	No. of drivers	No. of vehicles	No. of trips	No. of events	Total kilometers	IR	95%CL
DECEL	Without	28	28	31,734	27,673	407,123.63	0.594	0.413, 0.853
	With	18	8	1,727	953	22,915.48	0.204	0.104, 0.400
LAT	Without	28	28	31,734	37,916	407,123.63	0.611	0.401, 0.931
	With	18	8	1,727	2841	22,915.48	1.122	0.559, 2.253

Table 5-7. The model estimates for DECEL and LAT as response variables, respectively, comparing with and without ADAS presence

	ADAS presence	Est.	Std. Error	IRR	95%CL	Z-value	P-value
DECEL	With vs without	-1.0698	0.3910	0.3431	0.1594, 0.7382	-2.736	0.00621*
LAT	With vs without	0.6082	0.4158	1.8372	0.8132, 4.1505	1.463	0.144

5.3.2 ACC and LKA versus L0 segments

5.3.2.1 Descriptive statistics

One hundred twenty-one LKA segments were longer than one minute. The majority of trip segments were below five minutes, only four segments longer than twenty minutes (Table 5-8). Forty-five ACC trip segments longer than one minute were identified. Most segments were shorter than five minutes, only five segments longer than twenty minutes (Table 5-9). Twenty-eight segments longer than one minute and maintained a speed of at least 60 kilometers per hour were identified as L0 segments (Table 5-10).

Table 5-8. Descriptive statistics of 121 LKA segments

	Mean	SD	Median	Min	Max
Standard deviation of speed	7.52	3.36	7.16	0.78	20.37
Max speed (km/h)	99.88	15.19	101.41	65.41	139.05
Mean speed (km/h)	88.18	12.84	89.43	63.23	118.31
Duration (ms)	295,331	562,999	179,000	62,000	5,418,000
>1min, N=121 segments					
Duration (mins)	No. of segments		Proportion		
1-2	33		27.27%		
2-3	18		14.88%		
3-4	18		14.88%		
4-5	10		8.26%		
5-10	25		20.66%		
10-15	1		0.83%		
20-40	4		3.31%		

Table 5-9. Descriptive statistics of 45 ACC segments

	Mean	SD	Median	Min	Max
Standard deviation of speed	5.11	2.31	5.35	1.07	10.24
Max speed (km/h)	104.95	13.68	106.41	77.94	129.96
Mean speed (km/h)	97.11	13.57	95.58	67.26	120.21
Duration (ms)	493,688	821,741	214,000	61,000	4,612,700
>1min, N=45 segments					
Duration (mins)	No. of segments		Proportion		
1-2	12		24.44%		
2-3	6		13.33%		
3-4	9		17.78%		
4-5	4		8.89%		
5-10	6		13.33%		
10-15	1		2.22%		
15-20	2		4.44%		
20-40	3		6.67%		
40+	2		4.44%		

Table 5-10. Descriptive statistics of 28 L0 segments

	Mean	SD	Median	Min	Max

Standard deviation of speed	9.12	4.76	8.42	2.89	18.54
Max speed (km/h)	97.78	17.12	103.78	73.06	130.04
Mean speed (km/h)	83.13	11.50	82.77	67.54	101.74
Duration (ms)	158,036	100,630	127,500	62,000	418,000
>1min, min speed> 60kmh, N=28 segments					
Duration (mins)	No. of segments		Proportion		
1-2	12		42.86%		
2-3	8		28.57%		
3-4	5		17.86%		
6-7	3		10.71%		

5.3.2.2 Comparison result of LKA and ACC with L0 segments

The Mann-Whitney U test revealed that, while LKA was engaged, the absolute values of 15th percentile longitudinal deceleration (negative) were smaller in comparison to segments when both LKA and ACC were not engaged (L0 segments) (W = 2068.5, p-value = 0.025). The test results were summarized in Table 5-11. There were no significant differences observed between segments with ACC being engaged and both LKA and ACC being not engaged (L0 segments; Table 5-12).

Table 5-11. Mann-Whitney U test comparing LKA with L0 segments.

LKA vs L0	Kinematic driving behavior in longitudinal direction
85th percentile longitudinal acceleration value	W = 1911.5, p-value = 0.292

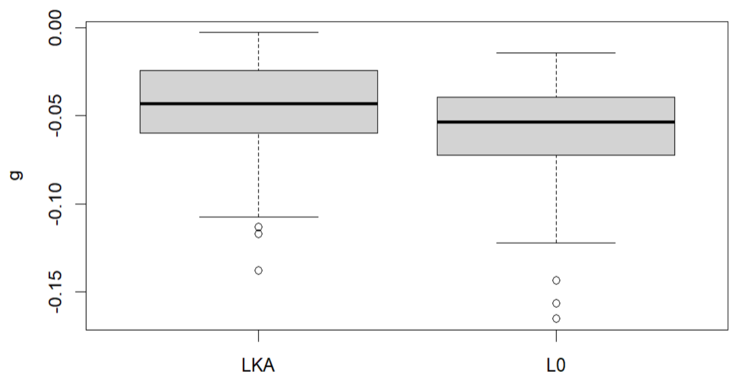
15^{th} percentile longitudinal deceleration value	W = 2068.5, p-value = 0.025 
85^{th} percentile longitudinal acceleration jerk value	W = 1550, p-value = 0.477
15^{th} percentile longitudinal deceleration jerk value	W = 1898.5, p-value = 0.312
Median longitudinal acceleration value	W = 1982.5, p-value = 0.161
Median longitudinal deceleration value	W = 2001, p-value = 0.0564

Table 5-12. Mann-Whitney U test results of comparing ACC with L0 segments.

ACC vs L0 Kinematic driving behavior in lateral direction	
85^{th} percentile lateral acceleration value	W = 568, p-value = 0.485
15^{th} percentile lateral deceleration value	W = 568.5, p-value = 0.654
85^{th} percentile lateral acceleration jerk value	W = 513, p-value = 0.173
15^{th} percentile lateral deceleration jerk value	W = 768, p-value = 0.110
Median lateral acceleration value	W = 499.5, p-value = 0.139
Median lateral deceleration value	W = 581.5, p-value = 0.766

5.3.3 Adaptation of ADAS vehicles

Changes of individual drivers in DECEL and LAT event rates over five-day exposture intervals were examined. The Analysis of Deviance (Wald chi-square tests) based on GLIMMIX indicated that influences of exposure intervals on DECEL (χ^2(1, N=5) = 61.626, p-value < 0.0001) and LAT event rates (χ^2(1, N=5) = 64.53, p-value < 0.0001) were significant. The Incidence Rates (IRs) for DECEL and LAT and the 95% CLs for each interval were displayed in the Table 5-13 and Figure 5-1. The IRRs and 95% CL presented in Table 5-14 indicated a gradual decreasing trend in DECEL rates. As displayed in Figure 5-1, there are some fluctuations, but starting from the fourth interval (16-20 days), the decline was significant. However, LAT rates exhibited an increasing trend over the exposure intervals, except for the fourth interval where LAT events dropped sharply to a value significantly below the initial rates.

Table 5-13. Incidence rates (IRs) and 95% CLs for DECEL and LAT per kilometer driven over the exposure time to ADAS

Exposure time	Total kilometers	No. of trips	DECEL		LAT	
			No. of events	IR (95% CL)	No. of events	IR (95% CL)
1-5	3,368.868	294	150	0.290 (0.114, 0.738)	470	1.145 (0.650, 2.02)
6-10	2,819.858	271	104	0.260 (0.102, 0.666)	367	1.409 (0.800, 2.48)
11-15	2,629.518	254	112	0.354 (0.139, 0.902)	392	1.411 (0.802, 2.48)
16-20	4,979.811	270	144	0.112 (0.044, 0.287)	483	0.726 (0.412, 1.28)
21-25	5,025.881	281	243	0.185 (0.073, 0.470)	519	1.203 (0.684, 2.12)
26-30	2,443.265	222	134	0.206 (0.081, 0.528)	397	1.560 (0.886, 2.75)

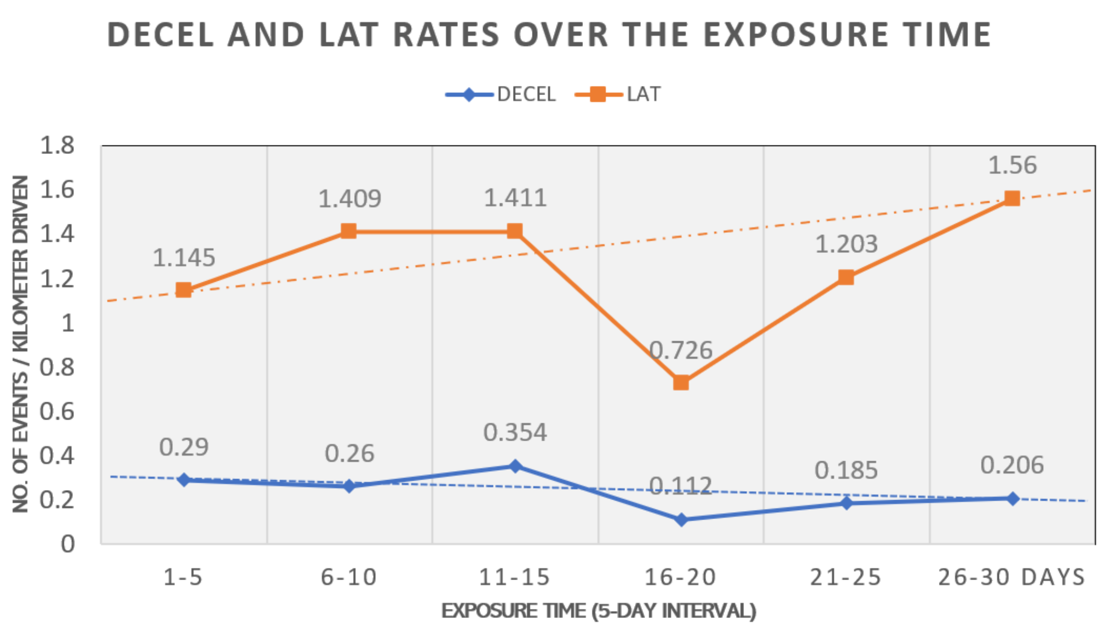


Figure 5-1. Mean estimated event rates and 95% confidence intervals for each interval by drivers based on general linear mixed models for Negative Binominal distribution

Table 5-14. Modeling results and IRRs and CLs for drivers comparing the individual-level rates for each subsequent interval with the first interval

	Exposure time	Est.	SE	IRR	95%CL	Z-value	P-value
DECEL	1-5	-	-	-	-	-	-
	6-10	-0.105	0.159	0.901	0.659, 1.23	-0.657	0.511
	11-15	0.194	0.166	1.214	0.877, 1.68	1.171	0.242
	16-20	-0.950	0.154	0.387	0.286, 0.523	-6.173	<0.0001*
	21-25	-0.445	0.162	0.641	0.467, 0.88	-2.752	0.006*
	26-30	-0.335	0.161	0.715	0.522, 0.98	-2.085	0.037*
LAT	1-5	-	-	-	-	-	-
	6-10	0.198	0.100	1.219	1.002, 1.484	1.983	0.047*
	11-15	0.194	0.099	1.214	0.999, 1.475	1.949	0.049*
	16-20	-0.453	0.105	0.636	0.518, 0.781	-4.311	<0.0001*
	21-25	0.041	0.106	1.042	0.847, 1.281	0.387	0.699
	26-30	0.302	0.099	1.353	1.114, 1.642	3.055	0.002*

5.4 Discussion

The study revealed that (1) driving vehicles with ADAS presence was associated with lower DECEL event rates; (2) the trip segments with LKA engaged tended to have smaller absolute values of 15th percentile longitudinal deceleration (i.e., hard braking); (3) over 5-day intervals of exposure to ADAS-equipped vehicles, DECEL event rates declined but LAT event rates increased.

5.4.1 Driving with versus without ADAS presence

Older drivers exhibited lower rates of DECEL events when driving vehicles with ADAS presence. This decrease in DECEL event rates indicates fewer rapid braking events, suggesting that driving with ADAS could have positive safety-related impacts because DECEL event rates have shown to related to crash risk (Simons-Morton et al., 2012). Some ADAS features (e.g., ACC, FCW) are designed to aid drivers in managing longitudinal vehicle control to reduce hard braking, such as, maintaining appropriate speeds and following distances, especially during the failure of detecting hazards in front of the vehicle. For instance, using ACC was found to improve older adults' speed control in simulated free-flow traffic conditions, built-up areas, and low speed limit areas (Guo, Blythe, Edwards, Pavkova, & Brennan, 2015).

5.4.2 ACC and LKA

Trips segments with LKA engaged had lower high longitudinal deceleration (at the 15th percentile) than those without LKA disengaged, indicating that older drivers tended to apply gentler braking when LKA was actively assisting their driving. This result may be due to drivers' perception of increased safety and confidence in the capabilities of LKA, thus leading to their active engagement with the driving task, including less aggressive braking. In the focus group conducted after the on-road driving session, older drivers expressed their confidence in ADAS functioning effectively, and topic modeling revealed that "confidence concerning ADAS as the 2nd most prevalent topic (refer to **Chapter 3**). This finding presents early, albeit incomplete, evidence that LKA provides positive safety-related impact on older drivers in naturalistic driving.

Studying the influences of single features with real vehicles, drivers, and traffic environment is more complicated than using simulators or controlled field studies. First, the sample size of trips or trip segments involving ADAS features being engaged could be unpredictable in NDS because participants can choose to use the features based on their preference. ACC and LKA usually require minimum vehicle speeds for activation, restricting their use on local roads or in other traffic settings. Thus, NDS may need more participants and longer participation periods in order to achieve sufficient sample size for different types of trips, events or technology use cases. Second, the persistent use of LKA and ACC presents a challenge because frequent activation and deactivation of both features are intrinsic to driving in the real world due to traffic situations or driver preference towards instinctive control in braking and steering in the presence nearby objects. This natural but noisy usage pattern imposes greater scale of data collection. Lastly, imperfect ADAS performance under adverse conditions, such as weather, lane markings, and road conditions, may suppress the use of advanced features or influence driver and vehicle behaviors. These factors may lead to confounding results on driving outcomes. Thus, using multiple variables from different aspects when measuring driving outcomes and their interaction with ADAS would be helpful.

5.4.3 Adaptation to ADAS

This study explored the adaptation of older drivers during their first several weeks of driving with ADAS in a naturalistic setting. A decline in DECEL events was observed over the exposure time, indicating less hard braking over time. This is an expected adaptation as drivers gradually familiarize themselves with ADAS and incorporate its capabilities into their driving patterns, leading to smoother and less abrupt braking events. Besides, as experience accumulates, more trust (Hoff & Bashir, 2015) in the capabilities of ADAS may result in reducing hard braking. Besides the adaptation to ADAS, the decline in hard brakes indicates improved driving proficiency or behavior as a result of ADAS adaptation. This finding is in line with the results of comparing with and without ADAS presence.

However, an increase in LAT rates was observed over exposure intervals, indicating more sudden maneuvers in lateral direction. These unintended negative effects may be the negative behavioral adaptation to automated systems, including ADAS, an area that has been studied by many researchers. For example, Noble, Miles, Perez, Guo,

& Klauer (2021) found like increased eyes off road time and glances to the instrument penal with extended exposure to the driving automation systems.

Error! Reference source not found. did not indicate any clear plateau of changes of high g-force event rates with respect to exposure time. Thus, the study is not able to provide insights into the time required for older drivers to adapt to ADAS fully. Future studies should consider longer than six weeks of data collection to capture behaviors of older adults after the adaptation phase.

5.4.4 Limitations

The major limitation of the study is that researchers lack the control of extraneous factors that may compromise the validity of the analysis. This is owing to the nature of observational studies, in which participants drive as they normally would. In this research, the extraneous factors that might greatly influence dependent measures of driving behavior include road and traffic environment (e.g., traffic volume, curviness of the roadway, road surface condition), weather (e.g., wind, rain, or fog) and traffic laws at the data collection site. When participants drive in the natural road environment, those factors could greatly influence steering input, acceleration, or deceleration, which are metrics for indicating safety-related impacts of ADAS in our study. This study could only control several demographically and geographically factors by matching SHRP 2 participants best the SMX participants. Many extraneous factors can be considered for future larger scale NDS.

The analysis on examining the impacts of LKA or ACC engagement has three limitations. The first one is potential carryover effects due to the nature of crossover design method adopted in this analysis. Specifically, the crossover design is susceptible to carryover effects of the impact of the LKA engaged being transferred over to any subsequent L0/control trips or ACC trips. This could confound the results that would challenge attributing observed effects solely to LKA or ACC. These effects may be particularly concerning in this study as drivers' behavior might be altered due to the adaptation to LKA, ACC, and/or simply the presence of ADAS. Though the segments of LKA or ACC engaged were drawn from trips that did not contain any of the control segments for comparison, it is still uncertain if the durations between the two sets of segments or trips were long enough to "wash-out" the "carry-over effects". As the dynamics of ACC or LKA on changing drivers' behavior are unknown pior to the study, we were not able to minimize carryover effects by planning for sufficiently long wash-out duration.

Second, the generalization of LKA and ACC analysis results is limited by the nature of case control retrospective design. Findings from a case-control study may not be generalized to other settings, for example, other vehicle models. The study's limited scope may restrict the generalization and applicability of its results. Besides, the retrospective design may not account for changes to road environments, weather, or traffic conditions, which could affect the functionality of LKA or ACC and driving behavior. These confounding factors were uncontrolled or unmeasured, which could impact the observed outcomes thus influencing the estimation of impacts of LKA or ACC.

Third, the LKA and ACC analysis was based on three small samples for comparison, which may not provide enough power to detect any differences or claim equivalence between segments with and without LKA or ACC engaged. In addition to power, the limited sample sizes were not able to represent the diversity of drivers and road conditions, thus limiting the generalization of the findings.

Adaptation to novel ADAS features and to an unfamiliar study vehicle are confounding factors. SMX participants drove an unfamiliar car, whereas SHRP 2 participants drove their own cars. It is unknown whether SMX participants had reached their stable behaviors of driving with the study vehicles and/or ADAS engaged, while SHRP 2 participants were likely driving in a stable, normal fashion. Therefore, longer study period could possibly limit these confounding factors or sampling enough participants owning vehicles equipped with or without ADAS presents an alternative study design.

The participants in SMX seem to be generally healthy and active, considering that they actively participated in the driving study, thus they may not necessarily be representative of the whole older driver population. As with many studies, there was unavoidable self-selection bias given the recruitment constraints.

5.5 Conclusion

This study investigated the safety-related impacts of ADAS for older drivers, revealing that driving vehicles equipped with ADAS displayed lower rates of DECEL. This decrease implies potential safety benefits associated with ADAS usage for older drivers. Additionally, when LKA was engaged, driving segments had lower high deceleration, indicating that older drivers tended to apply gentler braking. Older drivers exhibited fewer acceleration events but more deceleration events over several exposure intervals to ADAS-equipped vehicles, indicating adaptive behaviors to be relevant factor for future research.

6 Conclusion

The overarching goal of this dissertation research focuses on older drivers and ADAS. The overall objective is to understand and improve the safety and mobility of older adults by investigating the influence of ADAS. The dissertation addressed this overall objective by advancing our knowledge about older drivers from four perspectives: mobility, perception, safety measures, and safety.

Mobility: Structure equation modeling using SHRP 2 data was conducted to illustrate that older drivers' health is a reliable predictor of driving exposure, and cognitive and physical declines are predictive of their intention to reduce exposure and actual driving in challenging situations. These findings highlight that the aging population requires support for their mobility and likely road safety given their age-related impairments.

Perception: Structure topic modeling on a focus group of older adults driving vehicles equipped with ADAS for six weeks was conducted to reveal five key issues to older drivers (in the order of prevalence): (1) safety, (2) confidence concerning ADAS, (3) ADAS functionality, (4) user interface/usability, and (5) non-ADAS related features. The findings point to a need for holistic ADAS design that not only must consider safety concerns but also user interfaces accommodating older adults' preferences and limitations as well as in-depth training programs to operate ADAS given the technology limitations.

Safety measures: Correlation analysis and logistic regression on SHRP 2 data were conducted to reveal that the longitudinal deceleration events at greater than 0.60g and lateral acceleration events at greater than 0.40g appear most associated with older adults' driving risk and are predictive of near future CNCs occurrence and high-risk older drivers with acceptable accuracy. These findings indicate that high g-force events can be used to assess risk for older drivers, and the selection of thresholds should consider the characteristics of drivers.

Safety: Comparison on high g-force events between two NDS revealed that drivers who drove vehicles equipped with ADAS had lower longitudinal declaration rates, indicating benefits of ADAS presence on older drivers' safety. When LKA was engaged, lower high longitudinal deceleration was observed than when LKA was not engaged, indicating that older drivers tended to apply less aggressive braking when using LKA. Over several weeks of exposure to vehicles with ADAS presence, older drivers showed decreasing longitudinal deceleration but increasing lateral acceleration events. In other words, the potential of ADAS for positive safety-related impacts definitely exist but some refinement in the design to reduce lateral events might be necessary. In addition, some cautious is to this interpretation might be necessary as the older drivers might not have fully adapted to all the ADAS features.

This dissertation presents novel research on the mobility and potential impacts of ADAS on older drivers. Given that age-related declines do affect mobility or willingness to drive in some situations, the older population deserve support in their driving to maintain mobility. ADAS has the potential of being an effective intervention promoting older adults' mobility by compensating for these aging-related declines which hindered their driving safety. The current design of ADAS is generally appreciated by older drivers but vehicle manufacturers and policy makers should improve interface design and training programs to facilitate the adoption of ADAS by older drivers. When high g-force events are used as surrogate measurements of road safety, the thresholds catering specific to older drivers should be considered given the difference of their driving habits or characteristics compared to the rest of the population. Finally, vehicles equipped with ADAS presented both positive and negative safety-related impacts on older adults, who exhibit adaptive behaviors over multiple weeks. Thus, ADAS presents potential but requires some improvements in promoting the mobility and safety of older drivers.

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Appendix A. The maneuvers immediately before all CNCs in SHRP 2 NDS

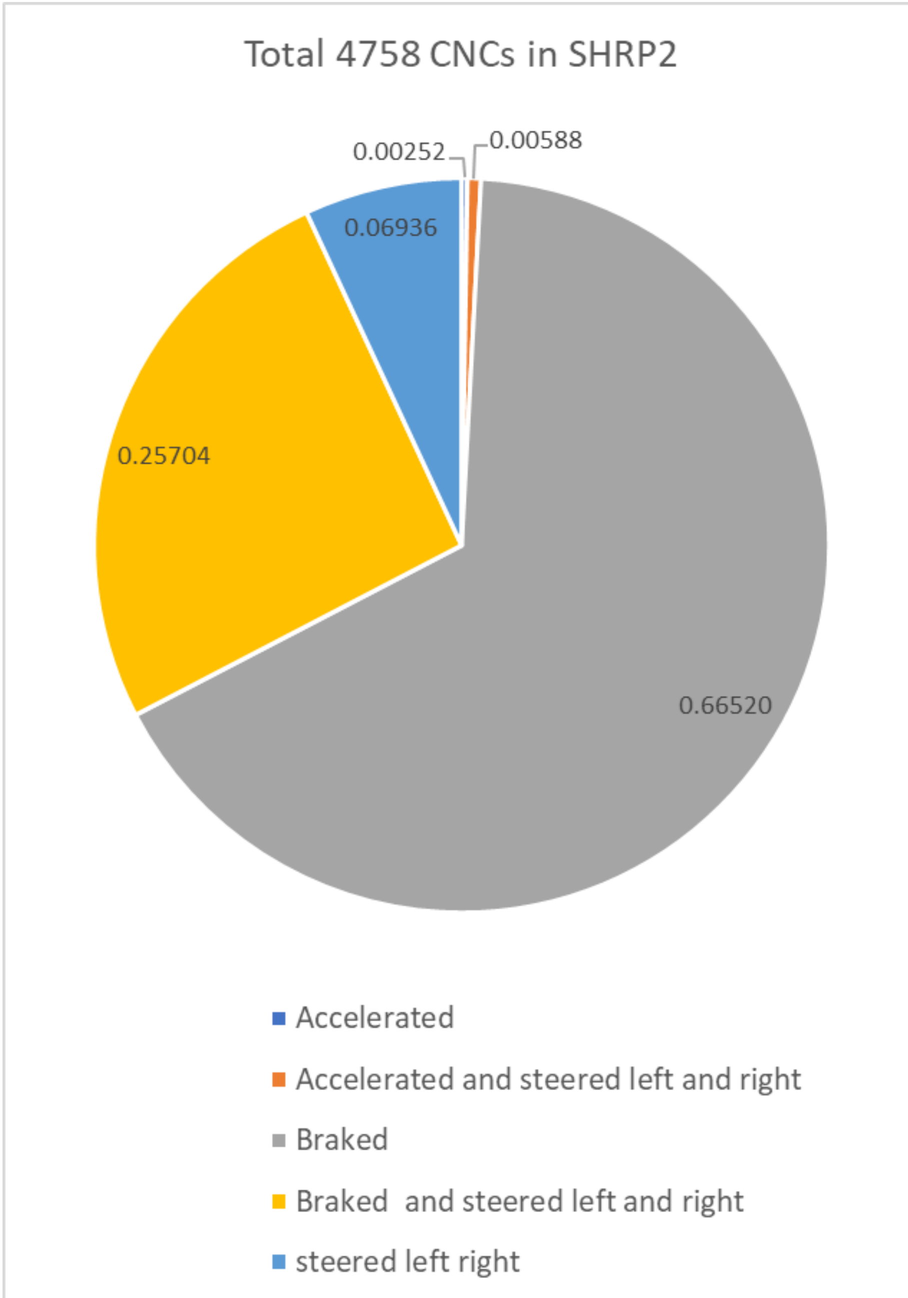

Figure. The proportion of the maneuvers immediately before all CNCs in SHRP 2 NDS

Appendix B. Number of high g-force events at different thresholds in SMX study

Table. Number of high g-force events at different thresholds in SMX

Event	Number
ACCEL≥0.30g	1377
ACCEL≥0.35g	571
ACCEL≥0.40g	192
ACCEL≥0.45g	61
ACCEL≥0.40g	9
DECEL≥0.30g	582
DECEL≥0.35g	215
DECEL≥0.40g	48
DECEL≥0.45g	10
DECEL≥0.50g	3
LAT≥0.30g	1830
LAT≥0.35g	738
LAT ≥0.40g	236
LAT ≥0.45g	57
LAT ≥0.50g	9
Yaw≥4°/s	433
Yaw≥5°/s	104
Yaw≥6°/s	49
Yaw≥7°/s	23
Yaw≥8°/s	13
Yaw≥9°/s	8
Yaw≥10°/s	4

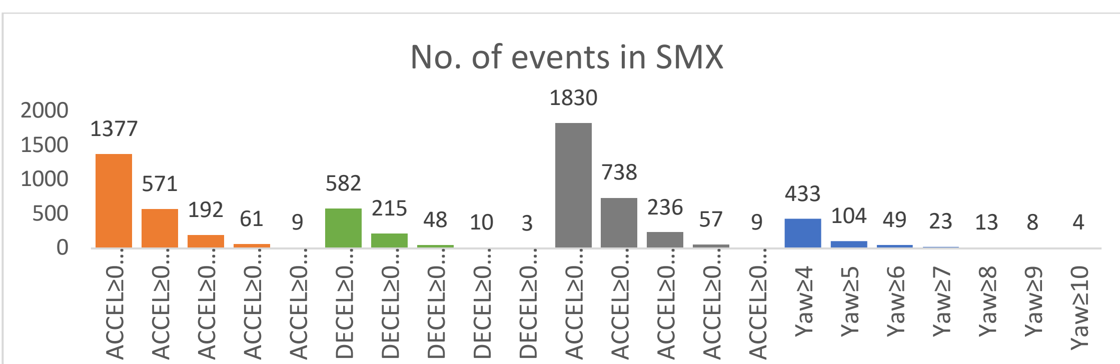

Figure. Number of events in SMX NDS

Appendix C. Examining the association of DECEL ≥ 0.30g and LAT ≥ 0.30g with CNCs using SHRP 2 data

1. Objective

The analysis aims to assess the suitability of using DECEL ≥ 0.30 and LAT ≥ 0.30 as appropriate safety measures for Study 4.

2. Data

This analysis used the same dataset as Study 3 in **Chapter 4.**

3. Analysis

A logistic regression model was used to examine the association between the occurrence of CNCs in a 1000km drive with the of DECEL ≥ 0.30 and LAT ≥ 0.30 in the proceeding 1000km of drive.
ROC curve and AUC were used to assess the predicative performance of the model.

4. Results

The logistic regression model using GEE includes the number of DECEL ≥ 0.30, LAT ≥ 0.30. The **Table** below summarized the results of fitting this model DECEL ≥ 0.30, LAT ≥ 0.30 both exhibited significantly positive associations with CNC risk. The AUC was 0.607, indicating an acceptable prediction performance.

Table. Logistic Regression with GEE for predicting CNC occurrence in a 1000km driven

	Est.	Rate Ratio (95% CI)	SE	Wald	p-value
Intercept					
DECEL ≥ 0.30g	0.00279	1.0028 (1.001, 1.0045)	0.00087	10.27	0.0013**
LAT ≥ 0.30g	0.000182	1.0018 (1.0005, 1.0031)	0.000656	7.69	0.0056**
					AUC = 0.607

p-value <0.05, **<0.01, *<0.001*

5. Conclusion

DECEL ≥ 0.30g and LAT ≥ 0.30g can be used to assess risk for older drivers.

Appendix D. IRB # 20-907 approval letter for study 1

VIRGINIA TECH.

Division of Scholarly Integrity and
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MEMORANDUM

DATE:	November 3, 2020
TO:	Nathan Ka Ching Lau, Dan Liang
FROM:	Virginia Tech Institutional Review Board (FWA00000572, expires October 29, 2024)
PROTOCOL TITLE:	Using Structural Equation Modeling to Examine Driving Exposure and Patterns among Seniors in a Naturalistic Driving Study
IRB NUMBER:	**20-907**

Based on the submitted project description and items listed in the Special Instructions section found on Page 2, the Virginia Tech Human Research Protection Program (HRPP) has determined that the proposed activity is not research involving human subjects as defined by HHS and FDA regulations.

Further review and approval by the Virginia Tech Human Research Protection Program (HRPP) is not required because this is not human research. This determination applies only to the activities described in the submitted project description and does not apply should any changes be made. If changes are made you must immediately submit an Amendment to the HRPP for a new determination. Your amendment must include a description of the changes and you must upload all revised documents. At that time, the HRPP will review the submission activities to confirm the original "Not Human Subjects Research" decision or to advise if a new application must be made.

If there are additional undisclosed components that you feel merit a change in this initial determination, please contact our office for a consultation.

Please be aware that receiving a "Not Human Subjects Research" Determination is not the same as IRB review and approval of the activity. You are NOT to use IRB consent forms or templates for these activities. If you have any questions, please contact the Virginia Tech HRPP office at 540-231-3732 or irb@vt.edu.

PROTOCOL INFORMATION:

Determined As:	**Not Human Subjects Research**
Protocol Determination Date:	**November 3, 2020**

ASSOCIATED FUNDING:

The table on the following page indicates whether grant proposals are related to this protocol, and which of the listed proposals, if any, have been compared to this protocol, if required.

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Appendix E. IRB # 17-1192 approval letter for study 2

VIRGINIA TECH.

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MEMORANDUM

DATE: December 16, 2019

TO: Jonathan Antin, Melissa Hulse, Nathan Ka Ching Lau, Christine M Link-Owens, Stephanie Ann Baker, Dan Liang, Lisa Eichelberger, Brian Wotring, Kelly Elizabeth Stulce, Leslie Christine Harwood, et. al.

FROM: Virginia Tech Institutional Review Board (FWA00000572, expires October 29, 2024)

PROTOCOL TITLE: Examining Senior Drivers Adaptation to Mixed Level Automated Vehicles: A Naturalistic Study

IRB NUMBER: **17-1192**

Effective January 8, 2019, the Virginia Tech Institution Review Board (IRB) approved the Continuing Review request for the above-mentioned research protocol.

This approval provides permission to begin the human subject activities outlined in the IRB-approved protocol and supporting documents.

Plans to deviate from the approved protocol and/or supporting documents must be submitted to the IRB as an amendment request and approved by the IRB prior to the implementation of any changes, regardless of how minor, except where necessary to eliminate apparent immediate hazards to the subjects. Report within 5 business days to the IRB any injuries or other unanticipated or adverse events involving risks or harms to human research subjects or others.

All investigators (listed above) are required to comply with the researcher requirements outlined at:

https://secure.research.vt.edu/external/irb/responsibilities.htm

(Please review responsibilities before beginning your research.)

PROTOCOL INFORMATION:

Approved As:	**Full Review**
Protocol Approval Date:	**January 23, 2019**
Protocol Expiration Date:	**January 22, 2020**
Continuing Review Due Date*:	**December 16, 2019**

*Date a Continuing Review application is due to the IRB office if human subject activities covered under this protocol, including data analysis, are to continue beyond the Protocol Expiration Date.

ASSOCIATED FUNDING:

The table on the following page indicates whether grant proposals are related to this protocol, and which of the listed proposals, if any, have been compared to this protocol, if required.

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Appendix F. IRB # 23-126 approval letter for study 3 and 4

VIRGINIA TECH.

Division of Scholarly Integrity and
Research Compliance
Institutional Review Board
North End Center, Suite 4120 (MC 0497)
300 Turner Street NW
Blacksburg, Virginia 24061
540/231-3732
irb@vt.edu
http://www.research.vt.edu/sirc/hrpp

MEMORANDUM

DATE:	February 6, 2023
TO:	Nathan Ka Ching Lau, Jonathan Antin, Dan Liang, Kelly Elizabeth Stulce
FROM:	Virginia Tech Institutional Review Board (FWA00000572)
PROTOCOL TITLE:	Analysis of Kinematic Data Collected in Examining Senior Drivers Adaptation to Mixed Level Automated Vehicles: A Naturalistic Study
IRB NUMBER:	**23-126**

Effective February 6, 2023, the Virginia Tech Human Research Protection Program (HRPP) determined that this protocol meets the criteria for exemption from IRB review under 45 CFR 46.104 (d) category(ies) 4(ii).

Ongoing IRB review and approval by this organization is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these activities impact the exempt determination, please submit an amendment to the HRPP for a determination.

This exempt determination does not apply to any collaborating institution(s). The Virginia Tech HRPP and IRB cannot provide an exemption that overrides the jurisdiction of a local IRB or other institutional mechanism for determining exemptions.

All investigators (listed above) are required to comply with the researcher requirements outlined at:

https://secure.research.vt.edu/external/irb/responsibilities.htm

(Please review responsibilities before beginning your research.)

PROTOCOL INFORMATION:

Determined As:	**Exempt, under 45 CFR 46.104(d) category(ies) 4(ii)**
Protocol Determination Date:	**February 6, 2023**

ASSOCIATED FUNDING:

The table on the following page indicates whether grant proposals are related to this protocol, and which of the listed proposals, if any, have been compared to this protocol, if required.

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