THE INFLUENCE OF THE BUILT ENVIRONMENT ON THE DRIVING BEHAVIORS AND MENTAL HEALTH OF OLDER ADULTS

by

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To my grandma, the late Lucy Short,

who inspired my research on aging, and aged

more successfully than anyone I know.

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ABSTRACT

Due to increases in life expectancy, the aging of the baby boom generation, and a decline in birth rates, the US population is aging rapidly. In the future, older people will not only comprise a larger proportion of the general population, but also the driving population. This issue is characterized by a conflict between roadway safety for those who can no longer safely drive, and loss of independence when driving reduction and cessation become necessary.

Previous research on driving decision making among older adults has largely focused on individual- and interpersonal-level factors. This study examined the influence of the physical transportation environment on driving reduction and cessation, after controlling for the effects of other predictors. Differences by gender and race were also assessed, as was the influence of the transportation environment on depressive symptoms. Longitudinal survival analysis techniques and generalized estimating equations were used to analyze seven waves of data spanning a 12-year period from 1998 through 2010.

Results showed that after controlling for the effects of demographics, health, and social support, there was a significant influence of the transportation environment on both driving reduction and driving cessation. As roadway density and congestion increased, the odds of driving reduction and cessation also increased. Men were more affected than women by the transportation environment, and Whites and Hispanics were more affected than African Americans and those of Other race. Driving reduction, driving cessation, and the transportation environment also significantly predicted the rate of depressive symptoms over time. Depressive symptoms were positively associated with driving limitations, while a more congested environment predicted fewer depressive symptoms. Other predictors of driving reduction and cessation included relationship status, household size, and having a friend who lives nearby. Results suggest that policy changes and modifications to the physical environment should be made to improve older drivers' ability to remain engaged in life. Creating mixed-use livable communities with goods and services in close proximity are warranted to mitigate some of the mobility challenges of older adulthood. Older individuals should also consider and plan for how their transportation environment will affect their desire to age in place.

CHAPTER 1

INTRODUCTION

Overview

Among older adults, transportation and health are connected in a cyclical relationship. As people age, health declines often result in loss of one's ability to safely drive (Boot, Stothart, & Charness, 2014; Eby, Molnar, & Kartje, 2009), and driving is by far the most common mode of transportation used in the United States (Federal Highway Administration, 2009). The loss of mobility and access associated with declines in driving ability can then lead to an increase in negative health and mental health outcomes (Curl, Stowe, Cooney, & Proulx, 2014; Dickerson et al., 2007), thus completing the cycle.

Data show that around age 75, exposure-adjusted motor vehicle crash risk increases markedly (Insurance Institute for Highway Safety, 2014). When people can no longer drive safely, many follow a continuum of driving reduction that ends with complete cessation (Eby et al., 2009). As people experience declines in their ability to safely drive, many begin to limit their driving to situations and locations with a low perceived risk of crashing, a process known as driving self-regulation (Carmel, Rechavi, & Ben-Moshe, 2014; Eby et al., 2009). Eventually, many stop driving completely, leaving men and women on average about seven and 10 years, respectively, of unmet mobility needs (Foley, Heimovitz, Guralnik, & Brock, 2002).

The process of driving reduction and cessation is complex, and differs for every individual. Most research to date has focused on individual and interpersonal predictors (e.g., medical conditions and family influence) of the decision to reduce or stop driving (see e.g., Connell, Harmon, Janevic, & Kostyniuk, 2012; Dickerson et al., 2007). The present research takes an ecological approach to this problem and explores the role played by physical aspects of older people's transportation environment in the process of driving reduction and cessation.

Purpose, research goals, and hypotheses

The overall purpose of this research was to explore the influence of factors in the physical transportation environment on individual health behaviors and outcomes among older people, with a specific focus on transportation and health. The analyses assessed the influence of the transportation environment, which was operationalized using variables from the Urban Mobility Report (UMR; Schrank, Eisele, & Lomax, 2012) and by calculating variables using Geographic Information Systems (GIS) data. The specific variables are discussed in detail in Chapter 3, but in general these variables provide information about the regional and zip code level transportation system within which people travel. As such, these indices can be conceptualized as proxies for the "mobility" of a given area, or how easy it is to travel in the area via automobile. In other words, this research explored the extent to which the mobility of a given area affected driving reduction, driving cessation, and depressive symptom onset among older adults in the US. This study will specifically address the following research goals:

1) Explore the extent to which aspects of the transportation environment affect driving reduction and cessation in older adulthood.

> Hypothesis 1 (H1) Individuals who live in an area with less mobility (e.g., higher levels of congestion, higher roadway density, etc.) will be more likely to engage in driving reduction/cessation than those who live in areas of high mobility.

2) Compare the extent to which differences in the transportation environment at the regional level affect driving reduction and cessation among older individuals who live there.

H2) Regions with less mobility will have higher average levels of driving reduction and cessation compared to regions with high mobility.

3) Examine whether factors in the transportation environment have a differential effect on driving reduction and cessation between men and women, and between Whites and non-Whites.

H3) Women will be more affected by factors in the transportation environment than men (i.e., more likely to reduce/stop driving in areas with less mobility).

H4) African Americans and Hispanics will be more affected by factors in the transportation environment than Whites (i.e., more likely to reduce/stop driving in areas with less mobility).

4) Examine whether aspects of the transportation environment moderate the relationship between driving reduction/cessation and depressive symptoms.

H5) Individuals who live in an area with less mobility will be more likely to develop depressive symptoms after driving reduction or cessation than those who live in higher mobility areas. In other words, the mental health consequences that arise from problems related to limited mobility (e.g., lower ability to access goods, services, other people) will be exacerbated by the environment.

All of these research goals and hypotheses are specifically related to the influence of the transportation environment on these driving-related behaviors and on symptoms of depression. This study will also explore how other predictors of driving reduction and cessation (individual- and interpersonal-level constructs) differ between men and women, and by race. Previous research has just begun to examine gender differences and very little research has explored differences by race. No specific hypotheses related to these differences will be tested, but this exploration is an important aspect of this research.

The remainder of this dissertation is organized as follows: a review of the literature provides background and context; the methodologies used in this research are described, including a detailed description of the variables and the statistical analysis plan. The results section follows, presented by research goal to allow for a clear understanding of whether each hypothesis was supported or not. Finally, the discussion explores potential reasons for these findings, puts the results into the context of what is already known in this area, and identifies next steps for future research.

CHAPTER 2

LITERATURE REVIEW

Aging population

Increases in life expectancy over the past century, the aging of the baby boom generation, and a decline in US birth rates since the 1960s, have collectively led to a shift in the demographics of our society toward an aging population (Kinsella & He, 2009; Ortman, Velkoff, & Hogan, 2014). In the coming decades, older people will make up an increasingly larger proportion of the total population than in the past (Kinsella & He, 2009). In fact, estimates suggest that by 2030, about one in every five people in the US will be over age 65 (US Census Bureau, 2013). This shift will be reflected not only in the *proportion* of older people to other age groups, but also in the sheer numbers of older people. In 2010, the US population included just over 40 million people age 65 or over (Vincent & Velkoff, 2010). By 2050, estimates suggest that there will be almost 90 million people in this age group, 20 million of whom will be 85 years old or older (Vincent & Velkoff, 2010). This dramatic demographic shift will have important implications for society, including health care, economics, labor force participation, and transportation.

Indeed, older people will not only make up a larger proportion of the future population, but will also comprise a larger proportion of US drivers. This increase will result from the older average age of the population, as well as an increasing trend toward licensure among older people (Liu, Utter, & Chen, 2007; Sivak & Schoettle, 2011). In 1983, about 79% of people in their 60s, and only 55% of those age 70 and above were licensed drivers (Sivak & Schoettle, 2011). By 2008, however, those percentages had increased to 94% and 78%, respectively. These increases are by far the largest of any age group, with many other age groups actually showing a decline in licensure (Sivak & Schoettle, 2011). As baby boomers move into older adulthood, these trends are likely to continue. By 2025, US drivers age 65 or older are expected to constitute about a quarter of all drivers (Loughran, Seabury, & Zakaras, 2007).

Built environment and the transportation system

Since the 1940s, the landscape of the US has changed in several keys ways that has increased the need for people to drive, even into older adulthood. Increases in urban sprawl – the expansion of metropolitan areas outward, away from central city areas – is one of these key changes. Many factors have contributed to sprawl, including the building of the interstate highways, and the shift of funding away from public transit to roadway construction and maintenance. In fact, the funding mechanism that allowed the interstate system to be implemented (starting in the late 1950s) could be considered the driving force that moved the US toward such an automobile-dominated system. The federal government offered states a 90% federal to 10% state match in funding for building the interstate system (Altshuler & Luberoff, 2003; Boarnet, 2014; Taylor, 2000). With such an enormous federal contribution, states transferred any available funds to building interstates, leading to the current auto-centric transportation system. The building of the highway system, coupled with cheaper land and housing near the outskirts of cities, resulted in people moving farther away and commuting to meet their needs (Gillham, 2002; Nechyba & Walsh, 2004).

As the interstate highway system was on the rise, few transportation funds were spent on improving or expanding public transportation (Jones, 1985; Taylor, 2000). The automotive industry also contributed to public transit's decline (Jones, 1985; Kwitny, 1981). Throughout the

1940s, General Motors used its economic power to take over and dismantle rail transit systems across the US, replacing them with diesel-powered buses (Jones, 1985; Kwitny, 1981). Although highway building has been a major driving force behind urban sprawl (and the resulting reliance on driving for transportation), other policies have also contributed. In many parts of the country, zoning laws require separate geographic areas for housing, shopping, offices, industry, and public spaces (Frumkin, 2009; Resnik, 2010). With such land use patterns, proximity to goods, services, and other people has been greatly extended. Conversely, mixed-use zoning polices specifically decrease the need for automobile travel. These policies allow (and sometimes even require) neighborhoods to have increased residential density, retail, commercial, and other types of areas in close proximity (American Planning Association, 2013; FindLaw, 2014; Resnik, 2010), which greatly reduces need to travel long distances.

Collectively, these historical policies have led, in part, to a transportation system that is much more auto-centric than it used to be. In fact, the average trip to work during 2009 was about 30% farther, and took about 24% longer than it did in 1977 (Santos, McGuckin, Nakamoto, Gray, & Liss, 2011). Driving is now required to make nearly every purchase, with personal vehicles used for 83.4% of all US trips (Santos et al., 2011). Public transportation in the US typically only exists in large cities, and estimates suggest that only about 16% of people in the US have access to public transportation that they consider to be satisfactory (US Census Bureau, 2006).

Aging and driving

Previous research in the field of aging and driving has primarily focused on identifying the issues that lead to declines in driving ability, and understanding the individual or interpersonal factors that cause older people to reduce or stop driving (see e.g., Boot, Stothart, et al., 2014; Dickerson et al., 2007; Eby et al., 2009). Researchers have also studied the negative health and well-being outcomes that result from reduced mobility associated with driving reduction and cessation (Curl et al., 2014; Fonda, Wallace, & Herzog, 2001; Marottoli, Mendes de Leon, Glass, & Williams, 1997; Ragland, Satariano, & MacLeod, 2005).

Medical conditions

The most common precursor to loss of driving ability is a change in medical status. Incidence and prevalence of medical conditions increase with age (Centers for Disease Control and Prevention, 2007; Salive, 2013), and the illnesses that affect driving ability often include declines in vision, cognition, and physical functioning (Boot, Stothart, et al., 2014; Eby, Molnar, Shope, Vivoda, & Fordyce, 2003). Vision problems are the most common conditions that lead to driving problems (Eby et al., 2009; Freeman, Muñoz, Turano, & West, 2005), with loss of acuity, contrast sensitivity problems, and reduction of the central and lower visual fields being the vision problems most predictive of driving reduction and cessation (Freeman et al., 2005).

In terms of cognition, differences in tests of visuoconstructive ability, psychomotor speed, and visuospatial memory are known to be significantly discriminative between crash-involved and non-crash-involved older drivers (Lundberg, Hakamies-Blomqvist, Almkvist, & Johansson, 1998). In a study that examined the link between crash involvement and performance on a battery of cognitive measures, drivers who performed in the lowest 10% on the cognitive measures were 1.5 times more likely to have been in a crash, compared to drivers who performed in the top 10% on the measures (Stutts, Stewart, & Martell, 1998). Recent work has begun to discriminate between different types of cognitive deficits to understand how each one predicts loss of specific driving skills. Aksan, Anderson, Dawson, Uc, and Rizzo (2015), for example, found that participants with diagnosed cognitive illnesses (e.g., Parkinson’s disease, Alzheimer’s disease) performed worse during an on-road test than did healthy participants. Those with memory deficits had trouble with navigation, while visuospatial construction problems were related to an increase in safety errors. In a longitudinal study, Edwards et al. (2008) investigated a number of possible contributors to driving cessation and found that the most important risk factor was slower cognitive processing speed. Declines in working memory and decision-making under time pressure are additional cognitive factors associated with recent crash-involvement among older adults (Lee, Lee, Cameron, & Li-Tsang, 2003).

Driving-related physical functioning involves the ability to control and orient one's body to perform tasks required to drive, and includes issues like reaction time, flexibility, and strength (Eby et al., 2009). Reaction time is crucial to safe driving, especially when negotiating congested or unfamiliar areas, and is known to decline with age (Anstey, Wood, Lord, & Walker, 2005; Boot, Charness, Mitchum, Landbeck, & Stothart, 2014). Impaired flexibility can increase one's blind spot, and therefore limit the ability to see other vehicles or objects in the periphery (Anstey et al., 2005). Loss of physical strength can negatively affect the ability to appropriately control vehicle speed and stopping, as well as one's grip when turning the steering wheel (Dobbs, 2005; Eby et al., 2009).

Although any of these conditions and symptoms can compromise the safety of older drivers, some have suggested that comorbidity (having multiple conditions at the same time) may actually be the key factor that increases crash risk, and even driving cessation, among older people (Choi & Mezuk, 2013; Eberhard, 2008; Papa et al., 2014). However, there are considerable individual differences in how conditions affect people, the number of conditions a given individual has, and even an individual's level of driving skill. In addition, many of the illnesses associated with aging require medications for symptom management (e.g., diabetes, heart disease), which can also have a negative effect on one's driving ability (Dobbs, 2005; Eby et al., 2009; Elvik, 2013). Given this variation, the mere presence of conditions or symptoms is not necessarily predictive of driving problems, or of driving reduction or cessation. Thus, it is not aging *per se*, that affects one's driving ability, but rather the combined influence of multiple factors and how they present themselves within a given individual.

Crash risk

When older people begin to experience declines in their driving ability, there are certain driving situations in which they are more likely to become crash-involved. These scenarios are the least forgiving of age-related declines. For example, driving through an intersection, and in particular failing to yield at an intersection, is the most common situation for a crash involving an older motorist (Insurance Institute for Highway Safety, 2007; Staplin, Lococo, Martell, & Stutts, 2012). This is probably the most complex situation one can encounter while driving, as it requires attention in all directions, and directed toward both static and dynamic objects.

In terms of overall risk, data show that around age 75, crash risk increases markedly when the amount of driving exposure is taken into account (Insurance Institute for Highway Safety, 2014). When a crash does occur, research suggests that older people are more likely to be ruled at-fault. Specifically, the likelihood of receiving a citation increases with increasing age (Dulisse, 1997; Kim, Li, Richardson, & Nitz, 1998). Because of the increased frailty that often accompanies aging, older people are also more susceptible to injury (Islam & Mannering, 2006; Liu et al., 2007). Noticeable increases in fragility begin after age 60, and continue to increase throughout the remaining lifespan. In fact, some researchers have suggested that frailty, rather than increased crash involvement, may explain at least in part the higher motor vehicle death rates among older people (Kahane, 2013), accounting for between 60-95% of the excess deaths (Li, Braver, & Chen, 2003).

Driving reduction and cessation

There are a number of different reasons why older people drive less than their younger counterparts, from major life changes to purposeful avoidance (Braitman & Williams, 2011; Molnar, Eby, et al., 2013). For example, many people age 65 or older have retired or partially retired from their jobs, and no longer need to make work-related trips. Indeed, work trips only account for about 10% of travel for people age 65 or older, compared to more than 25% of miles traveled for people of all ages (Santos et al., 2011). By age 75, the number of work-related trips drastically declines to less than 3%. This change is important because trips to work tend to occur at the same time of day, and often require a driver to engage in difficult driving situations (e.g., rush hour traffic). Eliminating work trips reduces the need to drive among older people, and allows more flexibility related to when driving occurs.

Aside from changes in life, some older people are also known to purposely avoid driving situations that would be difficult for them to successfully navigate, a process commonly referred to as driving self-regulation (Baldock, Mathias, McLean, & Berndt, 2006; Carmel et al., 2014; Charlton et al., 2006). Common driving situations that older people tend to avoid include driving at night, on long trips, in inclement weather, and during rush hour (Baldock et al., 2006; Charlton et al., 2006; Eby et al., 2009; Molnar, Charlton, et al., 2013). This avoidance behavior suggests that these drivers are aware that their health declines may affect their driving, and make conscious decisions to mitigate their risk of crashing. Experts have suggested that many older adults follow a continuum of driving reduction (self-regulation behaviors) over time, which often ends with driving cessation (Eby et al., 2009). Qualitative research has suggested that the process generally follows this path: reducing driving, acknowledging the possibility of eventually having to stop driving, planning for the possibility of stopping driving, actually stopping driving, hoping to drive again, and accepting not driving (Kostyniuk & Shope, 1998).

Not every driver follows the same continuum, however. There is a great deal of variation in the extent and the type of driving self-regulation in which people engage (Baldock et al., 2006; Charlton et al., 2006; Musselwhite & Shergold, 2012). In addition, some people suddenly stop driving following a crash or a change in health status (Eby et al., 2009; Musselwhite & Shergold, 2012), and others intend to continue driving right up until they pass away (Connell et al., 2012; Musselwhite & Shergold, 2012). The factors that cause these differences are currently not well-understood.

Self-regulation of driving may require a level of self-awareness that not everyone possesses. It could be disrupted by cognitive declines or other age-related problems, or it could be affected by differences in interpersonal relationships or in one's environment. Regardless of the underlying reasons, declining driving ability leads people down one of two pathways: they can continue driving, which results in an increased risk of crashing, injury, and death; or they can reduce driving (or stop driving completely), which often results in loss of independence and negative mental health consequences (Choi & DiNitto, 2015; Fonda et al., 2001; Marottoli et al., 1997; Ragland et al., 2005). These disparate pathways illustrate the inherent conflict faced by older drivers and their families: weighing the safety of the older driver and other motorists against the loss of independence and quality of life that accompanies driving cessation (Connell et al., 2012).

Reasons for driving cessation

Many older people eventually stop driving completely, but this is not a decision made easily. On average, men are estimated to have about seven years of unmet mobility need post driving cessation, and women have about 10 years (Foley et al., 2002). It often takes the onset of a debilitating medical condition (or confluence of conditions), or a serious motor vehicle crash before people agree to give up their keys. These scenarios have been supported by both quantitative and qualitative studies. For example, Johnson (1995; 2002) examined driving cessation among older people in rural areas (probably the group most reliant on automobiles to meet their needs), to see what influenced their decision to stop driving. A history of recent crashes, feeling insecure about one's ability to drive, impaired health, and the influence of family and friends were all significant factors. Interestingly, 68% of those who had given up driving stated that if they could make that decision again, they would have continued driving, even though they admitted to being unsafe (Johnson, 1995). The fact that this group would trade safety for independence speaks to the severity of the stress involved in driving cessation. Musselwhite and Shergold (2012) found that planning for this transition improved quality of life post driving cessation. Taking the time to gather information or explore other modes of transport seemed to mitigate some of the negative effects of driving cessation (Musselwhite & Shergold, 2012).

Gender is another factor known to affect driving cessation and the need for transportation. Women tend to live longer than men, but report more disability (Murtagh & Hubert, 2004; Rieker & Bird, 2000; Rochelle, Yeung, Bond, & Li, 2014). Because health status is the most important risk factor for declines in driving ability, a longer life with higher morbidity means more years of unmet mobility need. In addition, women actually stop driving earlier than men, even in better health, thus creating an even longer post-driving time span (Anstey, Windsor, Luszcz, & Andrews, 2006; Carr, Flood, Steger-May, Schechtman, & Binder, 2006; Dugan & Lee, 2013; Hakamies-Blomqvist & Siren, 2003). After controlling for health and functional declines, women are still three times more likely to give up driving than men, even when it may not be medically necessary (Dugan & Lee, 2013; Unsworth, Wells, Browning, Thomas, & Kendig, 2007). Indeed, some have suggested that women should continue driving (and can safely do so) later into life than is typical, to reduce their number of transportation-dependent years (Siren, Hakamies-Blomqvist, & Lindeman, 2004).

Although men and women are known to differ in terms of driving reduction and cessation, the reasons for these differences are not completely understood. They may be driven at least partially by traditional gender roles. Sociologists have long discussed the importance of roles to well-being, and how transitioning from a valued role can have a negative effect on this factor (George, 1993; Kim & Moen, 2002). Serving as a "provider" to one's family has traditionally been an important male role (Lyssens-Danneboom & Mortelmans, 2014), and providing transportation certainly fits that description. Although men's and women's driving patterns may be changing, research still suggests that when older men and women travel together, men remain much more likely to drive than women (Rosenbloom & Herbel, 2009; Siren & Hakamies-Blomqvist, 2006). If providing transportation is indeed a more highly valued or expected role among men than women, this could partially explain differences noted in the literature. To date, no research has examined the role the environment might play in explaining gender differences in this process; this factor will be explored in the current research.

Very little research on driving reduction and cessation addresses race. Of the published work in this area, most studies have examined only White and non-White differences (Choi, Mezuk, Lohman, Edwards, & Rebok, 2012; Dugan & Lee, 2013). Additionally, previous research has typically only included race as a stand-alone predictor of driving behaviors, which does not increase our understanding of how the process may be affected by race. The most comprehensive study to date was conducted by Choi and colleagues (2012). They examined interactions between race and other predictors (e.g., marital status, education, gender), as well as models stratified by race (using White and non-White as categories). Choi et al. (2012) found that race does play a role in driving cessation, and that racial differences in driving cessation grow wider with increasing age. These findings are consistent with preliminary results observed by Vivoda (2014) using HRS data, which indicate that African Americans are at much higher risk of losing the ability to drive compared to respondents who identify as White.

There are also known differences in driving history and transportation access by race among people of all ages, which could explain some of the racial differences in driving reduction and cessation observed among older adults. For example, African Americans are much less likely to drive at any age than Whites (Federal Highway Administration, 2006), and are also much less likely to own a vehicle (47% compared to 76%; Raphael, Stoll, Small, & Winston, 2001), or to even have access to one (19% of African Americans lack access to a car, compared to 4.6% of Whites; Bell & Cohen, 2009). These disparities are not due only to income differences as is often assumed. Among those considered poor, 33% of African Americans lack access to a car, compared to only 12% of poor Whites (Bell & Cohen, 2009). Because of these differences, African Americans are much more likely to be reliant on public transportation (Polzin & Chu, 2005). As such, it is possible that African Americans' greater familiarity using other modes of transportation influences their decision to reduce or stop driving in older adulthood. Overall, these differences in access and driving patterns could at least partially explain why race predicts different patterns of driving reduction and cessation in older adulthood.

In addition, driving reduction and cessation are often preceded by health declines, as discussed previously. African Americans are known to have a higher probability of developing chronic illnesses, developing them at younger ages, and dying from them (Barnett et al., 2001; Cabassa et al., 2013; Casper et al., 1999; Simonson & Lahiri, 2007). This disproportionately early health deterioration, a phenomenon sometimes referred to as the *weathering hypothesis*, is attributed to the cumulative impact of stress that results from socioeconomic disadvantage and discrimination (Geronimus, Hicken, Keene, & Bound, 2006). These health-related differences may also play a role in explaining how and why race affects driving reduction and cessation.

Distance from family and friends also affects the decision to stop driving (Betz et al., 2014; Johnson, 1995; Weeks, Stadnyk, Begley, & MacDonald, 2013). When many older people give up driving, they rely on members of their social network to provide tangible support in the form of rides (Choi & DiNitto, 2015; S. Kim, 2011; Kostyniuk & Shope, 2003; Taylor & Tripodes, 2001). In fact, getting a ride from someone is by far the most common and preferred way older people meet their mobility needs post driving cessation (Coughlin, 2001; Rosenbloom, 2001). In addition to tangible support for trips, distance from members of one's social network can also affect these decisions in other ways. If family and friends are far away, driving cessation could also mean a reduction in face-to-face emotional support. Although most "essential" trips (e.g., medically-related) will be provided for no matter what, "discretionary" trips are much more likely to be lost when people can no longer drive themselves (Davey, 2007; Musselwhite & Haddad, 2010; Parkhurst, Galvin, Musselwhite, Shergold, & Todres, 2013). This loss of access to discretionary trips, and the judgement of low value placed on these trips by others, is likely to play an important role in the decision to keep driving.

Consequences of driving reduction and cessation

Driving reduction and cessation are associated with a number of negative interpersonal and health outcomes. Although former drivers most commonly rely on family and friends to provide for their transportation needs (Choi & DiNitto, 2015; Coughlin, 2001; Kostyniuk & Shope, 1998), they are often reluctant to ask for rides. They report that they do not want to impose on others, or feel dependent on others (Kostyniuk, Connell, & Robling, 2009; Ritter, Straight, & Evans, 2002), but these feelings are often unavoidable (Harrison & Ragland, 2003). Relationships between a former driver and their social network members may become increasingly strained as these relationships change, and the older person becomes more reliant on these individuals (Taylor & Tripodes, 2001).

Former drivers are known to have less contact with family and friends than current drivers (Liddle, McKenna, & Broome, 2004), which can result in a smaller social network over time (Mezuk & Rebok, 2008). This could partially explain the reduced number of discretionary trips taken by former drivers. In fact, people age 65 or older who no longer drive are about three times more likely to stay home on any given day than those who still drive (National Household Travel Survey, 2001). Loss of personal identity, decreased life satisfaction, and less productive engagement in life can result from driving reduction and cessation (Curl et al., 2014; Harrison & Ragland, 2003). Driving cessation has also been shown to be a significant independent risk factor for entry into a long term care facility (Freeman, Gange, Muñoz, & West, 2006). These findings coincide with the psychological importance of remaining independent and actively engaged in life, keys to “successful aging” as described by Rowe and Kahn (1997).

The onset of depressive symptoms following driving cessation has been established prospectively, even when controlling for health status, cognitive function, and sociodemographic factors (Choi & DiNitto, 2015; Fonda et al., 2001; Marottoli et al., 1997; Ragland et al., 2005; Windsor, Anstey, Butterworth, Luszcz, & Andrews, 2007). Interestingly, it is not even necessary to completely give up driving for depressive symptoms to appear; simply *reducing* driving is also known to increase these symptoms over time (Fonda et al., 2001). Although the relationship between driving reduction (and cessation) and depression has been established, little is known about other potential factors that could influence this relationship (Dickerson et al., 2007). Windsor and colleagues (2007) examined perceived control as a potential mediator of this relationship, and found that loss of control explains at least part of this relationship. Regardless of the underlying cause or exact relationship pathway, previous research has established that there are often negative consequences resulting from driving limitation behaviors, even after health and other age-related changes are taken into account.

Application of theory

As described in previous sections, previous research has identified a number of medical conditions, interpersonal dynamics, and life transitions that lead to driving reduction and cessation. However, much of that previous work has been correlational in nature, and has largely lacked a foundation in established theory. There have been a few notable studies, however, that have used theory to guide their work. For example, Dobbs, Harper, and Wood (2009) used the *Transactional Model of Stress and Coping* to develop a coping intervention for older drivers with early stage dementia. Kostyniuk, Shope, and Molnar (2001) tested constructs from the *Precaution Adoption Process Model* to explain driving reduction and cessation. They found support for the role of perceived susceptibility in this process (Kostyniuk et al., 2001). Stalvey and Owsley (2003) used components of *Social Cognitive Theory*, the *Health Belief Model*, and the *Transtheoretical Model* to develop an intervention to help older drivers with declining vision cope with driving ability loss. These researchers found support over time for several of the constructs they tested, but did not find statistically significant changes in self-efficacy to engage in safer driving behavior (Stalvey & Owsley, 2003). Perceived control (a construct from several well-established behavior change theories) over one's driving has also been assessed, and was found to be associated with reduced driving risk avoidance (Windsor, Anstey, & Walker, 2008).

Although they have not been used to directly apply an entire theory to the issues of aging and driving, scales have also been created to study self-efficacy (a key construct in the *Health Belief Model*, *Theory of Planned Behavior*, and *Social Cognitive Theory*) specific to the driving context. For example, the Adelaide Driving Self-Efficacy Scale (George, Clark, & Crotty, 2007) and the Day and Night Driving Comfort Scales (Myers, Paradis, & Blanchard, 2008) were both developed and tested to measure aspects of driving self-efficacy, with the problems faced by older drivers in mind. A number of other theories could also be applied to better understand aspects of this complex topic. In fact, Choi, Adams, and Mezuk (2012) acknowledged the lack of established theory in understanding older drivers' decisions, and called for future research in this area to be theory-driven. It is easy to imagine the importance of attitudes toward driving reduction and cessation, individuals' intentions to stop driving, and subjective norms about driving in this process; all of which are constructs from the *Theory of Planned Behavior* (Ajzen, 1991). Likewise, there is little doubt that constructs from the *Health Belief Model* (Rosenstock, 1974; Strecher, Champion, & Rosenstock, 1997) play a key role in driving reduction and cessation. For example, when older adults consider engaging in driving reduction or stopping driving completely, it is likely that they and their families weigh the safety *benefits* of less driving exposure against *barriers* like loss of independence. Their *perceived susceptibility* to crashing, and the *perceived severity* of injury (to oneself and others) given a crash are also likely to be key predictors of these behaviors. Future research should answer the call of Choi and colleagues (2012) by applying these and other established theories to this issue.

Notably missing from this review of the theory-driven literature are studies using an ecologically-based theory or model. In fact, very little research in general (theory-driven or not) has explored the potential influence of the physical or social environment on driving reduction and cessation. When research has included these factors, it has primarily focused on the influence of social or policy issues, like the effectiveness of licensing policies on older driver safety (e.g., Langford, Fitzharris, Newstead, & Koppel, 2004).

The *Social Ecological Model* (SEM; see Figure 1) is a useful framework for conceptualizing how variables from different “levels” of the model differentially influence health behaviors and outcomes (see e.g., Bronfenbrenner, 1977; McLeroy, Bibeau, Steckler, & Glanz, 1988; Schulz & Northridge, 2004). Factors on the outermost levels of the SEM often have the broadest reach, and influence not only the individual, but also the factors on each of the consecutively smaller levels of the model. An individual’s behavior occurs within the context of their environment. As such, behavior is influenced by the policies, cultural norms, physical environment, community investment, etc. within their physical and social environment (Schulz & Northridge, 2004). One reason that the influence of factors on the outer levels of the SEM is often not recognized may be that these factors are more conceptually distal. This assertion is consistent with the earlier review of the driving and aging literature; most previous work in this area has been situated within the individual (e.g., medical conditions) and interpersonal (e.g., family dynamics) levels of the SEM. This is somewhat surprising given that driving occurs directly within the physical environment (community level), and is governed by laws and policies within the social environment (societal level). Consequently, there is a high likelihood that one's environment influences the decision to reduce and stop driving, as well as one's health and mental health post-driving cessation. The SEM was used to guide the present research, with a particular focus on understanding the influence of the physical environment (community level) on individuals' driving decisions and health.

Figure 1. Social Ecological Model.

Although it has not been applied to the arena of aging and transportation, the *Social Determinants of Health Theory* (SDH) is a specific ecological model (Schulz & Northridge, 2004) that was explored with one of the key research questions in this study. Figure 2 provides a simplified representation of this theory, adapted from Schulz and Northridge (2004). SDH posits that there are certain "fundamental" social factors that affect health through multiple pathways. These factors directly affect "intermediate" constructs like the built and social environment, which in turn affect "proximate" factors like stressors, health behaviors, and social support. Finally, the proximate factors directly affect health and well-being. SDH also suggests that factors on each level of the model can have a bidirectional influence, and it allows for direct influences of factors on non-adjacent levels (e.g., fundamental factors can directly affect proximate factors, without necessarily being mediated by intermediate factors).

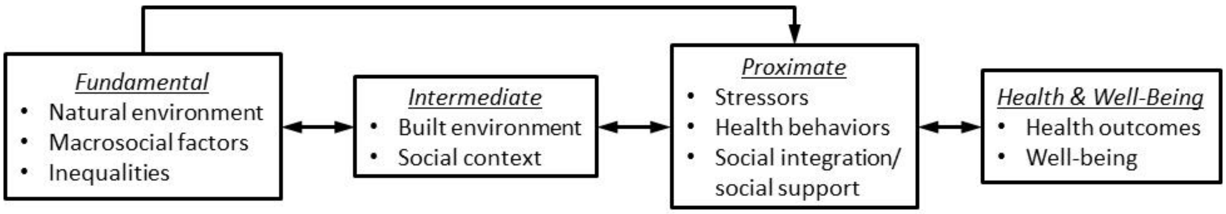

Figure 2. Social Determinants of Health Theory.

One of the goals of this research was to expand upon SDH by describing a new conceptualization of the relationships between constructs on the “higher” levels of the model (fundamental and intermediate) and those on the other levels, and then empirically test those relationships using data from the current study. Specifically, this new conceptualization involves the potential moderating effects of factors on the fundamental and intermediate levels, on the relationships between other constructs, and thus it is called the *Environmental Moderator Hypothesis* (EMH). The EMH suggests that higher level factors may at times serve primarily as moderators, in addition to the direct, mediating, and bidirectional effects discussed by Schulz and Northridge (2004). As described earlier, individuals make decisions about their health behaviors, and health and well-being outcomes develop, within the *context* created by factors on the higher levels of these models. For example, stressors shown on the proximate level of the model may lead to negative mental and physical health outcomes, depending upon factors in the built environment (intermediate) or inequalities in wealth distribution (fundamental). This new hypothesized relationship is represented by the dotted red lines in Figure 3. Conceptualizing fundamental and intermediate level factors in this way is the definition of a moderator (statistical interaction), which lends itself to empirical testing.

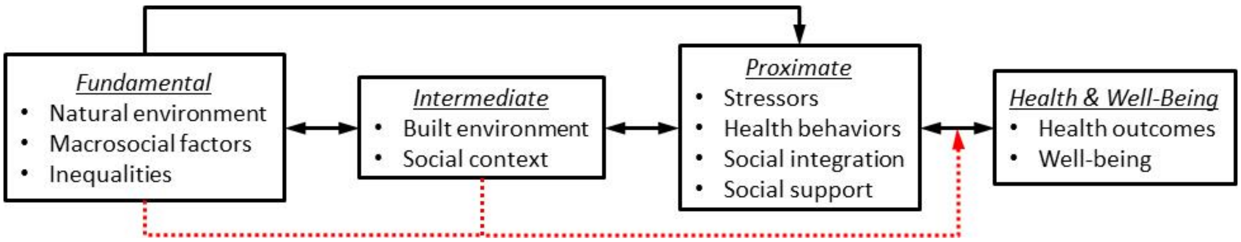

Figure 3. Social Determinants of Health Theory with first hypothesized interaction.

SDH focuses primarily on the outer levels (sometimes called “higher” levels) of the ecological model, so it does not include a number of other factors that are known to affect health and well-being. The *Theory of Planned Behavior,* for example, suggests that attitudes, subjective norms, self-efficacy (perceived behavioral control), and intentions affect engagement in health behaviors (Ajzen, 1991). The *Health Belief Model* includes the constructs perceived benefits and barriers, and perceived susceptibility and severity (Rosenstock, 1974; Strecher et al., 1997). If these factors were added to SDH, they would fit best on the proximate level, and the model might look similar to the expanded version shown in Figure 4 (these additional constructs are shown in the box labeled *psychological factors*). Once the psychological factors are included, additional moderating effects posited in the *Environmental Moderator Hypothesis* can be illustrated. Specifically, the relationship between psychological factors and engagement in health behaviors may also depend on fundamental and intermediate factors.

There are essentially four separate relationships proposed by the EMH, and each is illustrated by the dotted lines and numbers in Figure 4: 1) fundamental factors moderate the proximate-outcome relationship, 2) fundamental factors moderate the psychological factor-behavior relationship, 3) intermediate factors moderate the proximate-outcome relationship, and 4) intermediate factors moderate the psychological factor-behavior relationship.

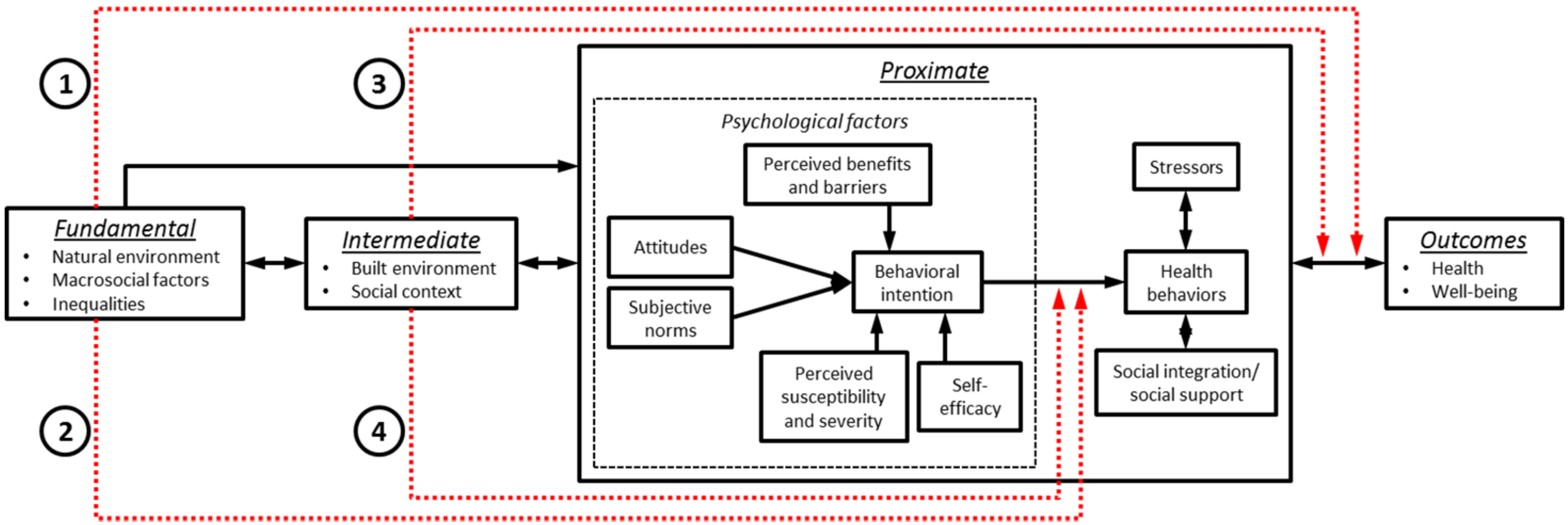

Figure 4. *Environmental Moderator Hypothesis relationships in Social Determinants of Health Theory.*

A literature search was conducted to assess the extent to which previous research supports the relationships posited by the EMH. Because the EMH is a general health behavior hypothesis, the literature related to many different types of health-related research was reviewed, not just the field of aging and transportation. The search identified empirical evidence that used a broad mixture of variables and research questions to support these relationships. Indeed, a clear strength of the EMH seems to be that it is broadly applicable to multiple contexts within the health arena. A synthesis of the published literature that supports each relationship posited in the EMH follows.

A number of studies have assessed the role that *fundamental* factors play in the relationship between *proximate* factors and *outcomes* (relationship 1 shown in Figure 4), and have found that they often play a modifying role. For example, Muckenhuber, Burkert, Großschädl, and Freidl (2014) studied absence from work due to sickness in 23 different European countries. These researchers found that income inequality (a fundamental factor), moderated the relationship between psychological job demand/stress (a proximate factor) and sickness that caused absence from work (an outcome). The relationship between job demands and sickness-related absences was stronger in countries with low income inequality (Muckenhuber et al., 2014). Mansyur, Amick, Harrist, and Franzini (2008) also studied the effect of income inequality on health using data from 47 different countries. They found that higher levels of income inequality increased the strength of the relationship between individual level income and self-rated health (Mansyur et al., 2008).

Several other fundamental factors have also been established as moderators of the proximate/outcome relationship. Community socioeconomic adversities (e.g., concentration of poverty) have been shown to moderate the relationship between family characteristics (e.g., parental acceptance) and mental health among adolescents (Wickrama & Bryant, 2003). Discrimination has been shown to serve as a moderator in several different contexts. Murry, Brown, Brody, Cutrona, and Simons (2001) studied African American families with young children to assess the links between various social contexts, family patterns, and stressful life events. These researchers found that stronger links existed between stressors and psychological distress when racial discrimination was perceived to be greater. In another study that focused on an African American sample, the relationship between poverty-related risk factors (including social, psychological, and biological factors) and subjective well-being was moderated by racism-related stress (Utsey & Constantine, 2008). Racism-related stress was measured in that study at the individual level, but given that racism was the underlying cause of the stress, it is conceptualized here as a fundamental factor.

Evidence also exists supporting the moderating role *fundamental* factors may play in the *psychological-behavior* relationship (relationship 2 in Figure 4). Conner and colleagues (2013) studied socioeconomic status (SES) to understand how it impacts the relationship between intention and engagement in health behaviors. These researchers conducted three separate studies and used SES measures at the school level (proportion of children receiving free lunches), zip code level, and individual occupational classification. The behaviors they studied were smoking initiation, breastfeeding, and physical activity. SES (measured on each of those levels) was shown to moderate the relationship between intention and these health behaviors, with lower SES weakening the relationship (Conner et al., 2013).

A number of research studies also support the moderating role *intermediate* factors play in the *proximate-outcome* relationship (relationship 3 in Figure 4) in a range of different contexts and populations. For example, Farone, Fitzpatrick, and Tran (2005) found that use of community services (specifically, the use of senior centers) moderated the stress-psychological distress (proximate-outcome) relationship among older Latinos. Although this study did not differentiate between the availability of senior centers, and individual differences in those who decide to use them, presence of a center is certainly a requirement of use. The density of fast food outlets in neighborhoods and the amount of green space in a given area have also been explored as moderators of the proximate-outcome relationship (Li, Harmer, Cardinal, Bosworth, & Johnson-Shelton, 2009; van den Berg, Maas, Verheij, & Groenewegen, 2010). As operationalizations of the built environment, these factors fit nicely as representations of constructs on the intermediate level. Researchers found that a high density of fast food outlets in one's neighborhood strengthened the relationship between eating behavior and obesity (Li et al., 2009). On a more positive note, amount of green space in one's living area seems to have a protective effect on the relationship between stressful life events and health problems (van den Berg et al., 2010). Regardless of the direction of influence, these studies support the idea that intermediate level factors often serve to create a context within which proximate factors differentially affect health outcomes.

The final relationship suggested by the EMH concerns *intermediate* level factors moderating the *psychological factor-behavior* relationship (relationship 4 in Figure 4). This proposed linkage fills a gap in many of the individual behavior change theories described earlier. Several examples of this relationship, from a variety of populations and using different operationalizations of factors on the intermediate level, were identified in the literature. Li, Fisher, Brownson, and Bosworth (2005), for example, found that the number of roadway intersections in one's neighborhood moderated the relationship between perceptions of safety and walking behavior among older adults. Rhodes, Brown, and McIntyre (2006) also studied walking behavior, and found that individuals' perceptions of proximity to recreation facilities moderated the relationship between intention to walk, and actual walking among Canadian adults. The local availability of sports facilities was also studied in a different project using GIS data to objectively assess this variable. Sports facility availability was found to strengthen the relationship between intention to participate in sports and actual participation among an adolescent sample (Prins et al., 2010). Finally, walkability (measured using an objective index) has been shown to moderate the relationship between perceived barriers to walking for transportation (as well as self-efficacy), and actual engagement in that behavior among older adults (Carlson et al., 2012).

In the current research, the EMH was assessed by operationalizing factors on the following levels of SDH: intermediate (i.e., built environment: the mobility of the transportation environment for a given region or zip code); proximate (i.e., health behaviors: driving reduction/cessation); and health and well-being (i.e., depressive symptoms). In other words, this study explored the extent to which the relationship between driving reduction/cessation and depressive symptoms depended upon the transportation environment within which an individual lived.

CHAPTER 3

METHODS

Data sources

The data used to explore the research goals for this study came from three primary sources: the Health and Retirement Study (HRS, 2013), the Urban Mobility Report (Schrank et al., 2012), and GIS data from StreetMap North America (ESRI Ltd., 2013). A few additional GIS files were also utilized from the Topologically Integrated Geographic Encoding and Referencing (TIGER) products from the US Census Bureau (US Census Bureau, 2014). The following provides additional details on each of these data sources.

The HRS is sponsored by the National Institute on Aging (grant number NIA U01AG009740), and is conducted by the University of Michigan. It is a large-scale longitudinal panel study of people over the age of 50 in the United States (HRS, 2013). The data comprise a nationally representative sample, and have been collected every two years since 1992. The base sample of the HRS was a stratified clustered sample from a multistage area probability sampling frame (see Survey Research Center, 2013, for more detailed information). The analyses for this study used seven waves of publicly released data spanning the 12 years from 1998 through 2010. Data from the 1998 wave were used as the baseline in these analyses because the original HRS and the *Assets and Health Dynamics Among the Oldest Old* (AHEAD) cohorts were separate studies until they were combined in 1998 (Chien et al., 2013). In addition to the public release data, restricted data product 1043 was obtained and used to link HRS respondents to data from the other sources. Data product 1043 contains the Cross-Wave Geographic Information data, which includes respondents' zip code information. The most recent year for which the restricted geographic data were available was 2010, so that wave was used as the final data point for all analyses.

The UMR provides regional transportation information at the Census Urban Area (UA) level, and has been compiled each year since 1982 by the Texas A&M Transportation Institute (TTI; Schrank et al., 2012). As noted earlier, variables in the UMR include indices that provide information about the physical transportation environment, and can be conceptualized as proxies for the "mobility" of a given area. These data are available for download at the following location: http://tti.tamu.edu/documents/ums/congestion-data/complete-data.xls.

Most of the GIS-based variables used in this research were calculated from the StreetMap North America dataset produced by the Environmental Systems Research Institute (ESRI). This dataset provides street display, routing, and geocoding for the United States (ESRI Ltd., 2013). Several variables were created from the GIS data by calculating totals within each zip code for the entire United States (e.g., density of roadway miles per zip code, number of exit ramps per zip code). To make these calculations, zip code boundary shapefiles and Urban Area boundary shapefiles were obtained from the US Census Bureau (US Census Bureau, 2014). ArcGIS software (version 10.2) was used for all GIS calculations in this study.

Data management and preliminary analyses

Merging

Data from HRS are available in two different publically available formats. Data from each individual wave and section of the HRS questionnaire can be downloaded, or a combined file developed by the RAND Corporation is also available. The RAND HRS v.M public release data file and the RAND-enhanced fat files for individual years 1998-2010 were downloaded and merged together. The RAND v.M file has all waves of data combined and cleaned, but does not include every HRS variable. Additional required variables were added from the RAND-enhanced fat files, and all unnecessary variables were dropped from the file. The HRS cross-wave geographic information data file (containing the restricted geographic data - respondent zip codes) was decrypted[1], and merged into the existing file using version 9.4 of the SAS System for Windows (SAS Institute Inc., 2013), which was also used to conduct all of the statistical analyses in this study.

Data from the UMR were downloaded from the TTI website (TTI, 2014). That data file contains the regional variable values for each year, however, each region is shown only by name, using Census "Urban Area" level nomenclature. To connect these data to HRS respondents (via zip codes), a file from the US Census Bureau containing the Urban Area-to-zip code relationships was downloaded and merged with the UMR file. This resulted in a new file with all the original UMR data, plus information about every zip code included within each of the Urban Areas.

Before these data were merged into the HRS file, HRS data were transposed from wide format (where each row of data represents an individual) to long format (where each row of data represents a person/wave), to account for HRS respondents who moved from one location to another over the years of study. Using this method, the appropriate data representing the transportation environment would be linked to a given HRS respondent, even if that respondent had moved between waves. The GIS-based data were also merged to the existing HRS/UMR dataset using zip codes as a linking variable, once those variables were calculated.

[1] A *Data Protection Plan* (DPP) which describes all the procedures taken to secure these data was approved by HRS personnel and the U-M Institutional Review Board prior to receipt of the restricted data. The DPP is available for review upon request.

Complex sample survey design elements

Because the HRS data include complex sample survey design elements (stratification, clustering, and weights), analyses were conducted that properly accounted for those design features. For example, many SAS commands include a SURVEY version of the procedure that incorporates these elements when calculating the parameter estimates and variance. The specific analysis plan for each research goal is described in more detail in later sections, but a brief description of the overall methods of accounting for complex elements follows.

The HRS RAND variables that were used to account for each design element included RAESTRAT for stratification, RAEHSAMP to identify clusters (ZIP and UA were also used, and are discussed later), and WTRESP to properly weight the analyses. Indicator variables were created to allow for the data to be analyzed by subgroups (domains) without actually subsetting the data, as required when analyzing complex sample survey data (Heeringa, West, & Berglund, 2010). The SURVEY commands were used for all analyses related to research goals 1 and 3. The DOMAIN option in SAS was used within the SURVEY commands to complete all subgroup calculations. Research goal 2 involved aggregating data within Urban Areas, so only the weighting function was used. Research goal 4 involved completely different analysis procedures which are described in detail later.

Sample

HRS respondents were only asked about their driving ability and behaviors if they were age 65 or older at the time of the interview, so only people in that age group were included in these analyses. The interview status variable was used to ensure that only those who actually participated in the wave were included (exit proxy interviews are conducted with relatives for recently deceased HRS respondents).

Once data were merged and indicator variables were created to account for the factors described previously, univariate descriptive statistics and distributions of the primary variables of interest were examined. Frequencies, means, standard deviations, and histograms were generated as appropriate. Differences in censoring (described later in the analysis plan), and in who was asked the driving reduction question (only those who reported that they could still drive), resulted in slightly different samples when the driving reduction variable was included, compared to models where driving cessation was included.

Across the years analyzed that included the driving cessation variable, there were an unweighted total of 15,060 individuals in the sample, of which 7,655 (50.5% weighted) were women, and 7,405 (49.5% weighted) were men. The weighted mean age of the respondents was 70.0 years. The unweighted numbers of respondents by racial group were 12,253 White (86.9% weighted), 1,657 African American (6.9% weighted), 956 Hispanic (4.8% weighted), and 190 Other (1.4% weighted). In terms of educational attainment, the weighted average was 12.6 years completed. Most of the respondents were married or partnered (68.3% weighted), 18.6% (weighted) were widowed, 10.3% (weighted) were separated or divorced, and 2.8% (weighted) had never been married.

The analyses that involved the driving *reduction* variable included a total of 10,690 individuals, including 4,786 women (44.7% weighted), and 5,904 men (55.3% weighted). The other characteristics were slightly different than the driving cessation sample, but followed the same general trends (weighted: 89.0% White, 5.5% African American, 4.2% Hispanic, 1.3% Other; 13.0 years of education; 73.3% married, 14.6% widowed, 9.5% divorced, 2.6% never married).

The Urban Mobility Report variables were only available for HRS respondents who lived in the 101 Census Urban Areas covered in that dataset, while the GIS variables were available for all respondents. Analyses that included UMR variables were conducted only on respondents for whom data were available, because data imputation for those variables would not be appropriate. Overall, the UMR variables were available for about 51% of the HRS respondents.

Across all waves analyzed in this study, the UMR sample that involved driving cessation included 7,652 people, with 5,420 in the driving reduction UMR sample. The UMR and full sample were similar in terms of respondent demographics, with the primary differences being that the UMR group included a larger proportion of non-White respondents, and more people who fall into the non-married categories. The weighted demographic breakdown for driving cessation was as follows: 50.2% female; 82.4% White, 9.1% African American, 6.8% Hispanic, 1.7% Other; 12.9 years of education; 67.6% married, 18.4% widowed, 11.0% divorced, 3.1% never married. For driving reduction, the weighted demographics were: 44.2% female; 84.8% White, 7.6% African American, 5.9% Hispanic, 1.8% Other; 13.3 years of education; 72.2% married, 14.6% widowed, 10.3% divorced, 3.0% never married.

Several variables were recoded prior to the analyses to collapse categories, assign values that were more appropriate for statistical analyses (e.g., 0,1 instead of 1,5), and to allow for more meaningful interpretation of the results. Prior to fitting regression models, bivariate associations were explored using correlations, chi-square tests, ANOVAs, and t-tests, as appropriate, between primary predictors and outcomes. These tests were also conducted between predictors where associations were considered likely, as a first step toward assessing potential multicollinearity problems when regression models were fit.

The survival analyses only included respondents who reported the ability to drive during their first eligible wave (first wave where they were age 65 or older). Those who were already unable to drive during their first wave were considered left-censored. Because that group was somewhat different than those included in the analyses, it is useful to provide a brief overview of the left-censored respondents compared to the overall sample. There were 4,289 left-censored respondents and Table 1 shows their demographic characteristics, health status, and household information alongside the same information for the overall non-censored driving cessation sample described earlier. Compared to those who could drive during their first eligible wave, those who could not drive (censored) were older; had less education; were more likely to be female, non-White, and non-married; and had worse health and vision. This was expected, as previous research has identified all of these factors as strong predictors of driving cessation (see e.g., Eby et al., 2009).

Table 1. Characteristics of full sample and left-censored respondents.

	Weighted mean / Weighted % (Unweighted N)	
	Overall sample (N=15,060)	Left-censored (N=4,289)
Age	70.0	75.8
Gender		
Male	49.5 (7,655)	24.9 (1,060)
Female	50.5 (7,405)	75.1 (3,229)
Education	12.6	9.9
Race		
White	86.9 (12,253)	65.4 (2,482)
Black/AA	6.9 (1,657)	18.2 (1,056)
Other	1.4 (190)	2.6 (93)
Hispanic	4.8 (956)	13.7 (658)
Relationship status		
Married/partnered	68.3 (10,632)	38.1 (1,589)
Divorced	10.3 (1,377)	12.8 (554)
Widowed	18.6 (2,722)	43.8 (1,933)
Never married	2.8 (318)	5.3 (209)
Friend in neighbor.	70.6 (10,454)	65.9 (2,734)
No. in household	2.0	2.0
No. of living child.	3.2	3.2
Health	2.7	3.6
Vision	2.7	3.4

Missing Data

Multiple imputation procedures were used to account for missing data. The procedures used here were based on those described by Berglund and Heeringa (2014). Missing data patterns were explored, and indicator variables were created that identified missing data cases. The data were transformed into wide format, and the fully conditional specification (FCS) method was used to complete five imputations. The FCS logistic, discriminant, and regression functions were employed to impute binary, non-binary classification, and continuous variables, respectively. To account for the complex survey sample elements, the cluster and stratification variables were combined, and were used along with the weight variable during the imputation process. The imputed data were checked by calculating means and frequencies for the imputed and non-imputed cases within each imputation using the aforementioned indicator variables. As expected, the means and frequencies were slightly different for each imputation, but reasonably similar to each other, and to those calculated with the non-imputed data. During final analyses, models were fit for each imputation, and the MIANALYZE procedure was used to combine parameter estimates across the results. Given the complex design of HRS, the EDF function was set to 56 to assign the correct complete data degrees of freedom for the models.

Overall, very little imputation of missing data was necessary. The GIS variables were calculated for every zip code in the US, and were thus available for all HRS respondents. As noted earlier, the UMR variables were only available for people in the 101 UAs of that dataset, but because those areas were all urban, imputing for the remaining sample (mostly rural and suburban) would not have been appropriate. Of the HRS data, there was none missing for respondent age, gender, or household size. The amount of missing data that were imputed was as follows: education (191), race (71), ethnicity (40), relationship status (84), having a friend in one's neighborhood (2,310), number of living children (2,399), self-rated health (92), and vision (173). In the full non-censored dataset, there were 136,977 rows (each representing a person-wave), which shows that even the variable with the most missing data had a very low percentage imputed.

Two-wave analyses

The analyses to address research goals 1, 3, and 4 required a longitudinal approach to examine changes in driving status and depressive symptoms over time. Data in both HRS and UMR were available over a number of years, which allowed for this approach. However, preliminary analyses were first conducted using only two waves of data, 2006 and 2010. The preliminary analyses utilized 2006 data as the baseline wave because one of the original variables of interest[2] was first asked in that year.

Two-wave analyses were used to assess the overall relationships between the predictor and outcome variables, and to compare with longitudinal analyses for consistency. Design-adjusted logistic regression and Poisson regression models were fit as appropriate to the outcome of interest, with variables from the baseline wave included as predictors, and variables from the follow-up wave as outcomes. For the analyses related to driving reduction and cessation outcomes, only people who reported the ability to drive (or no engagement in driving reduction for that outcome) during the baseline wave were included. This was done because these analyses focused on the influence of the predictors on a change in driving reduction and/or cessation over time. Overall, these analyses provided a cursory examination of the importance of the key predictors, the relationships among variables, and a way to identify potential errors. The results of all of the two-wave analyses were consistent with the longitudinal analyses conducted later. In

[2] This was the question that asked respondents if they have driven during the past month.

general, the same relationships were noted, just with less statistically significant results in the two-wave analyses, so the two-wave results are not reported here.

Variables

Dependent variables

The research goals of this study require the use of different dependent variables. Research goals 1-3 involve analyzing driving cessation and driving reduction as dependent variables. Research goal 4 assesses depressive symptoms as the outcome, and includes driving cessation and reduction as independent variables. The following subsections describe each variable in detail, including the operational definitions and any calculations that were required to develop the variable.

Driving cessation was operationalized using a combination of two HRS questions. The main question used here asks *Are you able to drive?* Although this question asks about one's ability to drive, rather than about one's engagement in driving behavior, it serves as a proxy for driving cessation, and has been used this way in several previous studies (see e.g., Choi & Mezuk, 2013; Dugan & Lee, 2013; Fonda et al., 2001; Freund & Szinovacz, 2002). For example, Choi and Mezuk (2013) recently used HRS data to explore differences between former drivers and older people who never drove. Dugan and Lee (2013) used HRS to study biopsychosocial risk factors of driving cessation.

However, to increase the likelihood of assessing driving *behavior* rather than reported ability, the question that asks *Do you have a car available to use when you need one?* was used here as described next.[3] Respondents who stated that they were unable to drive were considered

[3] HRS includes another question that asks respondents *Have you driven a car in the past month?* That question assesses behavior, but has only been available since the 2006 wave, so it could not be used here given that these are longitudinal analyses.

to be non-drivers. Those who stated that they were able to drive, but did not have a car available were also considered to be non-drivers. Respondents who stated that they were able to drive and had a car available were considered to be drivers. Figure 5 shows a brief diagram of this decision tree.

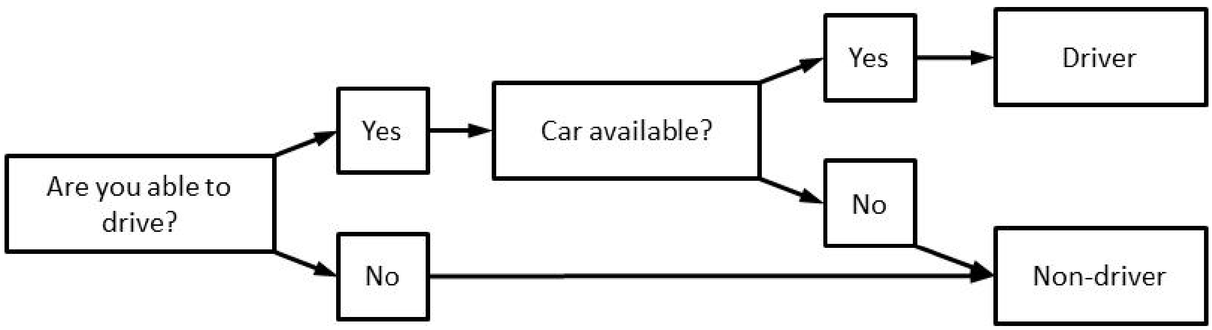

Figure 5. Decision tree for developing driving cessation variable

Driving reduction was operationalized using data from the HRS question that asked *Do you limit your driving to nearby places, or do you also drive on longer trips?* This question represents a common driving self-regulation behavior.

Depressive symptoms were operationalized in HRS using items from the short form of the Center for Epidemiologic Studies-Depression (CES-D) scale. The shortened 8-item version of this scale was used in HRS to reduce respondent burden. Previous research has established that this version of the scale has good psychometric properties and is comparable to longer versions (Turvey, Wallace, & Herzog, 1999). These items ask if respondents felt a certain way *much of the time, during the past week*. Specifically, respondents were asked if they felt depressed, happy, lonely, or sad, as well as if they felt like everything was an effort, if sleep was restless, if they enjoyed life, and if they could not get going. The combined scale based on these questions ranges from 0 to 8, and the positive items were reverse coded such that higher numbers represented more depressive symptoms.

Independent variables (predictors of interest)

The transportation environment was operationalized in several different ways. A number of variables assessed the environment using regional (Urban Area level) data from the UMR, while several others were calculated at the zip code level using GIS data. All of these variables measure different aspects of the transportation environment, and it is unknown which ones may be most predictive of the driving behaviors and mental health of older adults. However, the variables that seemed most promising in this regard are identified in this section as primary predictors, with the remaining transportation environment variables described at the end of this section. The formulas used by the UMR researchers to calculate these variables are included here for completeness, but more details are provided in their documentation (Schrank et al., 2012). All of the details about the GIS variable calculations are included in the relevant sections that follow.

Transportation environment – primary predictors

Travel Time Index was calculated by UMR researchers by dividing the travel time during the peak (busy) period by travel time during free-flow conditions (Schrank et al., 2012). For example, a Travel Time Index of 1.43 (the largest value in this index), indicates that a 20-minute free-flow trip would take about 28 and a half minutes during the peak period.

Delay is the annual amount of extra time spent traveling in the Urban Area that can be attributed to congestion. The formula for how this variable was calculated is shown next as described in Schrank et al., 2012, p. A-16.

$$Delay = \left(\frac{Daily\ Vehicle\ Miles\ of\ Travel}{Speed}\right) - \left(\frac{Daily\ Vehicle\ Miles\ of\ Travel}{Free\ Flow\ Speed}\right)$$

Roadway Congestion Index (RCI) can be interpreted as a measure of the density of traffic in the region. It essentially represents both intensity and duration of congestion, and a value greater than or equal to 1.0 is considered undesirable (Schrank et al., 2012). The formula UMR researchers used to calculate this index is shown next, as described in Schrank et al., 2012, p. A-35.

$$Roadway\ Congestion\ Index =$$

$$\frac{\left({}^{Freeway\ VMT}/_{LnMi}\right) \times Freeway\ VMT + \left({}^{Prin\ Art\ Str\ VMT}/_{LnMi}\right) \times Prin\ Art\ Str\ VMT}{14{,}000 \times Freeway\ VMT + 5{,}000 \times Prin\ Art\ Str\ VMT}$$

where LnMi is lane-miles of roadway, and Prin Art Str is principal arterial street.

Miles of roadway within each zip code were calculated separately for limited access (freeways) and non-limited access roads using GIS data. These roadway types were separated because older drivers are known to avoid limited access roadways as a self-regulation behavior (Eby et al., 2009; Molnar, Eby, et al., 2013). Only primary, secondary, and local roads were included so that a reasonable database size could be maintained on which to perform calculations (the file with all classes of roadway included over 40 million records), and because nearly all trips would require travel on at least one of these included roadway types. Census Feature Class Codes (CFCCs) is a standard way of classifying different roadway types (ESRI Ltd., 2014) and were included as described next.

Limited access roadways were included if they fell within the A10-A18 CFCCs. Non-limited access roadways with CFCCs that included A20-A28, A30-A38, A40-A48, A60, A62, and A64 were used in the calculations. Collectively, these codes encompassed all primary, secondary, and local roads, as noted earlier. To calculate miles per zip code, the *Intersect* tool in ArcMap (a sub-program of ArcGIS) was used to join the roadway file from StreetMap North America to the zip code shapefiles obtained from the US Census Bureau’s TIGER files archive. This join combined the data while intersecting each roadway line at the zip code border (many roads cross into more than one zip code). The miles of roadway were then summed within each zip code, separately for limited access and non-limited access roadways. This procedure allowed for the influence to be assessed of both types of roadways separately, total amount of roadway miles, and the ratio of limited access to non-limited access roadway miles.

Intersections: The number of roadway intersections within each zip code was calculated using GIS data for non-limited access roadways, and for all roadway types combined.[4] These calculations were made by first using the *Dissolve* tool to combine roadway segments that share an endpoint (for ease of mapping, some roadways are separated into segments, which would be identified in the software as an intersection, so these were eliminated). The *Intersect* tool was then used to identify points where two lines (roadways) crossed one another. Limited access roadways often involve multiple exits in the same general area (for traffic exiting in each direction), and divide traffic into the direction of flow, which are all geocoded separately in StreetMap. To reduce the potential bias resulting from an overestimation of intersections due to those created by limited access roadways, all intersections that fell within 0.1 miles of each other were considered one. This was accomplished using the *Integrate* tool, with an *XY Tolerance* setting of 0.1 miles, and then using the *Collect Events* tool to count. A new field was then created in the resulting data table that was set to "1" for each event. Finally, a *sum* calculation was performed during the join to add the total number of intersections per zip code.

Freeway exit ramps: The number of freeway exit ramps in each zip code was also calculated using GIS data. First, a new field was created in the exit ramp dataset and set to a value of "1." Then a *sum* calculation was performed during a join to add the total number of exits per zip code.

Roadway density: Measures of roadway density were developed for this study because the aforementioned GIS variables did not consider differences in the geographic size of zip codes

[4] Intersections for limited access roadways alone was not calculated, because these do not actually intersect on the same level (the ramps allow passage over or under, from one to the other without stopping).

throughout the country. These variables were calculated by dividing each of the *miles of roadway* variables (miles of limited access, non-limited access, and total miles of roadway per zip code) by the number of square miles within the zip code. As such, these variables can be thought of as rates adjusted within each zip code, rather than total counts.

Transportation environment – other potential predictors:

Distance from primary municipality in UA: Because many of the UAs are quite large, the UMR variables do not provide nuanced information about potential differences in the transportation environment that are likely to exist. A person who lives at the periphery of a UA, for example, may experience the transportation environment differently than someone who lives near the center of it. To account for those potential differences, the geographic distance from the primary municipality of the UA to every zip code within that UA (e.g., from Detroit to each zip code within the Detroit UA) was calculated in number of miles using ArcMap and GIS data. This was accomplished by spatially joining each zip code to the UA within which it was contained, and then removing all other zip codes from the dataset. Centroids for each zip code (the vertical/horizontal center point, based on latitude and longitude) were calculated, and the primary municipality around which each of the UAs focused was added to the dataset. The *XY to Line* tool was used to produce geodetic straight-line distances from the UA's primary municipality to each zip code centroid in the UA. The distances were calculated for only one UA at a time, so that the XY coordinate system of ArcMap could be changed to the appropriate projected coordinate system for each region of the country. State Plane NAD 1983 coordinate systems were used for each region, and the resulting distances were converted to US miles using the *Calculate Geometry* command within the data table.

Congested travel is the percent of peak vehicle miles of travel (VMT) in the region that was congested.

Congested system is the percent of lane-miles of roadway in the region that was congested.

Vehicle miles of travel are the average daily traffic on each roadway segment multiplied by the length of that segment. This was calculated separately for freeways and arterial streets.

Lane miles are the total number of actual miles of roadway in the UA, calculated separately for freeways and arterial streets.

Independent variables (controls and secondary predictors)

A number of other variables were included in the models to control for factors that are known or suspected to affect driving reduction, cessation, and depression, and to identify potential subgroup differences. These variables are described next, and include respondents' age, gender, race, education, health, social support, relationship status, and household characteristics.

Age, gender, race, and education were all assessed using HRS variables. Age was included as a continuous variable for most of the analyses, and was recoded into 5-year increments to allow for a more meaningful interpretation of the parameter estimates. In the analyses related to depressive symptoms, age was recoded into three groups: 65-74, 75-84, 85 and older. This was done because previous research has suggested that there may be a meaningful difference in the prevalence of depression among different older adult age groups (e.g., Choi & Kim, 2007).

Gender was identified in HRS as either male or female. Race was created using two variables. The first variable coded respondents as White/Caucasian, Black/African American, or Other, and the second identified respondents as Hispanic or non-Hispanic, regardless of their first answer. These variables were combined to create four mutually exclusive race/ethnicity groups as follows: White/Caucasian, Black/African American, Other, and Hispanic. To create this variable, anyone who identified as Hispanic was moved into that category from the three others. Education was defined as the highest level of education achieved.

Health was operationalized in HRS in several ways, and two different measures were assessed for this study: an objective and a subjective measure. The objective measure was included in the RAND dataset and represents comorbidity. It was created by summing the number of conditions each respondent reported having, from the following list: diabetes, cancer, lung diseases, heart problems, stroke, and arthritis. As noted earlier, symptoms from many of these illnesses can negatively affect driving ability, and some have suggested that comorbidity may actually be the key factor that increases crash risk for older people (Eberhard, 2008; Papa et al., 2014). Using an objective health measure calculated in this way allowed for one variable to represent several health conditions that could affect driving.

The subjective measure of health was operationalized using the question *Would you say your health is excellent, very good, good, fair, or poor?* This variable ranged from 1 to 5 where higher numbers represented worse health. Because loss of vision may be the most important health-related factor related to loss of driving ability, respondents' eyesight was entered into the models as a separate predictor. The HRS question that asks respondents if their corrected eyesight is excellent, very good, good, fair, or poor was used for this purpose. This variable ranged from 1 to 6, which included the five categories listed previously. Additionally, if a respondent volunteered that they were legally blind in response to this question, it was coded as 6, and as such, higher numbers represent worse vision.

Social support: Validated social support scales are not part of the core HRS questions, but have been included as experimental modules in certain past waves (1994, 2002), and as part of the "leave-behind" questionnaire since 2004 (HRS, 2013). The leave-behind questionnaires are designed to gather more information about the respondents, without increasing the length of the interviews (a paper-and-pencil format is used). Unfortunately, the experimental modules have only included these questions in the two waves just mentioned, and those modules are only administered to a subsample of the respondents. Likewise, only a subsample of HRS respondents (50%) are selected for the leave-behind questions (Smith et al., 2013). The subsampling procedure used in the experimental modules and leave-behind questionnaire does not allow for wave-to-wave comparisons, so those questions were not used in this research. Instead, other HRS variables from the core survey were used as proxies for social support. These variables do not measure social support as comprehensively as those just described, but cover several of the key aspects of social support and are asked of every respondent in every wave.

Variables that were used to represent social support in this study included respondents' relationship status, as well as variables related to respondents' children: if they have living children and if those children live nearby. Additionally, variables that assessed whether friends or relatives live in the respondents' neighborhood and the number of people who live in the respondents' household were also included.

Public transportation was operationalized in the UMR as the number of annual passenger-miles within each region. This included light rail, heavy rail, commuter rail, and bus systems.

Analysis plan

Statistical approach

Each research goal in this study involved a different statistical approach, so this section is subdivided by research goal, with the process described for each. Later goals that utilized a similar approach to what has already been described simply refer back to the appropriate section.

Research goal 1

A survival analysis approach was used to assess the extent to which the transportation environment affected driving reduction and cessation. These analyses included all seven waves of data, spanning the 12 year period from 1998 through 2010. Data from the UMR are produced once per year, and HRS data are collected every two years, so the unnecessary waves of UMR data were removed from the dataset. Given that these data are measured at intervals, discrete time (rather than continuous time) data analytic procedures were used; specifically, logistic regression models were fit. There were two outcomes of interest examined to answer this research question: driving reduction and driving cessation. Separate models were fit with each of these variables as the outcome. To simplify the description of the procedures, what follows discusses primarily driving cessation only, but the same procedures were used for both outcomes.

Prior to fitting the models, the data were prepared to account for respondents who had censored data or exhibited these behaviors in multiple spells. Respondents who never reported having the ability to drive, or reported that they were unable to drive the first time they were asked that question (exhibiting left-censored data), were excluded from these analyses. The vast majority of people engage in these behaviors as a single spell event. In other words, once they begin to avoid difficult driving situations or give up driving altogether, they do not return to unlimited driving. When multiple spells of these events occurred in the dataset, only the most recent cycle was retained to eliminate the bias that would result from including multiple occurrences with these procedures (Allison, 2010). Finally, a new variable was created that represented the amount of time each person was at risk of driving cessation. This variable identified each respondent’s first wave after age 65 (when they became “at risk” for driving cessation), and calculated the number of successive waves for which they remained in the sample until they left due to driving cessation (or reduction), death, or attrition of some other type.

For all of the respondent-level analyses in this study, regional and zip code level variables were applied to individual respondents. After statistical consultation with an expert, adjusting for the lack of variance introduced by this method was deemed unnecessary because the potential correlation within regions/zip codes was between predictors rather than the outcomes of interest. One simple way to account for this potential issue, however, is to use the regional (or zip code) variable with the cluster option in the SURVEY procedure commands (Allison, 2010). To assess the impact of these different approaches, models with the same variables were fit, alternately using the HRS variable, the UA variable, and the zip code variable in the cluster option. The results of this comparison are shown in Chapter 4 (Table 2). Out of an abundance of caution, the variables that identified the UA or zip code (depending upon whether UMR or GIS variables were in the model) were entered as the cluster variable in the final models.

The New York City metropolitan area is unique in terms of its transportation system. The public transportation system there is the largest in North America, serving roughly 15.1 million people and covering 5,000 square miles (Metropolitan Transportation Authority, 2015). Because many of the primary predictors in this study focused on roadway congestion, there was a concern that the analyses may not show significant effects with the inclusion of the New York City system, given its size and uniqueness. To address this concern, domain variables were created such that one value identified the entire sample, and the other value included the sample without the New York City area. When models were fit and comparisons were made of these two domains, the results were nearly identical. This suggested that the unique nature of New York's transit system was not biasing the overall sample. Consequently, all further analyses included all areas of the country.

The final model was built by adding groups of variables and fitting a series of early models. The first model included only the demographic variables. The next model added several different social support variables to the demographics. Relationship status, having a friend in the neighborhood, the number of people living in one's household, and the number of living children were all significant predictors, and were retained in the final models. Having a child living within 10 miles of one's home and having relatives who live in one's neighborhood were not significant, so these were removed from the final models. When the models were fit with driving reduction as the outcome (as opposed to driving cessation), the original social support variables were added again to assess the possibility that different social support variables might be differentially predictive of these two different outcomes. The same variables were found to be predictive of both outcomes, however, and were retained in the final models. The two different health variables (subjective and objective) were added to the models separately and assessed. Both were highly significant, but the subjective health measure was retained in future models as it was a slightly better predictor. The variable that represented *time at risk* was then added.

As described earlier, there were quite a few different variables that operationalized the transportation environment in different ways. To avoid multicollinearity problems, these variables were added to the models one at a time and analyzed. For each of these, the significance values and parameter estimates for each were compared, and the best predictor of the UMR transportation variables was retained in one set of final models. Likewise, the best predictor of the GIS transportation variables were also retained in another set of final models. Separate final models that included a UMR variable and a GIS variable were fit because these variables were available for different groups of HRS respondents, as discussed earlier (those in the 101 UAs, and the entire sample, respectively).

Although most of the UMR variables were related to driving in a vehicle, there were also variables that assessed public transportation in the region. Those variables were entered into the model as standalone transportation variables, and then also entered along with the best driving-related UMR variable. This process was followed because it was unknown if the public transit variables would explain additional variance in the outcomes of interest, or if they would simply serve as less specific variables related to the transportation environment. The public transportation variables were not retained in the final models because they were not independently significant.

A total of four final models were fit as follows to address the first research goal: 1) driving cessation as the outcome and the GIS transportation variable as the primary predictor, 2) driving cessation as the outcome and the UMR transportation variable as the primary predictor, 3) driving reduction as the outcome and the GIS transportation variable as the primary predictor, and 4) driving reduction as the outcome and the UMR transportation variable as the primary predictor.

Figure 6 shows the basic formula and Figure 7 shows the conceptual model of the variables that were included in these models. Although separate models were fit with the driving cessation and reduction variables as dependent variables, they are shown here together for simplicity. Likewise, the different variables representing the transportation environment are shown here as a generic representation of those constructs.

$$Driving\ reduction/cessation =$$

$$b_0 + b_1(age) + b_2(gender) + b_3(education) + b_4(race) + b_5(relationship\ status) +$$

$$b_6(friend\ in\ neighborhood) + b_7(household\ size) + b_8(no.living\ children) + b_9(health) + b_{10}(vision) +$$

$$b_{11}(time) + b_{12}(trans\ envir)$$

Figure 6. Formula for research goal 1.

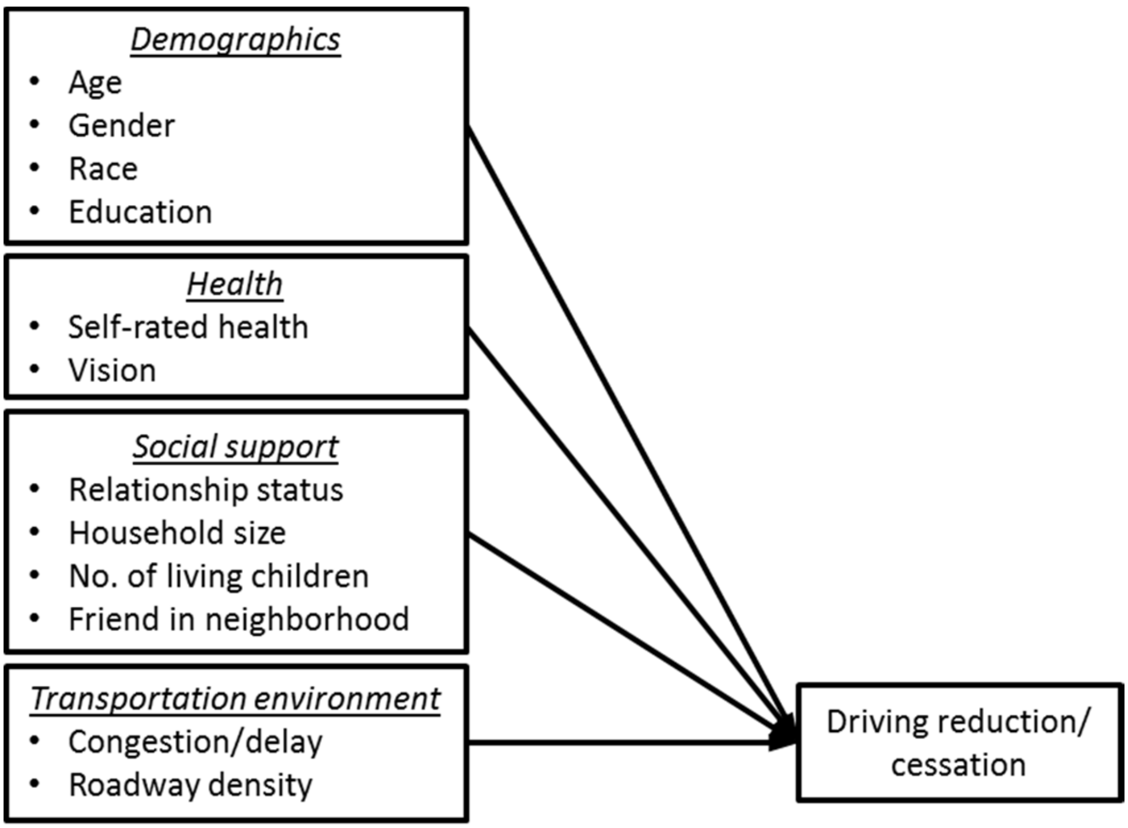

Figure 7. Conceptual model for research goal 1.

Research goal 2

The second research goal was complimentary to the first, but took a regional rather than a respondent-level approach. This hypothesis suggested that *regions* with different levels of transportation mobility would differ from each other in terms of the average driving reduction and cessation behavior of residents in the region. As such, the unit of analysis was regions, operationalized as the Urban Areas, Urban Clusters (UCs), and all other areas (essentially all rural areas were combined together) within which HRS respondents lived. This analysis was cross-sectional, using only the 2010 wave of data.

The first step of this analysis involved calculating weighted percentages of each of the variables of interest within the regions. Variables from the UMR were already calculated at the proper level, so those were not adjusted. The variables that involved counts per zip code (e.g., number of roadway miles per zip code, square miles per zip code) were summed within each of the regions to create region-wide totals. Rates were then calculated for count variables to convert them into rates (e.g., roadway density per region). The two outcome variables of interest were adjusted to represent percentages, and can be interpreted as: the percentage of people within each region who reported the ability to drive, and the percentage of people within each region who reported limiting their driving.

Final models were fit using linear regression procedures with each of these as separate dependent variables. In addition, two sets of analyses were conducted with each outcome using the UMR variables and GIS variables as predictors. UMR variables were only available for the 101 UAs in the UMR sample, but GIS variables were available for UAs, UCs, and rural areas. Independent variables in the final models included age, gender, education, race, relationship status, having friends nearby, number of household residents, number of living children, health, vision, and the transportation environment. As described earlier, the individual and household variables were calculated from HRS data and converted to represent a percentage of each category (classification variables), an average (continuous variables), or a sum within the region.

Figure 8 shows the formula for this model and Figure 9 shows the conceptual model that represents this research goal. Again, the driving cessation and driving reduction variables were dependent variables in separate models, but they are shown here together for simplicity.

$$Percent\ driving\ reduction/cessation\ =$$
$$b_0 + b_1(avg.age) + b_2(percent\ male) + b_3(avg.education) + b_4(percent\ of\ races) +$$
$$b_5(percent\ married/partnered) + b_6(percent\ w/\ friend\ in\ neighborhood) + b_7(avg.household\ size) +$$
$$b_8(avg.no.living\ children) + b_9(avg.health)\ +\ b_{10}(avg.vision) +\ b_{10}(trans\ envir)$$

Figure 8. *Formula for research goal 2.*

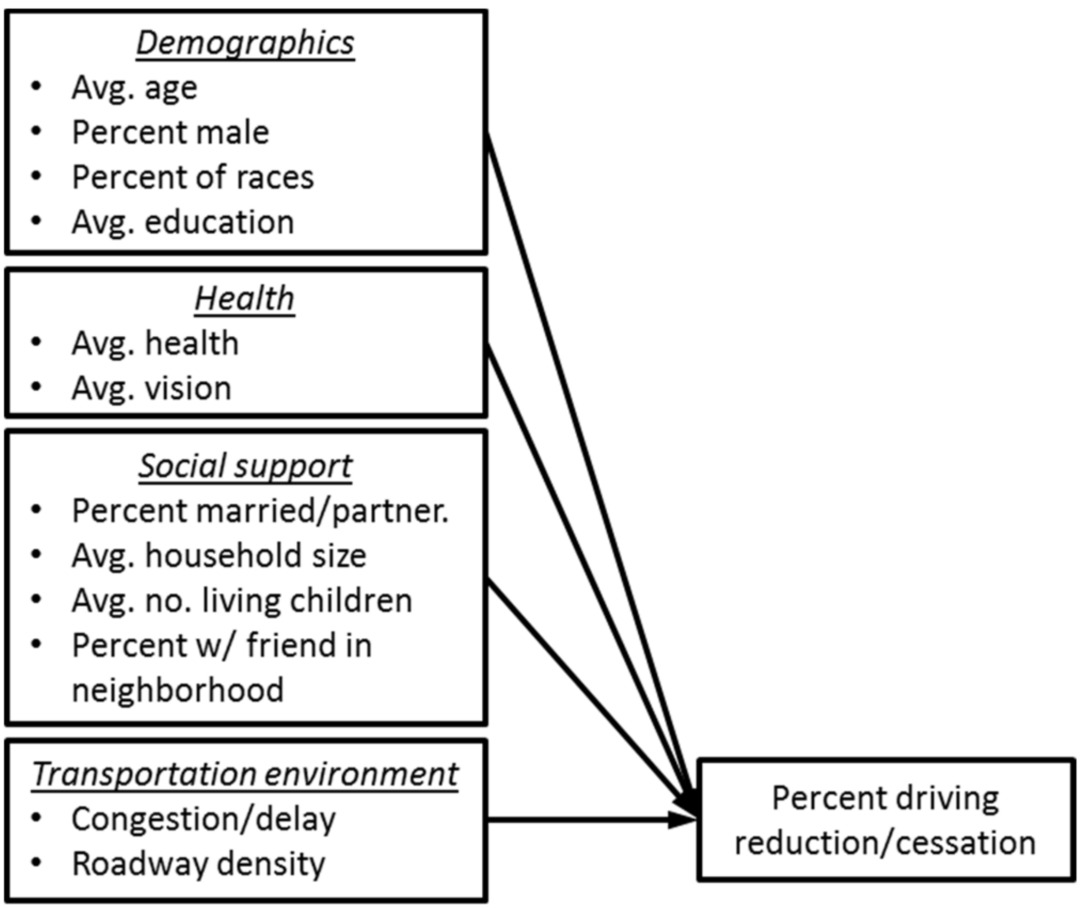

Figure 9. *Conceptual model for research goal 2.*

Research goal 3

This research goal focused on assessing how the transportation environment differentially influenced driving reduction and cessation by gender and race. The same procedures described for the first research goal were used as the starting point for this analysis plan. For a full description, see the *Statistical approach* section for *Research goal 1*. Several additional procedures were then implemented to assess these specific groups. The final models from the first research goal were used as a starting point, to which statistical interactions were added, and which were later stratified by these demographics. All of the models described in this section were fit separately using the best UMR transportation predictor, and then the best GIS-based transportation predictor, as described for *Research goal 1* and using the same sample-related rationale described in that section.

The primary focus of this goal involved assessing the potential statistical interaction between the transportation environment variable and gender for the first part of this goal, and the interaction between the transportation environment and race for the second part. As noted earlier, however, little past research has fully assessed differences in driving reduction and cessation by race, or even by gender. This study provided an excellent opportunity to fill part of that knowledge gap, particularly using longitudinal data from a nationally-representative sample. Consequently, *all* variables in the models were interacted with these demographics to identify any potential differences in these behaviors. As with earlier research goals, these analyses were conducted with driving reduction as the outcome, and then separately with driving cessation as the outcome. For each of these outcomes, models were fit where all independent variables were interacted with gender, and then separately where all variables were interacted with race.

Once the interacted models were complete, the same models were fit without the interactions, but were stratified by gender and then race using domain variables created for that purpose. The stratified models allowed for easier interpretation of the interactions noted in the earlier series of models. The formula in Figure 10 and conceptual model in

Figure 11 illustrate the variables that were included in the interacted analyses. As described earlier, interactions between gender and race were included in separate models but are shown here together for simplicity, and because the rest of the models were identical. Although gender/race were interacted with all variables in the model, only the interactions with the transportation environment are shown in the figures because that was the key issue related to this research goal.

$$Driving\ reduction/cessation =$$
$$b_0 + b_1(age) + b_2(gender\ OR\ race) + b_3(education) + b_4(relationship\ status) +$$
$$b_5(friend\ in\ neighborhood) + b_6(household\ size) + b_7(no.living\ children) + b_8(health) + b_9(vision) +$$
$$b_{10}(time) + b_{11}(trans\ envir) + b_{12}(trans\ envir * gender/race)$$

Figure 10. Formula for research goal 3.

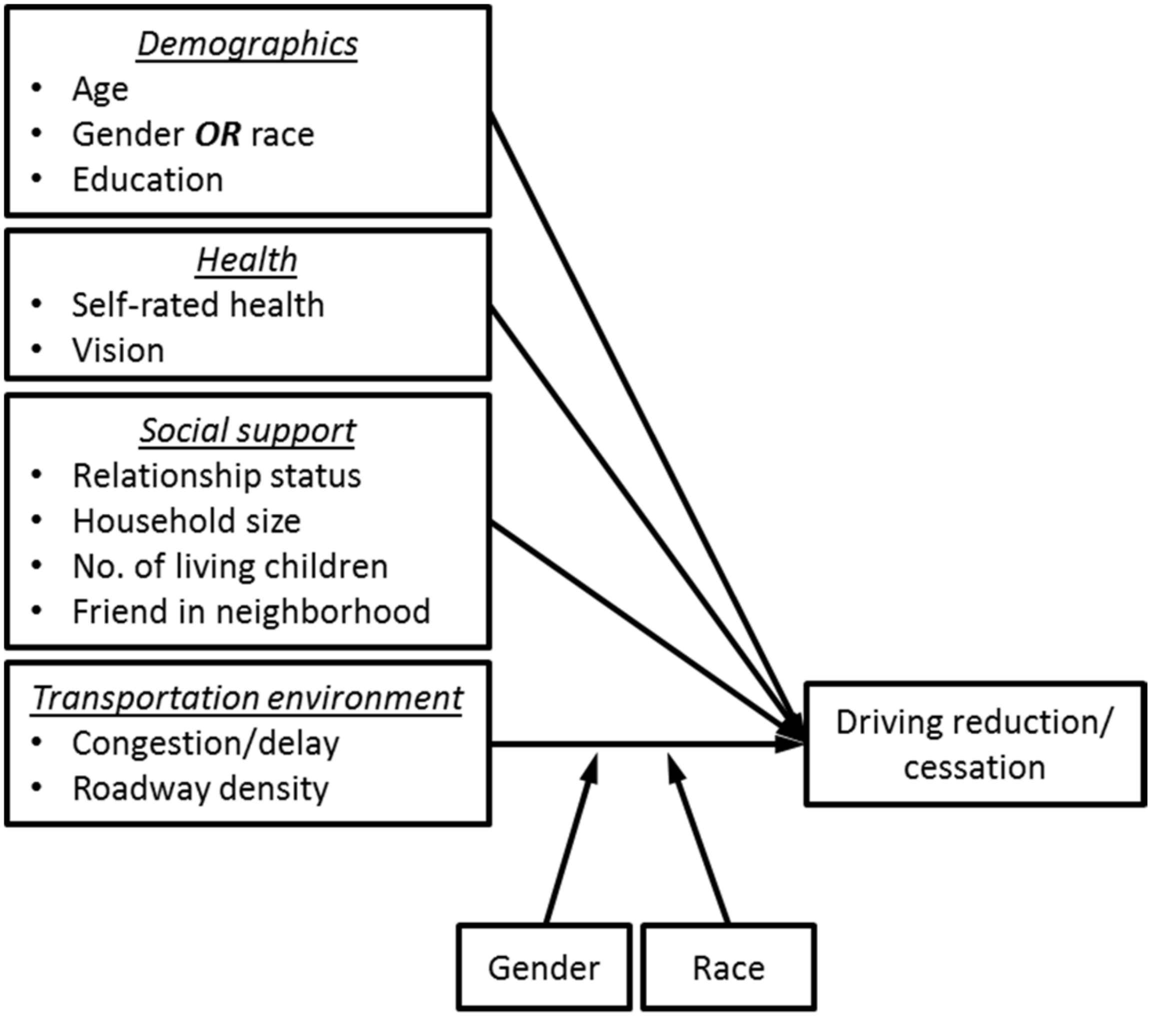

Figure 11. Conceptutal model for research goal 3.

Research goal 4

The outcome of interest related to this research goal was the number of depressive symptoms respondents reported experiencing. Specifically, this variable was a count that ranged from 0-8, and had a Poisson distribution with a mean of 1.59 (weighted mean=1.52). This research goal specifically involved exploring the potential moderation of the transportation environment on the relationship between driving reduction/cessation and depressive symptoms. It also provided an opportunity to use actual data to empirically test the *Environmental Moderator Hypothesis* in this context.

As with earlier analyses, the data analyzed here included complex sampling elements from HRS, but also required longitudinal Poisson regression to address the count data and the potential correlations resulting from repeated subjects (i.e., some respondents appear in the data only once, but most were in the dataset at least twice, and many for all seven waves of data). Unfortunately, a simple procedure does not exist to analyze count-based data while simultaneously accounting for the complex sampling elements and the repeated nature of the data. Two separate methods were compared that account for these issues separately. First, a generalized estimating equation (GEE) procedure was used, which adjusts for the repeated data, but only includes an option to account for survey weights, not for the clustering and stratification elements. Second, a SAS macro was used (developed by Berglund, 2015) that employs the Jackknife Repeated Replicates method to account for the weighting, clustering, and stratification, but does not adjust for repeated data. These methods were both applied separately and compared to each other, as well as to the standard method that does not account for any of these factors. The comparison revealed that although the numbers change slightly, the same conclusions would be reached with either method. Given that similarity, the GEE method was chosen because it was easier to use with multiple imputation of missing data, and it accounts for at least one of the complex sample elements (the survey weights). Because individuals appeared in the dataset for different amounts of time, an offset variable was calculated to use in these Poisson analyses. This variable was created by identifying the amount of time each individual was in the dataset, and then taking the log of that value.

The development of final models for this research goal followed similar procedures to those described for the other research goals. Demographic variables were entered first, followed by social support variables, health, driving variables, and those related to the transportation environment. The driving reduction and cessation variables that served as dependent variables in earlier analyses were included as primary predictors of interest here. The significance of all potential predictors (e.g., all of the original social support variables) was re-assessed throughout this process because the number of depressive symptoms is a very different dependent variable compared to the driving variables assessed earlier. Variables were retained in the final models if they were deemed important due to statistical significance, theory, or the literature in this area. Models were fit separately with driving reduction and driving cessation as predictors because of their relatedness, and because the driving reduction question is only asked of a subset of respondents (those who report the ability to drive). As during earlier analyses, the best UMR and GIS-based transportation variables were selected and retained in separate final models.

Although the primary interaction of interest was between the driving variables and transportation environment, fully interacted models were fit following the same rationale described earlier. Final sets of models included interactions between all variables in the model and the driving cessation (and reduction) variable (one model each for the best UMR and GIS variable). As with earlier analyses, stratified models were also fit to provide more nuanced information, and to allow for easier interpretation of the results. Because the transportation environment variables are continuous (and thus stratification by these variables was not possible), models stratified by driving reduction and driving cessation were fit.

The formula shown in Figure 12 and the conceptual model shown in Figure 13 illustrate the constructs that were used in this phase of the analysis. The formula includes a generic term for variables that were alternately entered into the model (e.g., the driving cessation and driving reduction variables).

$Depressive\ symptoms =$

$b_0 + b_1(age) + b_2(gender) + b_3(education) + b_4(race) + b_5(relationship\ status) +$

$b_6(friend\ in\ neighborhood) + b_7(health) + b_8(vision) + b_9(time) + b_{10}(driving\ reduction/cessation) +$

$b_{11}(trans\ envir) + b_{12}(driving\ reduction/cessation * trans\ envir)$

Figure 12. Formula for research goal 4.

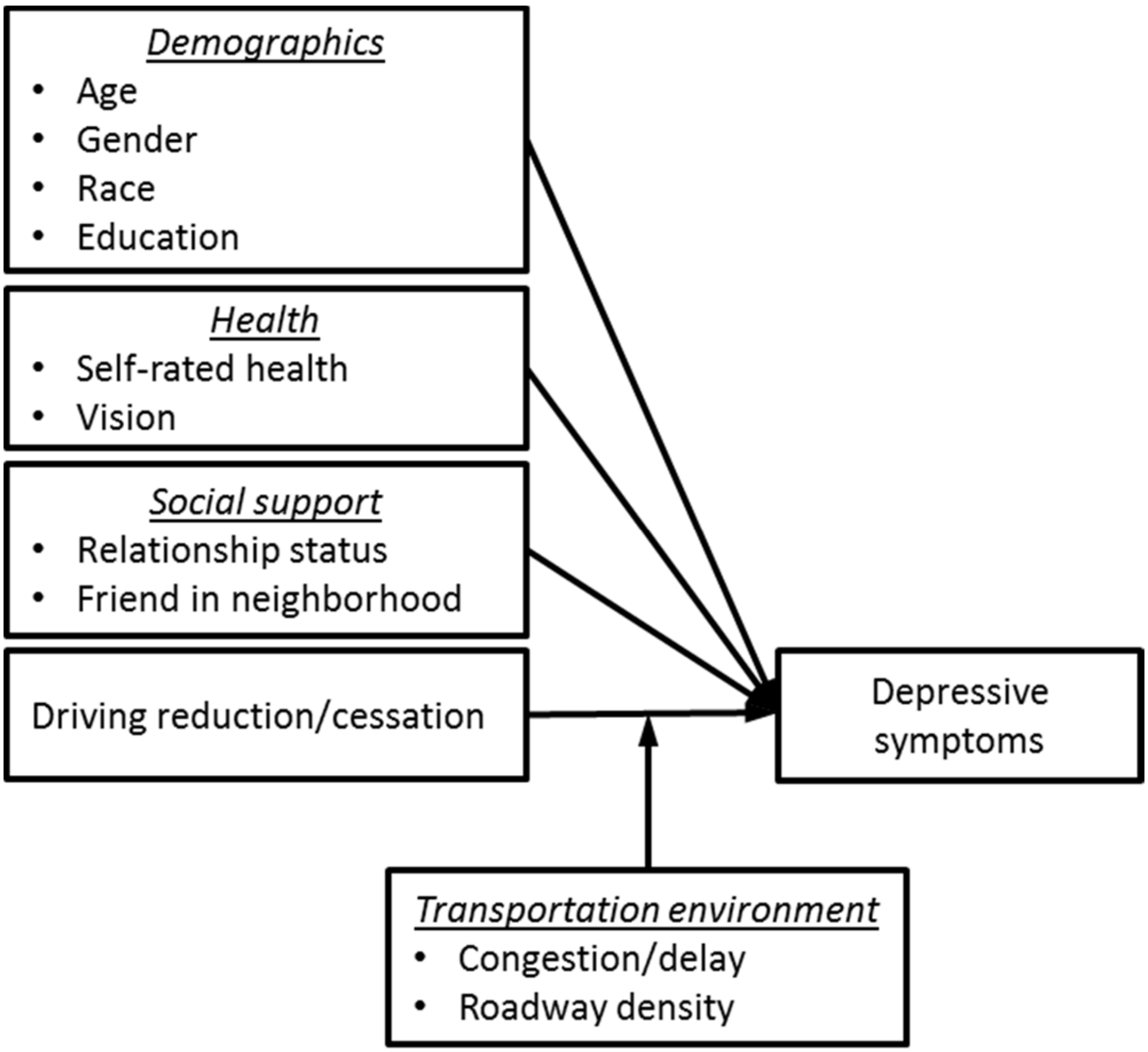

Figure 13. Conceptual model for research goal 4.

CHAPTER 4

RESULTS

Research goal 1

The first research goal focused solely on determining whether or not the transportation environment influenced driving reduction or cessation, after controlling for demographics, health, and social support. As described in Chapter 3, however, before assessing this goal, several models were fit to examine potential differences between using the HRS variable RAESAMP, the UA variable, and the GIS-based zip code variable in the cluster option of the SAS SURVEYLOGISTIC procedure. The results of this comparison are shown in Table 2, which includes the parameter estimates (betas), standard errors (SE), odds ratios (ORs), and statistical significance (*p*-values). Close inspection of the results shows that the parameter estimates and significance levels are nearly identical across the three models, and all conclusions drawn from the results would remain essentially the same. In general, the standard errors increased slightly, as expected, when the UA and GIS variables were used instead of the HRS cluster variable. The estimates calculated using the UA variable were the most different from the other two, but were still very similar. The slightly larger differences observed when using the UA variable may be due to the variance adjustment related to clustering, or it may be because the UA variables were only available for a subsample (domain) of HRS respondents.

Table 2. Comparison of the HRS cluster variable to UA and zip code (driving cessation)

	HRS (RAEHSAMP)			Urban Areas			GIS (zip code)		
	Param. Est.	SE	ORs	Param. Est.	SE	ORs	Param. Est.	SE	ORs
Age (5-years)	0.64***	0.02	1.90	0.64***	0.03	1.90	0.64***	0.02	1.90
Gender (ref=female)									
Male	-0.58***	0.06	0.56	-0.64***	0.07	0.53	-0.58***	0.05	0.56
Education	-0.01	0.01	0.99	-0.01	0.01	0.99	-0.01	0.01	0.99
Race (ref=White)									
Black/AA	0.25**	0.07	1.28	0.24*	0.10	1.27	0.24**	0.08	1.28
Other	0.21	0.22	1.24	0.21	0.37	1.24	0.21	0.20	1.23
Hispanic	0.39***	0.10	1.48	0.53***	0.11	1.70	0.39***	0.11	1.47
Relationship status (ref=marr./partner.)									
Divorced	0.38***	0.08	1.47	0.35**	0.11	1.42	0.39***	0.09	1.47
Widowed	0.36***	0.05	1.44	0.35***	0.08	1.42	0.36***	0.06	1.43
Never married	0.57**	0.19	1.77	0.40	0.25	1.49	0.57**	0.18	1.77
Friend in neighbor.	-0.27***	0.06	0.76	-0.25***	0.07	0.78	-0.27***	0.05	0.76
No. in household	0.36***	0.02	1.43	0.30***	0.04	1.35	0.36***	0.03	1.43
No. of living child.	0.02	0.01	1.02	0.03*	0.01	1.03	0.02	0.01	1.02
Health	0.50***	0.02	1.66	0.52***	0.04	1.68	0.51***	0.03	1.66
Vision	0.37***	0.03	1.46	0.44***	0.04	1.55	0.38***	0.03	1.46
Time	0.08***	0.01	1.08	0.09***	0.02	1.09	0.08***	0.01	1.08

Note. UA = Urban Area; HRS = Health and Retirement Study; GIS = Geographic Information System; SE = standard error; OR = odds ratio.
$*p < 0.05$. $**p < 0.01$. $***p < 0.001$.

The results from the model building process are shown in Table 3 and Table 4, respectively, for driving reduction and driving cessation. These tables include the parameter estimates, standard errors, and odds ratios for each preliminary model. In general, as each new set of variables was added to the model, the parameter estimates for the already included variables diminished slightly, but remained statistically significant. This was expected, and was true for both the driving reduction and driving cessation outcome variables. Across all years studied in these analyses, 21.8% of the sample eventually stopped driving, and 40.5% reported engagment in driving reduction.

Table 3. Preliminary models assessing driving reduction.

	Demographics only			Demographics and social support			Demographics, social support, and health			Demographics, social support, health, and time		
	Param. Est.	SE	ORs	Param. Est.	SE	ORs	Param. Est.	SE	ORs	Param. Est.	SE	ORs
Age (5-years)	0.56***	0.02	1.75	0.55***	0.02	1.74	0.54***	0.02	1.72	0.49***	0.02	1.63
Gender (ref=female)												
Male	-0.62***	0.05	0.54	-0.53***	0.05	0.59	-0.62***	0.05	0.54	-0.62***	0.05	0.54
Education	-0.09***	0.01	0.91	-0.09***	0.01	0.91	-0.06***	0.01	0.94	-0.06***	0.01	0.94
Race (ref=White)												
Black/AA	0.54***	0.06	1.71	0.44***	0.06	1.55	0.36***	0.07	1.44	0.37***	0.07	1.45
Other	0.59**	0.19	1.80	0.56**	0.18	1.75	0.52**	0.19	1.68	0.53**	0.19	1.70
Hispanic	0.45***	0.08	1.57	0.40***	0.07	1.49	0.31***	0.08	1.36	0.32***	0.08	1.38
Relationship status (ref=marr./partner.)												
Divorced				0.41***	0.07	1.51	0.36***	0.07	1.42	0.35***	0.07	1.43
Widowed				0.36***	0.05	1.44	0.32***	0.05	1.38	0.34***	0.05	1.40
Never married				0.60***	0.14	1.82	0.56***	0.15	1.75	0.56***	0.15	1.75
Friend in neighbor.				-0.11*	0.04	0.90	-0.07	0.04	0.94	-0.06	0.04	0.94
No. in household				0.10**	0.04	1.10	0.07	0.04	1.07	0.07	0.04	1.07
No. of living child.				0.01	0.01	1.01	0.01	0.01	1.01	0.01	0.01	1.01
Health							0.39***	0.02	1.47	0.39***	0.02	1.48
Vision							0.20***	0.03	1.22	0.20***	0.03	1.23
Time										0.08***	0.01	1.08

Note. SE = standard error; OR = odds ratio.
*p < 0.05. **p < 0.01. ***p < 0.001.

Table 4. Preliminary models assessing driving cessation.

	Demographics only			Demographics and social support			Demographics, social support, and health			Demographics, social support, health, and time		
	Param. Est.	SE	ORs	Param. Est.	SE	ORs	Param. Est.	SE	ORs	Param. Est.	SE	ORs
Age (5-years)	0.69***	0.02	2.00	0.72***	0.02	2.05	0.69***	0.02	1.99	0.64***	0.02	1.90
Gender (ref=female)												
Male	-0.53***	0.05	0.59	-0.51***	0.05	0.60	-0.59***	0.05	0.55	-0.58***	0.06	0.56
Education	-0.06***	0.01	0.94	-0.05***	0.01	0.95	-0.01	0.01	0.99	-0.01	0.01	0.99
Race (ref=White)												
Black/AA	0.54***	0.07	1.71	0.37***	0.07	1.44	0.24**	0.07	1.28	0.25**	0.07	1.28
Other	0.42	0.22	1.53	0.24	0.22	1.27	0.22	0.21	1.25	0.21	0.22	1.24
Hispanic	0.71***	0.09	2.03	0.52***	0.09	1.68	0.40***	0.10	1.49	0.39***	0.10	1.48
Relationship status (ref=marr./partner.)												
Divorced				0.52***	0.09	1.69	0.40***	0.07	1.50	0.38***	0.08	1.47
Widowed				0.42***	0.06	1.52	0.36***	0.05	1.43	0.36***	0.05	1.44
Never married				0.64***	0.18	1.90	0.59**	0.18	1.81	0.57**	0.19	1.77
Friend in neighbor.				-0.35***	0.06	0.71	-0.28***	0.06	0.75	-0.27***	0.06	0.76
No. in household				0.39***	0.03	1.48	0.36***	0.02	1.44	0.36***	0.02	1.43
No. of living child.				0.02	0.01	1.02	0.02*	0.01	1.02	0.02	0.01	1.02
Health							0.50***	0.02	1.65	0.50***	0.02	1.66
Vision							0.38***	0.03	1.46	0.37***	0.03	1.46
Time										0.08***	0.01	1.08

Note. SE = standard error; OR = odds ratio.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Table 5 contains the results of the final models related to driving reduction. As noted earlier, the UMR variables were only available for a subset of the HRS sample. Consequently, separate models were fit (using separate domain variables) when a UMR transportation variable was included as a predictor, and when a GIS transportation variable was included. The key predictors of interest here were the transportation environment variables. All of the estimates for both models (UMR and GIS samples) are included throughout this document for two reasons: 1) the estimates for the other variables in the model could change depending upon which variable related to the transportation environment was included, and most importantly, 2) the UMR variables were available for a subset of HRS respondents only, while the GIS variables were available for the full sample. A comparison of the estimates of the control variables (Table 5) reveals that in general, the differences between the UMR and GIS sample are minor. Most of the same conclusions would be drawn from either, but they are not identical. In order to provide a complete reporting of these analyses, the estimates for both samples are included here, as well as throughout the remainder of the results.

Table 5 shows that, as expected, increasing age was one of the most important predictors of driving reduction. For every five-year increase in age, the odds of driving reduction increased by 64% in the GIS sample, and 67% in the UMR sample ($p<0.001$ for both). Gender was also a key predictor of driving reduction, with male gender showing a protective effect (OR=0.53, $p<0.001$ in the full sample). Less education (OR=0.93, $p<0.001$) and increasing time at risk (OR=1.08 $p<0.001$) both significantly increased the odds of driving reduction, but only had small effects on this outcome; worse health (OR=1.48, $p<0.001$) and worse vision (OR=1.23, $p<0.001$) both had substantial influence on the odds of driving reduction. More people living in one's household slightly increased the odds of driving reduction in the GIS sample, but was not significant in the UMR sample. Having a friend in the neighborhood was not a significant predictor of driving reduction in either sample. Given that the driving reduction variable analyzed here was specifically related to taking long trips, it follows that having a friend who lives nearby would not necessarily be related to this outcome.

Race and relationship status were also found to be significant predictors of driving reduction. White respondents were much less likely to engage in driving reduction compared to people in the other three racial categories. Specifically, the odds were highest for those of Other race (OR=1.82; UMR sample), followed by African Americans (OR=1.49), and Hispanics (OR=1.27). In terms of relationship status, being married was highly protective against driving reduction. People who were divorced, widowed, or never married all had much higher odds of reducing their driving compared to married or partnered respondents (ORs=1.40, 1.39, 1.69, respectively in the full sample).

As described earlier, each of the UMR and GIS variables were added to the model individually, and the best predictor from each of these sets of variables was retained in the final models. Although most of the UMR variables were not significant predictors of driving reduction, the Travel Time Index was a strong predictor of this outcome. Among the GIS variables, overall Roadway Density was the strongest predictor from several that were also significant (e.g., ratio of limited access to non-limited access roadway miles, number of exit ramps, and roadway density for limited/non-limited access roads). These results indicate that as travel time in a given area increases, the odds of driving reduction also increase. Likewise, as roadway density increases, the odds of driving reduction increase. These results support the first research goal, specifically in the direction predicted by Hypothesis 1. It should also be noted that the parameter estimates and odds ratios for these two environmental variables were quite different from each other. This difference resulted from the fact that the underlying scales on which these variables were based were very different. The Travel Time Index was a relatively small scale (values in the dataset ranged from 1.03 to 1.42 on this variable), while the Roadway Density scale was quite large (it ranged from 0 to 26.80). Consequently, one-unit increases in these scales represented very different changes to the transportation environment.

Table 5. Final models assessing driving reduction.

	UMR variable (subsample)					GIS variable (full sample)				
	Param. Est.	SE	ORs	OR 95% CI		Param. Est.	SE	ORs	OR 95% CI	
				Low	Upp				Low	Upp
Age (5-years)	0.51***	0.02	1.67	1.60	1.75	0.49***	0.02	1.64	1.58	1.70
Gender (ref=fem.)										
Male	-0.61***	0.06	0.54	0.48	0.62	-0.64***	0.04	0.53	0.49	0.58
Education	-0.08***	0.01	0.93	0.91	0.94	-0.07***	0.01	0.93	0.92	0.95
Race (ref=White)										
Black/AA	0.40***	0.07	1.49	1.31	1.71	0.32***	0.07	1.38	1.20	1.59
Other	0.60**	0.21	1.82	1.20	2.76	0.56**	0.18	1.75	1.23	2.50
Hispanic	0.24*	0.10	1.27	1.03	1.55	0.30**	0.09	1.35	1.13	1.61
Relationship status (ref=marr./partner.)										
Divorced	0.28**	0.09	1.32	1.10	1.58	0.34***	0.08	1.40	1.20	1.63
Widowed	0.35***	0.09	1.42	1.20	1.69	0.33***	0.06	1.39	1.24	1.55
Never married	0.56*	0.23	1.76	1.12	2.77	0.53**	0.16	1.69	1.23	2.34
Friend in neighbor.	-0.03	0.05	0.97	0.87	1.08	-0.05	0.04	0.95	0.86	1.03
No. in household	0.03	0.04	1.03	0.95	1.11	0.07*	0.03	1.07	1.01	1.14
No. of living child.	0.00	0.01	1.00	0.97	1.03	0.01	0.01	1.01	0.99	1.03
Health	0.37***	0.03	1.45	1.35	1.55	0.29***	0.02	1.48	1.42	1.55
Vision	0.21***	0.03	1.23	1.15	1.32	0.21***	0.02	1.23	1.17	1.29
Time	0.09***	0.02	1.09	1.05	1.13	0.08***	0.01	1.08	1.06	1.10
Transport environ.										
TT Index	0.81*	0.36	2.26	1.10	4.65					
Road density						0.03**	0.01	1.03	1.01	1.04

Note. UMR = Urban Mobility Report; GIS = Geographic Information System; SE = standard error; OR = odds ratio. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

The results of the driving cessation analysis are shown in Table 6. As expected, many of the same predictors of driving reduction were similarly predictive of driving cessation. Indeed, increasing age, female gender, less education, non-married/partnered relationship status, worse health, worse vision, and increasing time at risk were all significant predictors of increased odds of both outcomes. Race was also an important predictor of driving cessation, but had a smaller effect on this outcome than for driving reduction. White respondents were significantly less likely than African Americans or Hispanics to engage in driving cessation. Specifically, the OR for driving cessation among African Americans was 1.26 compared to Whites ($p<0.05$; UMR sample), and was 1.56 for Hispanics compared to Whites ($p<0.001$). Interestingly, the number of people who live in one's household was highly predictive of driving cessation, and had a fairly large effect, in both the UMR and GIS sample (OR=1.34 and 1.43, respectively, $p<0.001$ for both). Recall that household size was only predictive of driving reduction for the full GIS sample, and its influence was quite small (OR=1.07). Having a friend in one's neighborhood was significantly protective against driving cessation (UMR OR=0.78, GIS OR=0.77), while it did not predict driving reduction.

In terms of the transportation environment, nearly all UMR variables and size-adjusted GIS variables were significantly predictive of this outcome. The strongest UMR predictor of driving cessation was the Roadway Congestion Index variable, while the Roadway Density variable was the strongest GIS predictor. Specifically, as roadway congestion or roadway density increased, the odds of driving cessation also increased, even after controlling for the effects of demographic differences, social support, and health. These results provide support for the first research goal and for Hypothesis 1 specifically.

Table 6. Final models assessing driving cessation.

	UMR variable (subsample)					GIS variable (full sample)				
	Param. Est.	SE	ORs	OR 95% CI		Param. Est.	SE	ORs	OR 95% CI	
				Low	Upp				Low	Upp
Age (5-years)	0.64***	0.03	1.90	1.79	2.01	0.64***	0.02	1.89	1.82	1.98
Gender (ref=female)	-									
Male	0.64***	0.07	0.53	0.46	0.60	-0.58***	0.05	0.56	0.50	0.62
Education	-0.02	0.01	0.98	0.96	1.00	-0.02	0.01	0.98	0.96	1.00
Race (ref=White)										
Black/AA	0.23*	0.10	1.26	1.03	1.54	0.17*	0.08	1.19	1.02	1.39
Other	0.16	0.36	1.17	0.57	2.39	0.21	0.20	1.24	0.83	1.85
Hispanic	0.45***	0.12	1.56	1.23	1.99	0.31**	0.11	1.36	1.09	1.69
Relationship status (ref=marr./partner.)										
Divorced	0.34**	0.11	1.41	1.14	1.74	0.37***	0.09	1.45	1.21	1.75
Widowed	0.34***	0.08	1.41	1.21	1.64	0.35***	0.06	1.42	1.26	1.60
Never married	0.41	0.25	1.51	0.92	2.49	0.56**	0.19	1.75	1.20	2.56
Friend in neighbor.	-0.24**	0.07	0.78	0.67	0.90	-0.26***	0.05	0.77	0.69	0.85
No. in household	0.29***	0.04	1.34	1.24	1.45	0.35***	0.03	1.43	1.34	1.52
No. of living child.	0.03*	0.01	1.03	1.00	1.06	0.02	0.01	1.02	1.00	1.04
Health	0.52***	0.04	1.69	1.57	1.81	0.51***	0.03	1.66	1.58	1.75
Vision	0.43***	0.04	1.55	1.44	1.67	0.38***	0.03	1.47	1.38	1.56
Time	0.09***	0.02	1.10	1.06	1.13	0.08***	0.01	1.09	1.06	1.11
Transport environ.										
RCI	0.54***	0.13	1.72	1.33	2.23					
Road density						0.03***	0.01	1.03	1.01	1.06

Note. UMR = Urban Mobility Report; GIS = Geographic Information System; SE = standard error; OR = odds ratio.
**p* < 0.05. ***p* < 0.01. ****p* < 0.001.

Research goal 2

The second research goal also assessed the influence of the built environment on driving reduction and cessation, but did so at the regional level using only cross-sectional data. Table 7 includes the parameter estimates, standard errors, and statistical significance for the driving reduction and driving cessation outcomes, including both the UMR and GIS transportation environment variables. These results show some of the same patterns identified in the previous analyses, but also some differences, with much more variance throughout. The variables related to the transportation environment were not found to be significant predictors of driving reduction or cessation, so these results do not lend support to Hypothesis 2.

Table 7. Final regional models assessing driving cessation.

	UMR variable (subsample)				GIS variable (full sample)			
	Reduction		Cessation		Reduction		Cessation	
	Param. Est.	SE	Param. Est.	SE	Param. Est.	SE	Param. Est.	SE
Age (5-years)	-6.27*	2.82	-2.68	2.26	5.17***	1.40	-7.56***	0.86
Gender (ref=female)								
Male	20.20	16.11	17.33	13.55	-17.37***	5.01	10.15**	3.37
Education	-1.20	1.81	-0.64	1.51	-3.52***	0.66	0.55	0.45
Race (ref=White)								
Black/AA	-8.00	12.19	29.04*	12.03	7.62	7.05	-5.09	4.70
Other	-57.97	34.15	-74.00***	16.80	1.17	15.59	-16.78	9.51
Hispanic	8.89	10.82	-20.97	10.60	-8.79	7.83	-19.68***	5.18
Relationship status								
Married/partner	-29.44	15.77	26.66*	12.66	-6.89	4.47	7.72**	2.97
Friend in neighbor.	39.18***	9.72	5.82	8.82	-1.10	3.65	2.57	2.50
No. in household	-13.37	7.59	-1.87	4.86	2.60	2.77	-4.65**	1.70
No. of living child.	-4.64*	1.77	3.68*	1.61	0.11	0.79	0.32	0.54
Health	16.91**	5.19	-5.01	4.62	5.89**	1.95	-3.60**	1.31
Vision	-1.48	4.86	-11.77**	4.41	2.00	2.25	-4.22**	1.46
Transport environ.								
RCI	-7.82	10.69	16.40	10.75				
Road density					1.20	1.45	-0.36	1.03

Note. UMR = Urban Mobility Report; GIS = Geographic Information System; SE = standard error.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Research goal 3

The third research goal focused on potential differences in how gender and race affect the relationship between the transportation environment and driving reduction/cessation. Fully interacted models and models stratified by gender/race were fit, and those results are included in the tables in this section.

Gender and driving reduction

The results related to gender and driving reduction are shown in Table 8 (with the UMR variable) and Table 9 (with the GIS variable). Significant interactions were observed between gender and relationship status in models that included both the UMR and GIS variables. Compared to being married/partnered, individuals who were never married displayed significantly increased odds of driving reduction. However, this effect was only observed for men, who had odds ratios of 3.08 and 2.96 for the UMR and GIS samples, respectively. In addition, a significant gender interaction was also observed in the GIS sample comparing married respondents to those who were divorced. The odds of driving reduction were significantly higher for divorced men compared to married men (OR=1.72, $p<0.001$), but this was not true for divorced women compared to married women (OR=1.19, n.s.).

In the UMR sample, a significant interaction was observed between gender and age. Examination of the results from the stratified models show that increasing age is significantly predictive for both genders, but it seems to affect women's driving reduction (OR=1.77, $p<0.001$) more than men's (OR=1.61, $p<0.001$). There was also a significant interaction between gender and health in the GIS model. Again, worse health is highly predictive of driving reduction for both men and women ($p<0.001$ for both), but was more so for men (OR=1.57 for men compared to 1.40 for women).

The primary interaction of interest in this part of the analysis was between gender and the transportation environment. Although the interaction term between gender and the Travel Time Index was not significant, the stratified models showed that this variable was significantly predictive of driving reduction among men (OR=3.31, $p<0.05$), but not women (OR=1.41, n.s.). The Roadway Density variable revealed a similar pattern, and the interaction term *was* statistically significant in that model ($p<0.05$). The stratified models for the GIS sample showed a highly significant effect for men ($p<0.001$), but not for women. Overall, these results provide support for the contention that the transportation environment affects driving reduction differently based upon gender, as suggested in Research goal 3. Interestingly, however, the result is in the opposite direction from the hypothesized relationship; the transportation environment affects only men's driving reduction.

Gender and driving cessation

Table 10 shows the fully interacted and stratified models related to gender and driving cessation with the UMR variable, and Table 11 shows the same relationships with the GIS variable. Once again, there was a significant interaction between relationship status and gender. Being married/partnered was significantly protective of driving cessation for men, but not for women. Compared to married/partnered men in the UMR model, the odds ratio for divorced men was 2.10 ($p<0.01$), for widowed men was 1.88 ($p<0.001$), and was 2.61 for men who were never married ($p<0.05$). None of these were significant predictors of driving cessation for women, and the ORs were all close to one. In the GIS model, the interaction term with gender and relationship status was significant for those who were widowed or never married, and was marginally significant for divorced individuals. The stratified models showed that marriage was highly protective for men compared to each of these other relationships (ORs=1.79, 1.74, and

2.65, for divorced, widowed, and never married, respectively). Among women, being married or partnered was only protective against driving cessation compared to those who were widowed (OR=1.23, $p<0.01$).

Other comparisons revealed that in the GIS model, age and gender significantly interacted. Specifically, increasing age was highly significant for both men and women ($p<0.001$), but aging seems to affect women even more than men (OR=1.97 for women, compared to 1.80 for men). The same pattern was observed in the UMR model, but the interaction term was only marginally significant. The interaction between gender and education was also marginally significant in the UMR model, and the stratified models showed that more education was only significantly protective for women ($p<0.05$), with only a very small effect (OR=0.96).

The interactions between gender and the transportation environment variables were not statistically significant for either the UMR or GIS variables. However, the stratified models showed that an increase in the Roadway Congestion Index was highly predictive of driving cessation for men (OR=2.16, $p<0.001$), and only somewhat predictive of driving cessation for women (OR=1.48, $p<0.05$). The ORs for the GIS variable (Roadway Density) were very similar in scope and significance for both men and women. Collectively, there was not clear support here for the third research goal, but there was evidence that the transportation environment may affect men's engagement in driving cessation to a greater extent than women's. This pattern was similar to the results observed for driving reduction.

Table 8. Interacted and stratified models: gender differences in driving reduction (UMR).

	Fully interacted model			Stratified models: Men					Stratified models: Women				
	Param. Est.	SE	OR	Param. Est.	SE	OR	OR 95% CIs Lower	OR 95% CIs Upper	Param. Est.	SE	OR	OR 95% CIs Lower	OR 95% CIs Upper
Age (5-years)	0.57***	0.04	1.77	0.48***	0.03	1.61	1.52	1.71	0.57***	0.04	1.77	1.64	1.91
Gender (ref=female)													
Male	-0.88	1.11	0.41										
Education	-0.09***	0.02	0.92	-0.07***	0.01	0.93	0.91	0.96	-0.09***	0.02	0.92	0.89	0.95
Race (ref=White)													
Black/AA	0.32**	0.11	1.37	0.54***	0.11	1.72	1.37	2.15	0.32**	0.11	1.37	1.09	1.73
Other	0.52†	0.27	1.68	0.67**	0.25	1.95	1.19	3.20	0.52†	0.27	1.68	0.97	2.91
Hispanic	0.29*	0.13	1.33	0.22	0.14	1.25	0.94	1.66	0.29*	0.13	1.33	1.02	1.74
Relationship status (ref=married)													
Divorced	0.17	0.12	1.18	0.44**	0.16	1.55	1.13	2.14	0.17	0.12	1.18	0.93	1.50
Widowed	0.28**	0.10	1.32	0.40**	0.13	1.49	1.15	1.94	0.28**	0.10	1.32	1.08	1.62
Never married	-0.01	0.22	0.99	1.12***	0.32	3.08	1.62	5.85	-0.01	0.22	0.99	0.64	1.53
Friend in neighbor.	0.03	0.08	1.03	-0.10	0.08	0.90	0.77	1.05	0.03	0.08	1.03	0.87	1.22
No. in household	0.02	0.06	1.02	0.06	0.06	1.06	0.94	1.20	0.02	0.06	1.02	0.91	1.15
No. of living child.	-0.01	0.02	0.99	0.00	0.02	1.00	0.96	1.04	-0.01	0.02	0.99	0.96	1.03
Health	0.34***	0.05	1.40	0.40***	0.04	1.49	1.37	1.63	0.34***	0.05	1.40	1.27	1.55
Vision	0.20***	0.05	1.22	0.22***	0.04	1.25	1.14	1.37	0.20***	0.05	1.22	1.10	1.34
Time	0.07**	0.03	1.08	0.10***	0.02	1.10	1.06	1.15	0.07**	0.03	1.08	1.02	1.13
Transport environ.													
TT Index	0.35	0.39	1.41	1.20*	0.58	3.31	1.04	10.48	0.35	0.39	1.41	0.65	3.06
Male*age	-0.09*	0.05	0.91										
Male*education	0.02	0.02	1.02										
Male*race													
Black/AA	0.22	0.18	1.25										
Other	0.15	0.32	1.16										
Hispanic	-0.06	0.19	0.94										
Male*relationship													
Divorced	0.27	0.21	1.32										
Widowed	0.12	0.14	1.13										
Never married	1.14**	0.37	3.11										
Male*friend	-0.14	0.12	0.87										
Male*no. in house	0.04	0.09	1.04										

Male*no. children	0.01	0.03	1.01
Male*health	0.06	0.06	1.06
Male*vision	0.03	0.06	1.03
Male*time	0.02	0.03	1.02
Male*transport			
TT Index	0.85	0.67	2.34

Note. UMR = Urban Mobility Report; SE = standard error; OR = odds ratio.
†*p* < 0.10. **p* < 0.05. ***p* < 0.01. ****p* < 0.001.

Table 9. Interacted and stratified models: gender differences in driving reduction (GIS).

	Fully interacted model			Stratified models									
				Men					Women				
	Param. Est.	SE	OR	Param. Est.	SE	OR	OR 95% CIs Lower	OR 95% CIs Upper	Param. Est.	SE	OR	OR 95% CIs Lower	OR 95% CIs Upper
Age (5-years)	0.51***	0.03	1.67	0.48***	0.03	1.62	1.54	1.70	0.51***	0.03	1.67	1.59	1.77
Gender (ref=female)													
Male	-0.81	0.65	0.45										
Education	-0.07***	0.01	0.93	-0.07***	0.01	0.94	0.92	0.95	-0.07***	0.01	0.93	0.91	0.96
Race (ref=White)													
Black/AA	0.30**	0.10	1.35	0.38***	0.10	1.47	1.21	1.79	0.30**	0.10	1.35	1.09	1.65
Other	0.66**	0.24	1.94	0.52*	0.23	1.69	1.06	2.69	0.66**	0.24	1.94	1.20	3.14
Hispanic	0.33*	0.13	1.39	0.28*	0.12	1.32	1.04	1.67	0.33*	0.13	1.39	1.08	1.79
Relationship status (ref=married)													
Divorced	0.18†	0.10	1.19	0.54***	0.12	1.72	1.36	2.19	0.18†	0.10	1.19	0.97	1.47
Widowed	0.24**	0.07	1.27	0.41***	0.09	1.51	1.26	1.82	0.24**	0.07	1.27	1.11	1.46
Never married	-0.03	0.21	0.97	1.08***	0.23	2.96	1.87	4.67	-0.03	0.21	0.97	0.64	1.48
Friend in neighbor.	-0.06	0.06	0.94	-0.05	0.06	0.95	0.83	1.08	-0.06	0.06	0.94	0.84	1.06
No. in household	0.04	0.04	1.04	0.11*	0.05	1.11	1.01	1.22	0.04	0.04	1.04	0.96	1.14
No. of living child.	0.01	0.01	1.01	0.01	0.01	1.01	0.99	1.04	0.01	0.01	1.01	0.98	1.04
Health	0.34***	0.03	1.40	0.45***	0.03	1.57	1.47	1.66	0.34***	0.03	1.40	1.32	1.49
Vision	0.21***	0.03	1.23	0.21***	0.03	1.23	1.15	1.31	0.21***	0.03	1.23	1.15	1.32
Time	0.07***	0.02	1.08	0.08***	0.02	1.08	1.05	1.12	0.07***	0.02	1.08	1.04	1.11
Transport environ.													
Road density	0.01	0.01	1.01	0.04***	0.01	1.04	1.02	1.07	0.01	0.01	1.01	0.98	1.03
Male*age	-0.03	0.04	0.97										

Male*education	0.00	0.02	1.00
Male*race			
Black/AA	0.09	0.14	1.09
Other	-0.14	0.32	0.87
Hispanic	-0.05	0.17	0.95
Male*relationship			
Divorced	0.37*	0.16	1.44
Widowed	0.17	0.11	1.19
Never married	1.11***	0.31	3.04
Male*friend	0.01	0.09	1.01
Male*no. in house	0.06	0.06	1.07
Male*no. children	0.00	0.02	1.00
Male*health	0.11*	0.04	1.12
Male*vision	0.00	0.05	1.00
Male*time	0.01	0.02	1.01
Male*transport			
Road density	0.04*	0.02	1.04

Note. GIS = Geographic Information System; SE = standard error; OR = odds ratio.
†$p < 0.10$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Table 10. Interacted and stratified models: gender differences in driving cessation (UMR).

	Fully interacted model			Stratified models									
				Men					Women				
	Param. Est.	SE	OR	Param. Est.	SE	OR	OR 95% CIs Lower	OR 95% CIs Upper	Param. Est.	SE	OR	OR 95% CIs Lower	OR 95% CIs Upper
Age (5-years)	0.69***	0.04	1.99	0.59***	0.43	1.79	1.65	1.96	0.69***	0.04	1.99	1.85	2.14
Gender (ref=female)													
Male	-0.43	0.95	0.65										
Education	-0.04*	0.02	0.96	0.00	0.02	1.00	0.97	1.04	-0.04*	0.02	0.96	0.93	0.99
Race (ref=White)													
Black/AA	0.21	0.13	1.23	0.30*	0.14	1.35	1.02	1.79	0.21	0.13	1.23	0.95	1.60
Other	0.58	0.51	1.79	-0.49	0.55	0.61	0.20	1.82	0.58	0.51	1.79	0.65	4.94
Hispanic	0.41*	0.15	1.50	0.49**	0.15	1.64	1.22	2.21	0.41*	0.15	1.50	1.10	2.05
Relationship status (ref=married)													
Divorced	0.08	0.13	1.09	0.74**	0.22	2.10	1.36	3.25	0.08	0.13	1.09	0.84	1.40
Widowed	0.13	0.09	1.14	0.63***	0.16	1.88	1.37	2.57	0.13	0.09	1.14	0.94	1.37
Never married	0.01	0.28	1.01	0.96*	0.39	2.61	1.18	5.80	0.01	0.28	1.01	0.58	1.78
Friend in neighbor.	-0.25**	0.09	0.78	-0.26*	0.10	0.77	0.63	0.95	-0.25**	-0.09	0.78	0.65	0.92
No. in household	0.23***	0.06	1.26	0.40***	0.07	1.49	1.30	1.71	0.23***	0.06	1.26	1.13	1.41
No. of living child.	0.03	0.02	1.03	0.05*	0.02	1.05	1.01	1.09	0.03	0.02	1.03	0.98	1.07
Health	0.57***	0.05	1.76	0.47***	0.06	1.59	1.40	1.81	0.57***	0.05	1.76	1.60	1.94
Vision	0.43***	0.04	1.53	0.46***	0.06	1.59	1.40	1.80	0.43***	0.04	1.53	1.41	1.67
Time	0.09***	0.02	1.09	0.10***	0.03	1.11	1.05	1.17	0.09***	0.02	1.09	1.05	1.13
Transport environ.													
RCI	0.39*	0.16	1.48	0.76***	0.21	2.16	1.41	3.31	0.39*	0.16	1.48	1.08	2.04
Male*age	-0.10†	0.05	0.90										
Male*education	0.04†	0.02	1.04										
Male*race													
Black/AA	0.09	0.19	1.10										
Other	-1.07	0.74	0.34										
Hispanic	0.09	0.19	1.09										
Male*relationship													
Divorced	0.65*	0.27	1.93										
Widowed	0.50*	0.20	1.65										
Never married	0.95†	0.48	2.58										
Male*friend	0.00	0.12	1.00										
Male*no. in house	0.17†	0.09	1.18										

Male*no. children	0.02	0.03	1.02
Male*health	-0.10	0.08	0.90
Male*vision	0.04	0.08	1.04
Male*time	0.02	0.03	1.02
Male*transport			
RCI	0.38	0.26	1.46

Note. UMR = Urban Mobility Report; SE = standard error; OR = odds ratio.
†*p* < 0.10. **p* < 0.05. ***p* < 0.01. ****p* < 0.001.

Table 11. Interacted and stratified models: gender differences in driving cessation (GIS).

	Fully interacted model			Stratified models										
				Men					Women					
	Param. Est.	SE	OR	Param. Est.	SE	OR	OR 95% CIs Lower	OR 95% CIs Upper	Param. Est.	SE	OR	OR 95% CIs Lower	OR 95% CIs Upper
Age (5-years)	0.68***	0.03	1.97	0.59***	0.03	1.80	1.69	1.91	0.68***	0.03	1.97	1.87	2.08
Gender (ref=female)													
Male	0.12	0.72	1.13										
Education	-0.03†	0.01	0.98	0.00	0.01	1.00	0.97	1.02	-0.03†	0.01	0.98	0.95	1.00
Race (ref=White)													
Black/AA	0.14	0.11	1.15	0.24†	0.13	1.27	0.98	1.65	0.14	0.11	1.15	0.93	1.42
Other	0.35	0.26	1.42	0.05	0.33	1.05	0.54	2.04	0.35	0.26	1.42	0.84	2.39
Hispanic	0.25†	0.14	1.29	0.36*	0.15	1.43	1.06	1.94	0.25†	0.14	1.29	0.96	1.72
Relationship status (ref=married)													
Divorced	0.22†	0.11	1.25	0.58***	0.16	1.79	1.30	2.47	0.22†	0.11	1.25	0.99	1.57
Widowed	0.21**	0.08	1.23	0.55***	0.10	1.74	1.41	2.14	0.21**	0.08	1.23	1.06	1.44
Never married	0.23	0.24	1.25	0.97***	0.27	2.65	1.54	4.56	0.23	0.24	1.25	0.77	2.04
Friend in neighbor.	-0.25***	0.07	0.78	-0.30***	0.08	0.74	0.63	0.88	-0.25***	0.07	0.78	0.68	0.89
No. in household	0.33***	0.04	1.39	0.40***	0.05	1.49	1.34	1.66	0.33***	0.04	1.39	1.29	1.51
No. of living child.	0.01	0.01	1.01	0.04*	0.02	1.04	1.00	1.06	0.01	0.01	1.01	0.98	1.04
Health	0.52***	0.03	1.68	0.50***	0.04	1.64	1.52	1.78	0.52***	0.03	1.68	1.57	1.80
Vision	0.35***	0.04	1.42	0.43***	0.05	1.53	1.39	1.68	0.35***	0.03	1.43	1.32	1.54
Time	0.08***	0.02	1.08	0.09***	0.02	1.09	1.06	1.13	0.78***	0.02	1.08	1.05	1.12
Transport environ.													
Road density	0.04**	0.01	1.04	0.04*	0.02	1.04	1.00	1.07	0.04**	0.01	1.04	1.02	1.07
Male*age	-0.09*	0.04	0.91										

Male*education	0.02	0.02	1.02
Male*race			
Black/AA	0.10	0.18	1.11
Other	-0.30	0.42	0.74
Hispanic	0.11	0.20	1.11
Male*relationship			
Divorced	0.36†	0.20	1.44
Widowed	0.34*	0.13	1.41
Never married	0.75*	0.35	2.11
Male*friend	-0.05	0.11	0.96
Male*no. in house	0.07	0.07	1.07
Male*no. children	0.03	0.02	1.03
Male*health	-0.02	0.05	0.98
Male*vision	0.07	0.06	1.07
Male*time	0.01	0.02	1.01
Male*transport			
Road density	-0.01	0.02	0.99

Note. GIS = Geographic Information System; SE = standard error; OR = odds ratio.
†$p < 0.10$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Race and driving reduction

The next series of tables shows the results of analyses of driving reduction by race. The results of the fully interacted models with both the UMR and GIS predictors are shown in Table 12, while Table 13 and Table 14 show the race-stratified models with the UMR and GIS predictors, respectively. Relationship status remained an important stand-alone predictor in these models, and also significantly interacted with race. The reference group for those interactions was married/partnered individuals of White race. Significant interactions were identified in the UMR model for all non-White races who were never married, and in the GIS model for widowed African Americans, and Hispanics who were never married. The stratified models show that marriage significantly reduced engagement in driving reduction for White and Hispanic respondents, but was not significant for African American respondents. The UMR and GIS models show mixed results for respondents who identify as Other race.

The interaction between race and household size was also statistically significant. Compared to White respondents, more people living in one's household increased engagement in driving reduction for Hispanic respondents (UMR and GIS models), but decreased engagement in driving reduction for those of Other race. The stratified models showed that this factor was consistently significant for Hispanic respondents (UMR: OR=1.34, $p<0.01$; GIS: OR=1.34, $p<0.01$), with those identified as Other only showing this significantly in the GIS model (UMR: OR=0.56, $p<0.10$; GIS: OR=0.61, $p<0.05$).

Race and time at risk also significantly interacted with each other in predicting driving reduction. More time at risk significantly increased the odds of engaging in driving reduction, but this factor influenced those who identify as Other and Hispanic more than those who identify as White. This effect was consistent within the UMR and GIS models, although the ORs were more pronounced in the UMR model (White: OR=1.08, African American: OR=1.12, Other: OR=2.10, Hispanic: OR=1.35).

Within the GIS model, two other interactions were also significant. As the number of living children increased, African Americans (stratified OR=1.05, $p<0.05$) and those of Other race (OR=1.24, $p<0.01$) were more likely than White respondents to reduce their driving behavior. Finally, the interaction between race and vision suggested that the difference between White and Hispanic respondents was significant on this factor ($p<0.01$). In the stratified models, worse vision significantly predicted driving reduction for Whites (OR=1.26, $p<0.001$), but not for Hispanic respondents (OR=0.89, n.s.).

The interactions between race and the transportation environment variables were not significant in either the UMR or GIS driving reduction models. In the stratified models, increases in the Travel Time Index and in Roadway Density were only significantly predictive of driving reduction for Whites. These models showed much more variance associated with these factors for African Americans, Hispanics, and those of Other race. The parameter estimates across the stratified GIS models were all fairly similar to each other. Overall, these results do not provide support for the third research goal, or specifically for Hypothesis 4.

Table 12. Interacted models: racial differences in driving reduction.

	UMR variable (subsample)			GIS variable (full sample)		
	Param Est.	SE	OR	Param Est.	SE	OR
Age (5-years)	0.51***	0.03	1.66	0.49***	0.02	1.63
Gender (ref=female)						
Male	-0.63***	0.07	0.53	-0.65***	0.05	0.52
Education	-0.08***	0.01	0.92	-0.07***	0.01	0.93
Race (ref=White)						
Black/AA	1.41	2.11	4.11	0.20	1.18	1.22
Other	2.34	8.46	10.36	1.90	3.34	6.66
Hispanic	-1.96	1.88	0.14	-2.20	1.43	0.11
Relationship status (ref=married)						
Divorced	0.27*	0.11	1.31	0.33***	0.09	1.40
Widowed	0.36***	0.10	1.43	0.33***	0.06	1.40
Never married	0.70**	0.26	2.01	0.60**	0.18	1.82
Friend in neighbor.	-0.05	0.06	0.95	-0.07	0.05	0.93
No. in household	0.03	0.04	1.03	0.07†	0.04	1.07
No. of living child.	-0.02	0.02	0.98	0.00	0.01	1.00
Health	0.37***	0.04	1.45	0.39***	0.02	1.48
Vision	0.23***	0.04	1.26	0.23***	0.03	1.26
Time	0.08***	0.02	1.08	0.07***	0.01	1.07
Transport environ.						
TT Index	0.92**	0.34	2.51			
Road density				0.03**	0.01	1.03
Race*age						
Black/AA	0.03	0.09	1.03	0.03	0.07	1.03
Other	-0.13	0.48	0.88	-0.07	0.22	0.93
Hispanic	0.01	0.09	1.01	0.10	0.10	1.10
Race*gender						
Black/AA	0.21	0.19	1.23	0.12	0.15	1.13
Other	-0.41	0.60	0.66	-0.29	0.49	0.75
Hispanic	-0.12	0.20	0.89	-0.09	0.18	0.92
Race*education						
Black/AA	0.03	0.03	1.03	0.01	0.02	1.01
Other	-0.08	0.09	0.92	0.01	0.07	1.01
Hispanic	0.05†	0.03	1.05	0.03	0.02	1.03
Race*relationship						
Divorced						
Black/AA	-0.24	0.24	0.78	-0.38†	0.22	0.68
Other	0.58	1.03	1.79	0.22	0.72	1.25
Hispanic	0.32	0.32	1.38	0.49†	0.28	1.63
Widowed						
Black/AA	-0.30	0.18	0.74	-0.35*	0.17	0.70
Other	0.79	0.67	2.21	0.57	0.46	1.77
Hispanic	0.21	0.29	1.23	0.04	0.23	1.04
Never married						
Black/AA	-1.38*	0.57	0.25	-0.86†	0.45	0.42
Other	3.39**	1.15	29.70	0.78	1.70	2.18
Hispanic	-1.60*	0.74	0.20	-1.39*	0.68	0.25
Race*friend						
Black/AA	0.16	0.21	1.18	0.23	0.16	1.26
Other	-0.69	0.77	0.50	-0.20	0.48	0.82
Hispanic	0.23	0.22	1.25	0.18	0.21	1.20

Race*no. in house						
Black/AA	-0.07	0.09	0.93	-0.07	0.08	0.93
Other	-0.60†	0.33	0.55	-0.56*	0.24	0.57
Hispanic	0.27*	0.11	1.31	0.22*	0.11	1.25
Race*no. children						
Black/AA	0.06†	0.03	1.06	0.05*	0.03	1.05
Other	0.32†	0.16	1.38	0.21**	0.08	1.24
Hispanic	0.05	0.03	1.05	0.07†	0.04	1.07
Race*health						
Black/AA	-0.16	0.10	0.85	-0.10	0.09	0.90
Other	0.22	0.31	1.25	0.06	0.20	1.07
Hispanic	0.23†	0.13	1.26	0.15	0.10	1.16
Race*vision						
Black/AA	-0.03	0.11	0.97	-0.10	0.09	0.90
Other	-0.14	0.24	0.87	-0.33	0.21	0.72
Hispanic	-0.20	0.12	0.82	-0.35**	0.11	0.70
Race*time						
Black/AA	0.04	0.05	1.04	0.04	0.04	1.04
Other	0.66**	0.25	1.94	0.34*	0.16	1.41
Hispanic	0.22**	0.08	1.25	0.20***	0.06	1.23
Race*transport						
TTI/Road dens.						
Black/AA	-1.10	1.21	0.33	0.00	0.02	1.00
Other	-0.24	2.28	0.78	-0.01	0.06	0.99
Hispanic	-0.03	1.09	0.97	-0.02	0.03	0.98

Note. UMR = Urban Mobility Report; GIS = Geographic Information System; SE = standard error; OR = odds ratio.
†$p < 0.10$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Table 13. Stratified models: racial differences in driving reduction (UMR).

	White					African American				
				OR 95% CIs					OR 95% CIs	
	Param. Est.	SE	OR	Low	Upp	Param. Est.	SE	OR	Low	Upp
Age (5-years)	0.51***	0.03	1.66	1.58	1.75	0.53***	0.08	1.71	1.45	2.01
Gender (ref=fem.)										
Male	-0.63***	0.07	0.53	0.46	0.61	-0.43**	0.16	0.65	0.47	0.90
Education	-0.08***	0.01	0.92	0.90	0.94	-0.06*	0.02	0.94	0.90	0.99
Relation. status (ref=married)										
Divorced	0.27*	0.11	1.31	1.06	1.62	0.02	0.22	1.02	0.66	1.60
Widowed	0.36***	0.10	1.43	1.17	1.74	0.05	0.17	1.05	0.76	1.47
Never marr.	0.70**	0.26	2.01	1.20	3.37	-0.68	0.53	0.51	0.18	1.46
Friend in neigh.	-0.05	0.06	0.95	0.84	1.07	0.11	0.19	1.11	0.76	1.63
No. in household	0.03	0.04	1.03	0.94	1.12	-0.05	0.09	0.95	0.80	1.13
No. living child.	-0.02	0.02	0.98	0.95	1.01	0.04	0.04	1.04	0.97	1.12
Health	0.37***	0.04	1.45	1.34	1.56	0.21*	0.09	1.23	1.03	1.48
Vision	0.23***	0.04	1.26	1.17	1.35	0.20†	0.10	1.22	1.00	1.49
Time	0.08***	0.02	1.08	1.04	1.12	0.11*	0.05	1.12	1.02	1.23
Transport environ.										
TT Index	0.92**	0.34	2.51	1.26	5.01	-0.18	1.18	0.83	0.08	8.89
	Other					Hispanic				
				OR 95% CIs					OR 95% CIs	
	Param. Est.	SE	OR	Low	Upp	Param. Est.	SE	OR	Low	Upp
Age (5-years)	0.38	0.48	1.46	0.56	3.80	0.51***	0.09	1.67	1.39	2.00
Gender (ref=fem.)										
Male	-1.05†	0.59	0.35	0.11	1.15	-0.76***	0.19	0.47	0.32	0.69
Education	-0.16†	0.09	0.85	0.71	1.02	-0.03	0.03	0.97	0.92	1.03
Relation. status (ref=married)										
Divorced	0.85	1.03	2.34	0.30	18.29	0.59*	0.29	1.81	1.00	3.25
Widowed	1.15†	0.64	3.16	0.87	11.49	0.56*	0.26	1.76	1.04	2.97
Never marr.	4.09***	1.13	59.93	6.15	584.05	-0.90	0.68	0.41	0.10	1.58
Friend in neigh.	-0.74	0.78	0.48	0.10	2.27	0.17	0.21	1.19	0.77	1.82
No. in household	-0.57†	0.33	0.56	0.29	1.09	0.29**	0.10	1.34	1.09	1.65
No. living child.	0.30†	0.16	1.35	0.98	1.87	0.03	0.04	1.03	0.96	1.11
Health	0.59†	0.30	1.81	0.99	3.29	0.60***	0.13	1.82	1.40	2.36
Vision	0.09	0.24	1.10	0.68	1.76	0.03	0.13	1.03	0.80	1.33
Time	0.74**	0.24	2.10	1.30	3.39	0.30***	0.07	1.35	1.17	1.56
Transport environ.										
TT Index	0.68	2.27	1.97	0.02	186.91	0.89	1.18	2.44	0.23	26.09

Note. UMR = Urban Mobility Report; SE = standard error; OR = odds ratio.
†$p < 0.10$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Table 14. Stratified models: racial differences in driving reduction (GIS).

	White					African American				
				OR 95% CIs					OR 95% CIs	
	Param. Est.	SE	OR	Low	Upp	Param. Est.	SE	OR	Low	Upp
Age (5-years)	0.49***	0.02	1.63	1.56	1.69	0.51***	0.07	1.67	1.46	1.92
Gender (ref=fem.)										
Male	-0.65***	0.05	0.52	0.48	0.57	-0.52***	0.14	0.59	0.45	0.79
Education	-0.07***	0.01	0.93	0.92	0.95	-0.06**	0.02	0.94	0.91	0.98
Relation. status (ref=married)										
Divorced	0.33***	0.09	1.40	1.18	1.66	-0.05	0.21	0.95	0.63	1.45
Widowed	0.33***	0.06	1.40	1.23	1.58	-0.02	0.16	0.98	0.71	1.36
Never marr.	0.60**	0.18	1.82	1.28	2.59	-0.26	0.42	0.77	0.33	1.77
Friend in neigh.	-0.07	0.05	0.93	0.84	1.02	0.16	0.15	1.17	0.87	1.58
No. in household	0.07†	0.04	1.07	0.99	1.15	-0.01	0.07	0.99	0.86	1.15
No. living child.	0.00	0.01	1.00	0.98	1.02	0.05*	0.02	1.05	1.01	1.10
Health	0.39***	0.02	1.48	1.41	1.55	0.29**	0.09	1.33	1.12	1.59
Vision	0.23***	0.03	1.26	1.20	1.33	0.13	0.09	1.14	0.96	1.36
Time	0.07***	0.01	1.07	1.05	1.10	0.11*	0.04	1.12	1.02	1.22
Transport environ.										
Road density	0.03**	0.01	1.03	1.01	1.05	0.03	0.02	1.03	0.98	1.07

	Other					Hispanic				
				OR 95% CIs					OR 95% CIs	
	Param. Est.	SE	OR	Low	Upp	Param. Est.	SE	OR	Low	Upp
Age (5-years)	0.41†	0.22	1.51	0.97	2.36	0.58***	0.09	1.79	1.49	2.16
Gender (ref=fem.)										
Male	-0.94†	0.48	0.39	0.15	1.03	-0.74***	0.18	0.48	0.34	0.68
Education	-0.06	0.07	0.94	0.82	1.08	-0.04†	0.02	0.96	0.92	1.01
Relation. status (ref=married)										
Divorced	0.56	0.71	1.75	0.42	7.27	0.82**	0.27	2.28	1.32	3.93
Widowed	0.90†	0.46	2.47	0.99	6.20	0.37	0.22	1.45	0.93	2.28
Never marr.	1.38	1.69	3.97	0.13	117.85	-0.79	0.66	0.45	0.12	1.70
Friend in neigh.	-0.27	0.47	0.76	0.29	1.98	0.11	0.21	1.12	0.74	1.69
No. in household	-0.49*	0.24	0.61	0.38	0.98	0.29**	0.10	1.34	1.09	1.64
No. living child.	0.21**	0.08	1.24	1.06	1.44	0.07†	0.04	1.07	1.00	1.15
Health	0.46*	0.20	1.58	1.07	2.34	0.54***	0.10	1.72	1.41	2.10
Vision	-0.10*	0.21	0.91	0.59	1.39	-0.12	0.11	0.89	0.72	1.10
Time	0.41	0.16	1.51	1.09	2.10	0.28***	0.06	1.32	1.18	1.48
Transport environ.										
Road density	0.02	0.06	1.02	0.90	1.15	0.01	0.03	1.01	0.96	1.07

Note. GIS = Geographic Information System; SE = standard error; OR = odds ratio.
†$p < 0.10$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Race and driving cessation

The results of the analyses of racial differences in driving cessation are included in Table 15, Table 16, and Table 17. Fully interacted models are shown first, with the parameter estimates, standard errors, odds ratios, and significance levels included. The results from the race-stratified models are in the two tables that follow. The fully interacted models revealed that several factors affect driving cessation differently by race. In the UMR model, for example, the interaction term between race and age suggests that as people get older, their odds of driving cessation increases, but this factor affects White respondents significantly more than African Americans. Being divorced significantly reduces the odds of driving cessation for those of Other race. In the GIS model, there was also a significant gender-race interaction for African Americans compared to Whites (OR=1.44, $p<0.05$), which was also marginally significant in the UMR model (OR=1.38, $p<0.10$). These results indicate that being male was protective against driving cessation, but it was significantly more protective for White respondents (stratified GIS OR=0.54, $p<0.001$) than African Americans. Among the latter group, men and women were not significantly different in terms of driving cessation (OR=0.77, n.s.).

Other significant interactions included having a friend in the neighborhood for those of Other race, and vision for Hispanic and Black respondents. Specifically, having a friend in one's neighborhood decreased the odds of driving cessation significantly for those of White race (stratified UMR OR=0.73, $p<0.001$), but was not significant for those of Other race. In general, decreases in vision significantly increased everyone's odds of driving cessation, but this factor had more of an influence on Whites (OR=1.60, 1.51, in the UMR and GIS models, respectively, $p<0.001$) than those who identify as Hispanic (OR=1.30, $p<0.05$, UMR model) or African American (OR=1.22, $p<0.05$, GIS model).

The interaction between race and the transportation environment was statistically significant for both the UMR and GIS predictors, revealing a difference between Whites and Hispanics. The stand-alone transportation environment predictors remain highly significant in the interacted models, suggesting that as congestion and roadway density increases, the odds of driving cessation also increase. Interestingly, the interactions suggest that there are significant differences between White and Hispanic respondents, but in opposite directions. Increases in the Roadway Congestion Index resulted in significantly increased odds of driving cessation among Whites (stratified OR=1.96, $p<0.001$), but not for Hispanics (OR=0.86, n.s.). In terms of Roadway Density (GIS), however, increases in this variable resulted in an increase in the odds of driving cessation for both Whites (OR=1.04, $p<0.01$) and Hispanics (OR=1.11, $p<0.001$). Although both are affected by this variable, the interaction term indicates that Hispanics are affected significantly more than Whites (interaction OR=1.08, p<0.05). This result provides partial support for Hypothesis 4. African Americans were not affected by the transportation environment more than Whites, as hypothesized, but Hispanics respondents were.

Table 15. Interacted model: racial differences in driving cessation.

	UMR variable (subsample)			GIS variable (full sample)		
	Param Est.	SE	OR	Param Est.	SE	OR
Age (5-years)	0.66***	0.03	1.94	0.65***	0.02	1.91
Gender (ref=female)						
Male	-0.68***	0.07	0.51	-0.62***	0.06	0.54
Education	-0.02	0.01	0.98	-0.02†	0.01	0.98
Race (ref=White)						
Black/AA	3.16†	1.64	23.47	2.76*	1.05	15.76
Other	2.31	8.38	10.03	0.91	4.78	2.48
Hispanic	3.16*	1.32	23.66	1.81	1.45	6.14
Relationship status (ref=married)						
Divorced	0.31*	0.14	1.37	0.36**	0.11	1.43
Widowed	0.34***	0.09	1.40	0.34***	0.07	1.41
Never married	0.42	0.29	1.52	0.57*	0.22	1.76
Friend in neighbor.	-0.31***	0.08	0.73	-0.31***	0.06	0.73
No. in household	0.31***	0.05	1.36	0.38***	0.04	1.46
No. of living child.	0.04*	0.02	1.04	0.02†	0.01	1.02
Health	0.55***	0.04	1.73	0.53***	0.03	1.70
Vision	0.47***	0.04	1.60	0.41***	0.03	1.51
Time	0.10***	0.02	1.10	0.09***	0.01	1.09
Transport environ.						
RCI	0.67***	0.17	1.96			
Road density				0.03**	0.01	1.04
Race*age						
Black/AA	-0.15*	0.08	0.86	-0.09	0.06	0.92
Other	0.00	0.46	1.00	0.02	0.27	1.02
Hispanic	-0.01	0.09	0.99	-0.05	0.08	0.95
Race*gender						
Black/AA	0.32†	0.18	1.38	0.36*	0.17	1.44
Other	-0.78	0.83	0.46	-0.34	0.51	0.71
Hispanic	0.13	0.19	1.13	0.13	0.20	1.14
Race*education						
Black/AA	0.03	0.04	1.03	0.02	0.02	1.02
Other	0.04	0.17	1.04	-0.02	0.07	0.98
Hispanic	-0.01	0.02	0.99	0.00	0.03	1.00
Race*relationship						
Divorced						
Black/AA	-0.01	0.26	0.99	0.16	0.24	1.18
Other	-10.59***	0.85	0.00	-11.09***	0.65	0.00
Hispanic	0.33	0.30	1.40	0.10	0.32	1.11
Widowed						
Black/AA	0.09	0.22	1.09	0.20	0.20	1.22
Other	0.53	0.81	1.70	0.34	0.50	1.40
Hispanic	-0.16	0.25	0.85	-0.20	0.26	0.82
Never married						
Black/AA	-0.15	0.42	0.86	0.11	0.42	1.12
Other	0.91	1.02	2.48	-0.20	0.91	0.82
Hispanic	0.25	0.92	1.29	0.03	0.74	1.03
Race*friend						
Black/AA	0.21	0.18	1.24	0.24	0.16	1.28
Other	1.86†	0.98	6.40	1.14*	0.53	3.12
Hispanic	0.25	0.20	1.28	0.35†	0.19	1.41

Race*no. in house						
Black/AA	-0.05	0.10	0.95	-0.16†	0.08	0.85
Other	-0.30	0.40	0.74	-0.09	0.29	0.91
Hispanic	0.01	0.08	1.01	0.01	0.10	1.01
Race*no. children						
Black/AA	0.00	0.04	1.00	0.01	0.03	1.01
Other	-0.09	0.16	0.91	-0.09	0.10	0.92
Hispanic	-0.04	0.04	0.96	-0.01	0.04	0.99
Race*health						
Black/AA	-0.05	0.10	0.95	-0.14†	0.08	0.87
Other	-0.38	0.37	0.68	0.19	0.25	1.21
Hispanic	-0.23†	0.12	0.79	-0.22†	0.11	0.80
Race*vision						
Black/AA	-0.21†	0.12	0.81	-0.21*	0.09	0.81
Other	-0.13	0.39	0.88	-0.61†	0.30	0.54
Hispanic	-0.21*	0.10	0.81	-0.13	0.12	0.87
Race*time						
Black/AA	0.00	0.05	1.00	-0.06	0.04	0.94
Other	-0.22	0.23	0.80	-0.03	0.12	0.97
Hispanic	0.00	0.04	1.00	0.02	0.05	1.02
Race*transport						
RCI/Road dens.						
Black/AA	-0.13	0.53	0.88	-0.02	0.03	0.98
Other	-0.40	1.70	0.67	0.08	0.11	1.09
Hispanic	-0.83*	0.38	0.44	0.07*	0.03	1.08

Note. UMR = Urban Mobility Report; GIS = Geographic Information System; SE = standard error; OR = odds ratio. †p < 0.10. *p < 0.05. **p < 0.01. ***p < 0.001.

Table 16. Stratified models: racial differences in driving cessation (UMR).

	White					African American				
				OR 95% CIs					OR 95% CIs	
	Param. Est.	SE	OR	Low	Upp	Param. Est.	SE	OR	Low	Upp
Age (5-years)	0.66***	0.03	1.94	1.81	2.07	0.51***	0.06	1.66	1.46	1.88
Gender (ref=fem.)										
Male	-0.68***	0.07	0.51	0.44	0.58	-0.36†	0.18	0.70	0.49	1.00
Education	-0.02	0.01	0.98	0.95	1.01	0.00	0.03	1.00	0.94	1.07
Relation. status (ref=married)										
Divorced	0.31*	0.14	1.37	1.04	1.80	0.30	0.22	1.35	0.87	2.11
Widowed	0.34***	0.09	1.40	1.17	1.67	0.43*	0.20	1.54	1.03	2.30
Never marr.	0.42	0.29	1.52	0.85	2.70	0.26	0.43	1.30	0.55	3.06
Friend in neigh.	-0.31***	0.08	0.73	0.62	0.86	-0.10	0.17	0.91	0.65	1.27
No. in household	0.31***	0.05	1.36	1.22	1.51	0.26**	0.08	1.29	1.10	1.52
No. living child.	0.04*	0.02	1.04	1.00	1.08	0.04	0.03	1.04	0.98	1.11
Health	0.55***	0.04	1.73	1.59	1.89	0.50***	0.09	1.65	1.37	1.98
Vision	0.47***	0.04	1.60	1.47	1.73	0.26*	0.11	1.30	1.05	1.61
Time	0.10***	0.02	1.10	1.06	1.14	0.10*	0.05	1.10	1.01	1.20
Transport environ.										
RCI	0.67***	0.17	1.96	1.40	2.75	0.54	0.48	1.72	0.65	4.53
	Other					Hispanic				
				OR 95% CIs					OR 95% CIs	
	Param. Est.	SE	OR	Low	Upp	Param. Est.	SE	OR	Low	Upp
Age (5-years)	0.66	0.46	1.93	0.76	4.88	0.65***	0.08	1.91	1.62	2.25
Gender (ref=fem.)										
Male	-1.47†	0.82	0.23	0.04	1.21	-0.56**	0.18	0.57	0.40	0.82
Education	0.01	0.17	1.01	0.72	1.42	-0.03	0.02	0.97	0.93	1.01
Relation. status (ref=married)										
Divorced	-15.42***	0.79	0.00	0.00	0.00	0.64*	0.26	1.91	1.13	3.21
Widowed	0.87	0.80	2.38	0.48	11.84	0.18	0.24	1.20	0.74	1.94
Never marr.	1.32	0.94	3.76	0.57	24.91	0.67	0.87	1.95	0.34	11.24
Friend in neigh.	1.54	0.99	4.68	0.64	34.33	-0.07	0.19	0.94	0.64	1.36
No. in household	0.00	0.40	1.00	0.45	2.23	0.32***	0.07	1.38	1.21	1.57
No. living child.	-0.05	0.17	0.95	0.68	1.33	0.00	0.04	1.00	0.93	1.08
Health	0.17	0.37	1.18	0.56	2.48	0.32**	0.10	1.37	1.11	1.69
Vision	0.34	0.39	1.41	0.65	3.05	0.26*	0.10	1.30	1.06	1.59
Time	-0.12	0.23	0.88	0.56	1.40	0.10*	0.04	1.10	1.02	1.19
Transport environ.										
RCI	0.27	1.65	1.31	0.05	36.05	-0.15	0.31	0.86	0.46	1.59

Note. UMR = Urban Mobility Report; SE = standard error; OR = odds ratio.
†p < 0.10. *p < 0.05. **p < 0.01. ***p < 0.001.

Table 17. Stratified models: racial differences in driving cessation (GIS).

	White					African American				
				OR 95% CIs					OR 95% CIs	
	Param. Est.	SE	OR	Low	Upp	Param. Est.	SE	OR	Low	Upp
Age (5-years)	0.65***	0.02	1.91	1.83	2.01	0.56***	0.06	1.75	1.56	1.97
Gender (ref=fem.)										
Male	-0.62***	0.06	0.54	0.48	0.61	-0.26	0.16	0.77	0.56	1.07
Education	-0.02†	0.01	0.98	0.96	1.00	0.00	0.02	1.00	0.96	1.04
Relation. status (ref=married)										
Divorced	0.36**	0.11	1.43	1.15	1.78	0.52*	0.20	1.69	1.12	2.54
Widowed	0.34***	0.07	1.41	1.23	1.61	0.54**	0.18	1.72	1.19	2.49
Never marr.	0.57*	0.22	1.76	1.14	2.72	0.68†	0.36	1.97	0.96	4.06
Friend in neigh.	-0.31***	0.06	0.73	0.65	0.83	-0.07	0.14	0.94	0.70	1.25
No. in household	0.38***	0.04	1.46	1.35	1.57	0.22**	0.07	1.24	1.07	1.44
No. living child.	0.02†	0.01	1.02	1.00	1.05	0.03	0.02	1.03	0.99	1.08
Health	0.53***	0.03	1.70	1.61	1.80	0.39***	0.08	1.47	1.26	1.72
Vision	0.41***	0.03	1.51	1.41	1.62	0.20*	0.08	1.22	1.04	1.44
Time	0.09***	0.01	1.09	1.07	1.12	0.03	0.03	1.03	0.96	1.11
Transport environ.										
Road density	0.03**	0.01	1.04	1.01	1.06	0.01	0.02	1.01	0.96	1.06
	Other					Hispanic				
				OR 95% CIs					OR 95% CIs	
	Param. Est.	SE	OR	Low	Upp	Param. Est.	SE	OR	Low	Upp
Age (5-years)	0.67*	0.27	1.96	1.14	3.36	0.60***	0.08	1.82	1.55	2.13
Gender (ref=fem.)										
Male	-0.96†	0.50	0.38	0.14	1.05	-0.49*	0.19	0.61	0.42	0.89
Education	-0.03	0.07	0.97	0.85	1.10	-0.02	0.02	0.98	0.94	1.03
Relation. status (ref=married)										
Divorced	-15.74***	0.62	0.00	0.00	0.00	0.46	0.30	1.59	0.88	2.88
Widowed	0.68	0.50	1.97	0.73	5.35	0.14	0.25	1.15	0.69	1.91
Never marr.	0.37	0.89	1.44	0.24	8.62	0.60	0.71	1.82	0.44	7.53
Friend in neigh.	0.83	0.53	2.29	0.78	6.68	0.04	0.18	1.04	0.72	1.49
No. in household	0.29	0.29	1.33	0.74	2.38	0.39***	0.10	1.48	1.21	1.80
No. living child.	-0.06	0.09	0.94	0.78	1.13	0.01	0.03	1.01	0.95	1.09
Health	0.72**	0.24	2.06	1.26	3.37	0.31**	0.11	1.36	1.09	1.69
Vision	-0.19	0.30	0.82	0.45	1.51	0.28*	0.11	1.32	1.06	1.65
Time	0.06	0.12	1.07	0.83	1.36	0.11*	0.04	1.11	1.02	1.22
Transport environ.										
Road density	0.12	0.11	1.13	0.91	1.40	0.11***	0.03	1.11	1.05	1.18

Note. GIS = Geographic Information System; SE = standard error; OR = odds ratio.
†$p < 0.10$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Research goal 4

The fourth research goal focused on how driving behaviors and the built environment affect depressive symptoms over time. Specifically, the hypothesis associated with this research goal suggested that increases in the congestion or density of the transportation environment would result in increased depressive symptoms, but only for those who could no longer drive (or who limited their driving). As described in Chapter 3, a comparison between two separate methods was completed before the final models were fit, to assess the best statistical approach to this analysis. The results of these two analysis methods are shown in Table 18. As this table reveals, the two methods resulted in nearly identical parameter estimates and standard errors, and all major conclusions remained the same with both methods. Because of this similarity, and the rationale provided in Chapter 3, all results that follow were calculated using the GEE method.

Table 18. Comparison between generalized estimating equation method and jackknife repeated replicate macro.

	GEE			JRR Macro		
	Param. Est.	SE	IRR	Param. Est.	SE	IRR
Age (ref=65-74)						
75-84	0.09***	0.02	1.10	0.10***	0.02	1.11
85+	0.13***	0.03	1.13	0.14***	0.03	1.15
Gender (ref=female)						
Male	-0.12***	0.02	0.89	-0.16***	0.02	0.85
Education	-0.03***	0.00	0.97	-0.02***	0.00	0.98
Race (ref=White)						
Black/AA	-0.07*	0.03	0.93	-0.08*	0.03	0.93
Other	-0.20*	0.09	0.82	-0.17	0.09	0.85
Hispanic	0.00	0.04	1.00	0.01	0.05	1.01
Relationship status (ref=marr./partner.)						
Divorced	0.34***	0.03	1.40	0.32***	0.03	1.37
Widowed	0.31***	0.02	1.36	0.29***	0.03	1.34
Never married	0.25***	0.05	1.29	0.23***	0.06	1.25
Friend in neighbor.	-0.05**	0.02	0.96	-0.11***	0.01	0.90
Health	0.29***	0.01	1.34	0.40***	0.01	1.49
Vision	0.07***	0.01	1.07	0.09***	0.01	1.09
Time	-0.39***	0.01	0.68	-0.38***	0.01	0.68

Note. GEE = generalized estimating equation; JRR = jackknife repeated replicate; SE = standard error; IRR = incidence rate ratio.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Table 19 shows the results of the preliminary models fit with depressive symptoms as the outcome. This table includes the parameter estimates, standard errors, incidence rate ratios (the measure of exponentiated betas in Poisson regression), and significance levels. As each set of variables were added to the model, the estimates and significance levels changed somewhat, as expected. All of the original social support variables were reassessed in this model to examine their potential significance with this new outcome. Having a child who lives within 10 miles of one's home, and having relatives who live in one's neighborhood were not significant predictors and therefore were not retained. Additionally, the number of people who live in one's household, and the number of living children (two variables that were significantly predictive of driving reduction and cessation) were not significant in these models, so they were also removed. The full preliminary model showed that older age, female gender, less education, non-married/partnered relationship status, having no friends in one's neighborhood, and worse health and vision were all predictive of a higher rate ratio of depressive symptoms.

Table 19. Preliminary models assessing depressive symptoms.

	Demographics only			Demographics and social support			Demographics, social support, and health			Demos, social support, health, and time		
	Param. Est.	SE	IRR	Param. Est.	SE	IRR	Param. Est.	SE	IRR	Param. Est.	SE	IRR
Age (ref=65-74)												
75-84	-0.55***	0.01	0.57	-0.58***	0.01	0.56	-0.62***	0.01	0.54	0.08***	0.01	1.09
85+	-0.81***	0.03	0.44	-0.87***	0.03	0.42	-0.94***	0.03	0.39	0.12***	0.02	1.12
Gender (ref=female)												
Male	-0.21***	0.02	0.81	-0.14***	0.02	0.87	-0.15***	0.02	0.86	-0.13***	0.02	0.88
Education	-0.08***	0.00	0.92	-0.08***	0.00	0.92	-0.05***	0.00	0.95	-0.03***	0.00	0.97
Race (ref=White)												
Black/AA	0.10***	0.03	1.10	0.05*	0.03	1.06	-0.02	0.02	0.98	-0.03	0.02	0.97
Other	-0.05	0.08	0.95	-0.05	0.08	0.95	-0.07	0.07	0.93	-0.10	0.07	0.91
Hispanic	-0.06	0.04	0.94	-0.07	0.04	0.93	-0.11***	0.03	0.89	0.00	0.03	1.00
Relationship status (ref=marr./partner.)												
Divorced				0.30***	0.03	1.36	0.26***	0.03	1.29	0.35***	0.02	1.42
Widowed				0.20***	0.02	1.22	0.18***	0.02	1.20	0.30***	0.02	1.35
Never married				0.13*	0.05	1.14	0.10*	0.05	1.11	0.22***	0.04	1.24
Friend in neighbor.				-0.06***	0.01	0.94	-0.03*	0.01	0.97	-0.06***	0.01	0.94
Health							0.29***	0.01	1.34	0.29***	0.01	1.33
Vision							0.07***	0.01	1.07	0.07***	0.01	1.08
Time										-0.38***	0.00	0.69

Note. SE = standard error; IRR = incidence rate ratio.
**p* < 0.05. ***p* < 0.01. ****p* < 0.001.

Table 20 shows the results of the final non-interacted models of depressive symptoms. Each model was fit separately with the driving reduction and driving cessation predictors included. A comparison of these two models indicates that the parameter estimates and variance for all of the other variables remained very similar when the driving cessation predictor was swapped in for driving reduction. The addition of the driving reduction, cessation, and transportation environment variables also resulted in a slight increase in the significance of the race variable, with African American and Other race showing lower rate ratios of depressive symptoms compared to Whites.

The driving reduction and cessation variables included in these models are different from the dependent variables related to these behaviors modeled earlier. These variables represent *no engagement* in driving reduction/cessation, rather than the presence of that behavior as modeled earlier. As such, these results suggest that not reducing or stopping driving is predictive of a lower rate ratio of depressive symptoms over time, echoing previous research. The transportation environment variable shows that as travel time increases, the rate of depressive symptoms decreases.

Table 20. Final non-interacted models assessing depressive symptoms.

	Driving reduction					Driving cessation				
	Param. Est.	SE	IRR	IRR 95% CI		Param. Est.	SE	IRR	IRR 95% CI	
				Low	Upp				Low	Upp
Age (ref=65-74)										
75-84	0.11***	0.02	1.12	1.07	1.17	0.09***	0.02	1.09	1.05	1.14
85+	0.21***	0.04	1.23	1.14	1.33	0.13***	0.03	1.14	1.07	1.20
Gender (ref=female)										
Male	-0.06*	0.03	0.94	0.89	1.00	-0.12***	0.02	0.89	0.85	0.93
Education	-0.02***	0.00	0.98	0.97	0.99	-0.03***	0.00	0.97	0.97	0.98
Race (ref=White)										
Black/AA	-0.10**	0.04	0.91	0.84	0.97	-0.07*	0.03	0.93	0.88	0.98
Other	-0.16	0.12	0.86	0.68	1.08	-0.20*	0.10	0.82	0.68	0.99
Hispanic	0.00	0.05	1.00	0.90	1.10	0.00	0.04	1.00	0.93	1.07
Relationship status (ref=marr./partner.)										
Divorced	0.34***	0.04	1.41	1.31	1.52	0.34***	0.03	1.40	1.32	1.49
Widowed	0.37***	0.03	1.44	1.36	1.53	0.31***	0.02	1.36	1.30	1.42
Never married	0.17*	0.08	1.19	1.02	1.38	0.24***	0.06	1.28	1.14	1.42
Friend in neighbor.	-0.07**	0.02	0.94	0.90	0.97	-0.05**	0.02	0.95	0.92	0.99
Health	0.30***	0.01	1.35	1.32	1.39	0.30***	0.01	1.34	1.32	1.37
Vision	0.07***	0.01	1.07	1.05	1.09	0.07***	0.01	1.07	1.05	1.09
Time	-0.41***	0.01	0.67	0.66	0.68	-0.38***	0.01	0.68	0.67	0.70
Driving vars.										
No reduction	-0.20***	0.02	0.82	0.78	0.85					
No cessation						-0.08***	0.02	0.93	0.88	0.97
Transport environ.										
TTIndex	-0.34**	0.14	0.71	0.54	0.94	-0.33**	0.11	0.72	0.58	0.89

Note. SE = standard error; IRR = incidence rate ratio.
**p* < 0.05. ***p* < 0.01. ****p* < 0.001.

Fully interacted and stratified models were fit to assess the hypothesis that the transportation environment affects the relationship between driving reduction/cessation and depressive symptoms. The stratified models were fit separately for people who engage in driving reduction and those who do not. As described previously, the depressive symptoms variable was a count of the number of symptoms a respondent reported experiencing, which ranged from zero to eight. The weighted mean number of depressive symptoms overall was 1.52. Those who reported that they were still able to drive had a weighted mean of 1.21, and those who had stopped driving averaged 2.23 depressive symptoms. As noted earlier, the driving limitation question was only asked of those who reported the ability to drive. Given that, the sample is reduced to only those people. Within that group, the weighted average number of depressive symptoms for those who limit their driving was 1.88, with a mean of 1.01 for those who do not. The results of the interacted and stratified models with the driving reduction variable included are shown in Table 21 and Table 22 for the UMR and GIS samples, respectively.

Within both samples, there were significant interactions between driving reduction and age, education, widowhood status, and time. The relationship between gender and driving reduction was also significant in the GIS sample. Overall, respondents in the 75 to 84 and the 85 and older age group, had significantly higher rates of depressive symptoms than the 65 to 74 year olds. This effect was significantly more pronounced among those who did not limit their driving. There was a very small but significant difference in education, such that more education was slightly more protective for those who did not limit their driving (IRR=0.97, $p<0.001$, stratified UMR model) compared to those who did (IRR=0.99, $p<0.05$). Being married or partnered was protective against depressive symptoms for everyone, but the interaction within this relationship significantly affected only those who were widowed. Specifically, becoming widowed increased the rate of depressive symptoms significantly more for those who did not limit their driving (IRR=1.54), compared to those who did (IRR=1.34).

The results also indicated that after controlling for the other variables in the model, increased time is significantly protective against the incidence rate of depressive symptoms for both those who reduce and those who do not reduce their driving. The significant interaction suggested a small increase in this protective effect for those who did not reduce their driving (IRR=0.65), compared to those who did (IRR=0.69). Finally, the interaction between driving reduction and gender showed that male gender was significantly protective against developing depressive symptoms in the GIS sample (IRR=0.90, $p<0.001$), but only for people who do not limit their driving.

The interactions between the driving reduction variable and the transportation environment variables were not significant in either model. The stratified GIS models also revealed nearly identical parameter estimates. The UMR sample, however, showed that the Travel Time Index was significantly predictive of depressive symptoms for those who have reduced their driving (IRR=0.66, $p<0.05$), but not for those who drive without restriction (IRR=0.85, n.s.). Although the interaction term was not significant, these results suggest that the influence of the transportation environment on depressive symptoms is worth continuing to explore, particularly among those who limit their driving. Overall, however, Hypothesis 5 was not supported in this phase of the analysis.

Table 21. Interacted and stratified models: depressive symptoms by driving reduction (UMR).

				No driving reduction					Driving reduction				
	Param. Est.	SE	IRR	Param. Est.	SE	IRR	IRR 95% CI Low	IRR 95% CI Upp	Param. Est.	SE	IRR	IRR 95% CI Low	IRR 95% CI Upp
Age (ref=65-74)													
75-84	0.17***	0.03	1.18	0.17***	0.03	1.19	1.11	1.27	0.05†	0.03	1.05	1.00	1.11
85+	0.30***	0.06	1.35	0.31***	0.07	1.37	1.21	1.56	0.14**	0.05	1.15	1.05	1.26
Gender (ref=female)													
Male	-0.07*	0.04	0.93	-0.08*	0.03	0.92	0.85	1.00	-0.03	0.04	0.97	0.90	1.05
Education	-0.03***	0.01	0.97	-0.03***	0.01	0.97	0.96	0.98	-0.01*	0.01	0.99	0.98	1.00
Race (ref=White)													
Black/AA	-0.11*	0.05	0.90	-0.11*	0.05	0.90	0.81	0.99	-0.10*	0.05	0.91	0.83	0.99
Other	-0.12	0.14	0.90	-0.17	0.15	0.84	0.63	1.14	-0.16	0.16	0.85	0.62	1.16
Hispanic	-0.03	0.07	0.97	0.04	0.07	0.96	0.83	1.11	0.01	0.06	1.01	0.90	1.13
Relationship status (ref=marr./partner.)													
Divorced	0.35***	0.06	1.43	0.35***	0.06	1.42	1.27	1.59	0.30***	0.05	1.35	1.23	1.47
Widowed	0.45***	0.04	1.57	0.43***	0.04	1.54	1.42	1.68	0.29***	0.03	1.34	1.25	1.43
Never married	0.18†	0.10	1.19	0.13	0.11	1.14	0.92	1.42	0.15	0.09	1.16	0.96	1.40
Friend in neighbor.	-0.04	0.03	0.96	-0.06†	0.03	0.95	0.89	1.01	-0.09**	0.03	0.91	0.87	0.97
Health	0.31***	0.02	1.36	0.32***	0.02	1.38	1.33	1.42	0.30***	0.01	1.34	1.31	1.38
Vision	0.09***	0.02	1.09	0.09***	0.02	1.10	1.06	1.13	0.06***	0.01	1.06	1.03	1.09
Time	-0.43***	0.01	0.65	-0.43***	0.01	0.65	0.64	0.66	-0.38***	0.01	0.69	0.67	0.70
Driving reduction	-0.34	0.34	0.72										
Transport environ.													
TTIndex	-0.21	0.20	0.81	-0.17	0.20	0.85	0.57	1.27	-0.41*	0.18	0.66	0.46	0.95
Reduction*age													
75-84	-0.10*	0.04	0.90										
85+	-0.14*	0.07	0.87										
Reduction*gender													
Male	0.03	0.05	1.03										
Reduction*educ.	0.02**	0.01	1.02										
Reduction*race													
Black/AA	0.01	0.06	1.01										
Other	-0.14	0.20	0.87										
Hispanic	0.04	0.08	1.04										
Reduction*rel. stat.	-0.03	0.07	0.97										

Divorced			
Widowed	-0.15**	0.05	0.86
Never married	-0.03	0.13	0.97
Reduction*friend.	-0.04	0.04	0.96
Reduction*health	-0.01	0.02	0.99
Reduction*vision	-0.03†	0.02	0.97
Reduction*time	0.05***	0.01	1.05
Reduction*tr. envir.			
TTIndex	-0.24	0.25	0.79

Note. UMR = Urban Mobility Report; SE = standard error; IRR = incidence rate ratio.
†$p < 0.10$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Table 22. Interacted and stratified models: depressive symptoms by driving reduction (GIS).

				No driving reduction					Driving reduction				
	Param. Est.	SE	IRR	Param. Est.	SE	IRR	IRR 95% CI Low	IRR 95% CI Upp	Param. Est.	SE	IRR	IRR 95% CI Low	IRR 95% CI Upp
Age (ref=65-74)													
75-84	0.15***	0.02	1.16	0.14***	0.02	1.15	1.10	1.21	0.02	0.02	1.03	0.99	1.06
85+	0.27***	0.18	1.31	0.25***	0.05	1.28	1.17	1.41	0.07*	0.03	1.07	1.01	1.14
Gender (ref=female)													
Male	-0.10***	0.03	0.90	-0.11***	0.03	0.90	0.85	0.94	-0.02	0.03	0.98	0.94	1.03
Education	-0.04***	0.00	0.96	-0.04***	0.00	0.96	0.96	0.97	-0.02***	0.00	0.98	0.98	0.99
Race (ref=White)													
Black/AA	-0.04	0.05	0.96	-0.06	0.05	0.94	0.85	1.04	-0.06†	0.03	0.94	0.89	1.01
Other	-0.02	0.11	0.98	-0.06	0.12	0.95	0.75	1.19	-0.06	0.09	0.94	0.79	1.26
Hispanic	-0.01	0.06	0.99	-0.03	0.06	0.97	0.86	1.08	0.01	0.04	1.01	0.93	1.10
Relationship status (ref=marr./partner.)													
Divorced	0.38***	0.04	1.46	0.37***	0.02	1.45	1.33	1.57	0.33***	0.03	1.39	1.31	1.48
Widowed	0.45***	0.03	1.58	0.43***	0.03	1.54	1.45	1.63	0.30***	0.02	1.34	1.28	1.41
Never married	0.18*	0.08	1.19	0.13	0.08	1.14	0.97	1.35	0.16*	0.07	1.17	1.02	1.33
Friend in neighbor.	-0.07**	0.02	0.93	-0.08***	0.02	0.92	0.88	0.96	-0.09***	0.02	0.91	0.88	0.95
Health	0.31***	0.01	1.36	0.33***	0.01	1.39	1.36	1.42	0.29***	0.01	1.34	1.31	1.37
Vision	0.08***	0.01	1.08	0.09***	0.01	1.09	1.06	1.12	0.06***	0.01	1.07	1.04	1.09
Time	-0.43***	0.01	0.65	-0.42***	0.01	0.65	0.64	0.66	-0.37***	0.01	0.69	0.68	0.70
Driving reduction	0.01	0.10	1.01										
Transport environ.													
Road density	0.00	0.01	1.00	0.00	0.01	1.00	0.99	1.01	0.00	0.00	1.00	0.99	1.01
Reduction*age													
75-84	-0.11***	0.03	0.90										
85+	-0.16**	0.05	0.85										
Reduction*gender													
Male	0.07*	0.03	1.08										
Reduction*educ.	0.02***	0.00	1.02										
Reduction*race													
Black/AA	-0.02	0.05	0.98										
Other	-0.05	0.13	0.95										
Hispanic	0.01	0.06	1.01										
Reduction*rel. stat.													
Divorced	-0.04	0.05	0.96										
Widowed	-0.15***	0.03	0.86										

Never married	-0.02	0.10	0.98
Reduction*friend.	-0.01	0.03	0.99
Reduction*health	-0.01	0.01	0.99
Reduction*vision	-0.02	0.02	0.98
Reduction*time	0.05***	0.01	1.05
Reduction*tr. envir.			
Road density	0.00	0.01	1.00

Note. GIS = Geographic Information System; SE = standard error; IRR = incidence rate ratio.
†$p < 0.10$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

The results from models testing the influence of driving *cessation* and the transportation environment on depressive symptoms are shown in Table 23 and Table 24. Several significant interactions were observed between driving cessation and other variables in the models. For example, age did not significantly affect depressive symptoms as a standalone predictor, but was significant when interacted with driving status. Compared to 65 to 74 year olds, older age was significantly predictive of a higher rate of depressive symptoms among those in the 75 to 84 and 85 and older age groups who still drive (UMR IRR=1.14 and IRR=1.28, respectively, $p<0.001$ for both). In the UMR sample, age did not significantly predict depressive symptoms among those who had stopped driving. Interestingly, in the full sample the opposite effect was noted between the stratified models. As before, increasing age was predictive of an increase in depressive symptoms for those who retained the ability to drive, but among those who could no longer drive, being in the oldest age group predicted a significant *decrease* in depressive symptoms (IRR=0.91, $p<0.01$).

Relationship status was also significantly predictive of depressive symptoms, and influenced this factor differently for those who still drive compared to those who do not. Specifically, being divorced or widowed significantly increased one's rate of developing depressive symptoms over time, compared to being married, and this effect was significantly stronger for those who were still able to drive. People who were divorced and still drove, for example, had an IRR of 1.44 in the UMR sample, and an IRR of 1.26 among the non-drivers ($p<0.001$ for both), with very similar estimates in the GIS sample. Health predicted depressive symptoms in the same way. As health declined within either group, the rate of depressive symptoms increased, but the effect was most notable among the drivers (UMR driver IRR=1.38; non-driver IRR=1.26, $p<0.001$ for both). Having a friend living in one's neighborhood decreased depressive symptoms for both groups, and did so significantly more for drivers than non-drivers in the GIS sample.

The final significant interactions involved driving cessation, educational attainment, and time. After controlling for the other variables, an increase in time and education decreased the rate of depressive symptoms. Both of these interactions were significant (time in both samples, and education in the GIS sample only), but the stratified models showed that the differences between the two were relatively small (time, GIS: drivers IRR=0.68; non-drivers IRR=0.71; education: drivers IRR=0.97; non-drivers IRR=0.98). The interactions between driving cessation and the transportation environment variables were not significant, and the stratified models showed essentially the same parameter estimates for both groups. As such, these results did not support the moderating effect suggested in Hypothesis 5.

Table 23. Interacted and stratified models: depressive symptoms by driving cessation (UMR).

				Able to drive					Not able to drive				
	Param. Est.	SE	IRR	Param. Est.	SE	IRR	IRR 95% CI Low	IRR 95% CI Upp	Param. Est.	SE	IRR	IRR 95% CI Low	IRR 95% CI Upp
Age (ref=65-74)													
75-84	-0.02	0.04	0.98	0.12***	0.02	1.14	1.09	1.19	-0.03	0.04	0.97	0.90	1.05
85+	-0.03	0.05	0.97	0.25***	0.04	1.28	1.20	1.38	-0.06	0.05	0.94	0.85	1.04
Gender (ref=female)													
Male	-0.14***	0.04	0.87	-0.11***	0.03	0.89	0.85	0.94	-0.15***	0.04	0.86	0.80	0.93
Education	-0.02***	0.00	0.98	-0.03***	0.00	0.97	0.96	0.98	-0.02***	0.00	0.98	0.98	0.99
Race (ref=White)													
Black/AA	-0.09*	0.04	0.91	-0.07†	0.04	0.93	0.87	1.00	-0.10*	0.04	0.90	0.83	0.98
Other	-0.26*	0.14	0.77	-0.15	0.12	0.86	0.68	1.08	-0.25†	0.14	0.78	0.59	1.02
Hispanic	0.00	0.05	1.00	-0.01	0.04	0.99	0.90	1.08	0.00	0.05	1.00	0.90	1.11
Relationship status (ref=marr./partner.)													
Divorced	0.22***	0.05	1.25	0.37***	0.04	1.44	1.36	1.55	0.23***	0.05	1.26	1.14	1.39
Widowed	0.12**	0.04	1.12	0.38***	0.03	1.46	1.38	1.54	0.10**	0.04	1.11	1.03	1.20
Never married	0.18*	0.08	1.20	0.23***	0.07	1.26	1.10	1.44	0.16†	0.08	1.17	0.99	1.38
Friend in neighbor.	-0.02	0.03	0.98	-0.06**	0.02	0.94	0.90	0.98	-0.04	0.03	0.96	0.91	1.02
Health	0.22***	0.01	1.25	0.32***	0.01	1.38	1.35	1.41	0.23***	0.01	1.26	1.22	1.29
Vision	0.06***	0.01	1.06	0.08***	0.01	1.08	1.06	1.11	0.06***	0.01	1.06	1.03	1.09
Time	-0.36***	0.01	0.70	-0.39***	0.01	0.67	0.67	0.68	-0.36***	0.01	0.70	0.68	0.71
Driving cessation	-0.60*	0.30	0.55										
Transport environ.													
TTIndex	-0.34†	0.19	0.71	-0.27†	0.14	0.77	0.59	1.00	-0.31	0.19	0.74	0.51	1.06
Cessation*age													
75-84	0.15**	0.04	1.16										
85+	0.26***	0.06	1.30										
Cessation*gender													
Male	0.03	0.05	1.04										
Cessation*educ.	-0.01	0.01	0.99										
Cessation*race													
Black/AA	0.02	0.06	1.02										
Other	0.09	0.18	1.10										
Hispanic	-0.02	0.07	0.98										
Cessation*rel. stat.													
Divorced	0.14*	0.02	1.15										
Widowed	0.27***	0.05	1.30										

Never married	0.05	0.11	1.06
Cessation*friend.	-0.04	0.03	0.96
Cessation*health	0.10***	0.02	1.10
Cessation*vision	0.02	0.02	1.02
Cessation*time	-0.03**	0.01	0.97
Cessation*tr. envir. TTIndex	0.02	0.24	1.02

Note. UMR = Urban Mobility Report; SE = standard error; IRR = incidence rate ratio.
†$p < 0.10$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Table 24. Interacted and stratified models: depressive symptoms by driving cessation (GIS).

	Param. Est.	SE	IRR	Able to drive: Param. Est.	SE	IRR	IRR 95% CI Low	IRR 95% CI Upp	Not able to drive: Param. Est.	SE	IRR	IRR 95% CI Low	IRR 95% CI Upp
Age (ref=65-74)													
75-84	-0.03	0.03	0.97	0.11***	0.02	1.11	1.08	1.15	-0.04	0.03	0.96	0.91	1.01
85+	-0.06†	0.03	0.94	0.20***	0.03	1.22	1.16	1.29	-0.10**	0.03	0.91	0.85	0.97
Gender (ref=female)													
Male	-0.16***	0.03	0.86	-0.12***	0.02	0.89	0.85	0.92	-0.15***	0.03	0.86	0.80	0.92
Education	-0.02***	0.00	0.98	-0.04***	0.00	0.97	0.96	0.97	-0.02***	0.00	0.98	0.98	0.99
Race (ref=White)													
Black/AA	-0.08*	0.03	0.92	-0.04	0.03	0.96	0.91	1.02	-0.07*	0.03	0.93	0.87	0.99
Other	-0.20†	0.12	0.82	-0.04	0.07	0.96	0.83	1.12	-0.20†	0.11	0.82	0.65	1.02
Hispanic	-0.02	0.04	0.98	-0.01	0.04	0.99	0.92	1.06	-0.02	0.04	0.98	0.90	1.07
Relationship status (ref=marr./partner.)													
Divorced	0.20***	0.04	1.22	0.38***	0.03	1.47	1.39	1.55	0.20***	0.04	1.22	1.13	1.32
Widowed	0.10***	0.03	1.11	0.37***	0.02	1.45	1.39	1.51	0.09**	0.03	1.09	1.03	1.16
Never married	0.07	0.07	1.07	0.21***	0.05	1.24	1.11	1.37	0.04	0.08	1.04	0.89	1.20
Friend in neighbor.	-0.02	0.02	0.98	-0.08***	0.01	0.93	0.90	0.95	-0.03	0.02	0.97	0.93	1.01
Health	0.21***	0.01	1.23	0.32***	0.01	1.37	1.35	1.39	0.22***	0.01	1.24	1.22	1.27
Vision	0.06***	0.01	1.06	0.08***	0.01	1.08	1.07	1.10	0.06***	0.01	1.06	1.04	1.08
Time	-0.35***	0.01	0.71	-0.39***	0.00	0.68	0.67	0.68	-0.35***	0.01	0.71	0.70	0.71
Driving cessation	-0.52***	0.10	0.59										
Transport environ.													
Road density	0.01	0.00	1.01	0.00	0.00	1.00	1.00	1.01	0.01	0.00	1.01	1.00	1.01
Cessation*age													
75-84	0.14***	0.03	1.15										
85+	0.25***	0.04	1.29										
Cessation*gender													
Male	0.04	0.04	1.04										
Cessation*educ.	-0.01*	0.00	0.99										
Cessation*race													
Black/AA	0.05	0.04	1.05										
Other	0.15	0.13	1.16										
Hispanic	0.01	0.06	1.01										
Cessation*rel. stat.	0.18***	0.05	1.20										

Divorced			
Widowed	0.27***	0.03	1.31
Never married	0.15	0.09	1.16
Cessation*friend.	-0.06*	0.03	0.94
Cessation*health	0.10***	0.01	1.11
Cessation*vision	0.02	0.01	1.02
Cessation*time	-0.04***	0.01	0.96
Cessation*tr. envir.			
Road density	0.00	0.01	1.00

Note. GIS = Geographic Information System; SE = standard error; IRR = incidence rate ratio.
†p < 0.10. *p < 0.05. **p < 0.01. ***p < 0.001.

CHAPTER 5

DISCUSSION

The primary purpose of this research was to examine the extent to which the transportation environment affected driving limitation behaviors and the mental health of older adults in the US. In terms of the *Social Ecological Model,* the transportation environment is conceptualized as a community-level factor that influences other factors and outcomes on various levels of the model. The overall influence of the environment on study outcomes was assessed, as was the differential influence of the environment within subgroups.

In addition to determining the role played by the transportation environment, a secondary aim of this research was to explore the influence of individual- and interpersonal-level factors on driving reduction and cessation, particularly by gender and race. This chapter will first discuss the key results related to the influence of the transportation environment on study outcomes, and will then present and interpret the secondary findings from this research. Discussion of implications, future research directions, strengths, and limitations, followed by a summary and conclusion end this chapter.

Transportation environment

The first set of analyses assessed whether or not the transportation environment played a role in driving reduction and cessation, after controlling for the effects of demographics, social support, and health. This relationship was assessed in two ways: at the respondent level using longitudinal data, and at the regional level using cross-sectional data. Although the cross-sectional analysis did not find a significant influence of the transportation environment on study outcomes, the longitudinal analyses did. Given that the cross-sectional data were aggregated within large regions (making region the unit of analysis), and only used a single wave of data, the results related to the longitudinal approach are more dependable. Consequently, only the longitudinal results are discussed in this manuscript.

As predicted, a more congested or dense transportation environment increased the odds of both driving reduction and cessation. Of the UMR transportation environment variables only the Travel Time Index predicted driving *reduction*, while nearly all significantly predicted driving *cessation*. It is unclear why only the Travel Time Index was related to driving reduction, but each UMR variable measured the environment in a slightly different way. For example, the Travel Time Index focused on differences in travel within a region during peak time versus non-peak time, while most of the other UMR variables focused on overall congestion or delay. The driving reduction variable analyzed here was related to taking long trips, which may have been more sensitive to peak-time travel issues.

Among the GIS transportation environment predictors, nearly all of the size-adjusted variables (i.e., those that accounted for differences in the geographic sizes of zip codes) predicted both driving reduction and cessation. These variables focused exclusively on the transportation infrastructure and were available for all respondents in the HRS sample, whether they lived in an urban area or not. The greater number of significant GIS predictors of driving reduction (compared to UMR predictors) may be due to the exclusive focus on the infrastructure, as opposed to the UMR predictors which also account for how people experience that environment and how different times of the day play a role (e.g., rush hours). Given that avoiding difficult driving situations is one way older people continue driving safely, it is possible that they avoid congested areas or certain times of the day whenever possible. In contrast, younger adults often have little choice about the time they drive if they have to travel to work, for example. Consequently, older adults may be less affected by congestion measures than people of other ages.

Whatever the reason, the breadth of significant environmental predictors related to driving cessation, and their higher levels of significance, suggest that the transportation environment is a stronger predictor of driving cessation than driving reduction. This finding is important because driving cessation has more serious consequences than simply reducing one's driving, particularly given that the reduction variable used in this study only assessed limiting long trips. Although limiting one's driving is associated with both positive (e.g., increased safety) and negative (e.g., increased depressive symptoms) implications, previous research suggests that driving cessation can have negative impacts on relationships, mental health, and a sense of independence and well-being (Eby et al., 2009; Fonda et al., 2001; Harrison & Ragland, 2003).

This research revealed that a congested and dense transportation environment poses unique driving problems for older adults, but the *reasons* are still unknown. It may be that increased congestion and roadway density in the environment taxes the declining driving abilities of older adults to the point that they reduce or stop their driving. As discussed earlier, there is evidence that older drivers are more likely than younger people to crash in complex driving situations (Insurance Institute for Highway Safety, 2007; Staplin et al., 2012). Navigating an intersection is probably the most complicated driving situation, and is one that older people often try to avoid (Braitman, Kirley, Ferguson, & Chaudhary, 2007; Broberg & Willstrand, 2014). Living in an area that requires interaction with more of these difficult scenarios may lead to a crash, or to lower driving self-efficacy, and precipitate driving reduction and cessation. These decisions may be fueled by safety concerns, either from the older driver or from their family and friends.

An alternative explanation also exists. Although locations with dense or congested transportation infrastructure may be difficult to navigate, they may also provide easier and more readily available alternatives to driving. For example, people may have a larger or closer social network in such locations, which could provide easier access to more people who can provide rides. These more congested areas may also require shorter travel distances to meet one's needs if businesses are more densely located. If these explanations account for this difference, it may be that older adults are not overwhelmed by driving in a daunting environment, but are perhaps more willing to reduce or stop driving because they have more viable alternatives available. These potential explanations are both plausible, but have very different implications for stress, mental health, and feelings of independence among older adults.

The findings from this study also show that there are gender and race differences in how the transportation environment affects driving reduction and cessation. Greater roadway density increased driving reduction, but only among men. Although the interaction term was not significant for driving cessation, the stratified models revealed the same pattern, with a larger odds ratio and a higher significance level for men than women, particularly in the urban sample. Given that men tend to drive longer than women, even with the same health situations and relationship status (Dugan & Lee, 2013), this result was unexpected. It was hypothesized that a congested and dense environment would affect women more than men, and thus partially explain the gender gap in driving cessation. It is unclear why the opposite result was observed here, and this finding should be explored in future research.

One potential explanation may be related to overall gender differences in driving reduction and cessation. If men continue to drive longer than would be ideal given their health status and functional declines, they may be poorer drivers than women on average, with all other things being equal. If that is the case, men may be more affected by the transportation environment than women because they struggle more with complex driving situations. Because women tend to stop driving earlier than men, those who continue to drive at the same age, with the same health conditions, and so on, may be more able to successfully navigate a congested and dense transportation system, and thus be less affected by this factor.

The analyses assessing race differences in the effect of the transportation environment on driving reduction found that these groups were essentially the same. The interaction between race and the transportation environment was not significant in the urban area sample or the full sample. Both stratified analyses revealed that the result was only significant for White respondents, but that lack of significance was primarily the result of more variance in this factor among non-Whites. The reason for more variance among these groups is unclear, as there were sufficient numbers of African American, Hispanic, and Other respondents in the sample. Significant differences in the effect of the environment were noted, however, when driving *cessation* was explored. Interestingly, these analyses revealed mixed results. In the urban sample, White respondents were affected significantly more than Hispanic respondents. Specifically, more congestion led to higher odds of driving cessation among Whites compared to Hispanic respondents. In the full (GIS) sample, however, higher levels of roadway density increased the odds of driving cessation for both White and Hispanic respondents. This factor affected Hispanics significantly more than Whites.

The reason for these differences is unclear, but there are several potential explanations. For example, race may impact responses to the environment due to differences in social support between Whites and non-Whites. Previous research has suggested that there are differences by race and ethnicity in how people seek out and obtain social support (Kaniasty & Norris, 2000; McAdoo, Younge, Hughes, Hanshaw, & Murray, 2003; Xu & Burleson, 2001). For example, in emergency situations, all groups seek out needed support, but in situations considered less critical, Hispanics are more likely to seek support than are Whites or African Americans (Kaniasty & Norris, 2000). Research suggests that social support often serves as a buffer against negative outcomes like driving reduction and driving cessation (Thoits, 2011). Although indicators of social support were included and controlled for in these analyses (e.g., relationship status, number of people in household, friend in the neighborhood, number of living children), these measures may not capture the full breadth of this construct. For example, if African Americans experience more informational (i.e., feedback on their driving) or instrumental (i.e., rides from others) social support than Whites, they may respond by giving up driving earlier, thus minimizing the effect of the transportation environment.

Other potential explanations of this difference may lie with differences in nativity status or driving history between Whites and Hispanics. Estimates from 2012 indicate that among Hispanic adults in the US, 49.8% were born in another country (Krogstad & Lopez, 2014). Driving patterns likely differ in other countries, which would affect an individual’s driving history and comfort in difficult driving situations. Additionally, there is recent evidence to suggest that the driving experiences of Hispanics in the US may differ from Whites because of fear of immigration enforcement (LeBrón, 2015). In that study, Hispanic respondents reported changing their driving behaviors (e.g., avoiding driving unless absolutely necessary, driving for other members of their social network, etc.) depending upon their documentation status and whether they could obtain a driver's license (LeBrón, 2015). Respondents indicated that driving was an extremely important activity, but it also potentially exposed them (and their family and friends) to an increased risk of deportation (LeBrón, 2015). The LeBrón (2015) study was conducted with a younger female-only sample, but the results suggest that there may be differences across racial and ethnic groups that differentially influence driving decisions. In this case, concerns about immigration surveillance through policing of driving activities, along with the increased likelihood of immigration enforcement in larger municipalities (where increased roadway density is more likely), could explain the racial differences observed in the current study.

The mixed results observed by race between the UMR and GIS samples are also important to consider. Because each transportation environment variable operationalizes this factor in a slightly different way, it is possible that the congestion measure affected the races differently than did the roadway density measure. Another possible explanation lies with the fact that the congestion measure was only available for respondents who live in the 101 UAs studied in the UMR dataset. The most important distinction between the UAs and the rest of the US is that the UAs comprise the largest population areas in the country. As such, those areas are more urban and suburban than the excluded areas. Consequently, the mixed results observed with this interaction (as well as several other variables noted in Chapter 4) may be due to the influence of living in areas that differ along the urban-rural spectrum. Only a few studies have examined urban-rural differences in driving behaviors among older adults (e.g., Hanson & Hildebrand, 2011; Johnson, 2002), but evidence from that work suggests that there may indeed be a difference. Drivers who live in isolated environments report that they continue driving even when their health declines because they do not have practical alternatives (Hanson & Hildebrand, 2011; Johnson, 2002). In is also possible that Whites and Hispanics respond differently to driving in a more urban or rural environment.

The final set of analyses related to the transportation environment explored how this factor affected the onset of depressive symptoms, with a focus on differences between respondents who have limited or stopped driving compared to those who have not. The results of this study echoed previous research in that limiting one's driving or losing the ability to drive were both associated with increases in the rate of depressive symptoms (Fonda et al., 2001; Windsor et al., 2007). The current analysis did not find a significant interaction between driving status and the transportation environment as hypothesized, and therefore did not provide support for the *Environmental Moderator Hypothesis*. However, the literature review contained in Chapter 2 identified a number of other studies that *did* support the EMH, so future research should continue to assess the relationships posited in that hypothesis.

As a stand-alone predictor, the transportation environment was significantly associated with depressive symptoms regardless of whether older people drove without restriction, limited their driving, or had stopped driving completely. This finding was surprising given that the results were in the opposite direction hypothesized. Hypothesis 5 suggested that higher roadway density and congestion in the transportation environment would lead to more depressive symptoms, because those areas are more difficult to traverse and take more time to navigate. As it turned out, more congestion in the transportation environment led to a *lower* rate of depressive symptoms.

This counter-intuitive finding may be explained if a congested transportation environment is serving as a proxy for an area that allows people to remain engaged and active, at least in terms of predicting depressive symptoms. Although such environments are more difficult to navigate, they may provide greater access to goods, services, and opportunities. Recent research suggests that understanding an area's "accessibility" rather than simply its mobility is important (Grengs, 2015; Grengs, Levine, Shen, & Shen, 2010). The accessibility of an area focuses on the ease of reaching valued places, which includes metrics of mobility, but also considers proximity and connectivity (Grengs et al., 2010). For example, if an area consists of highly congested roadways, its mobility may be considered poor. However, if there are many nearby places for residents to meet their needs (e.g., stores, banks, doctor's offices, etc.), the close proximity of those locations would mitigate the lack of mobility in the area. Likewise, members of one's social network may be closer and more easily accessible in such environments, thus enabling them to provide rides when people can no longer drive themselves. Getting a ride from a family member or friend remains the most popular method of transportation used by most non-drivers (Choi & DiNitto, 2015; Eby et al., 2009; Kim, 2011). Whatever the underlying reason, research related to how *accessibility* affects health and mental health is warranted, in addition to expanding upon the mobility measures explored in this study.

The discussion to this point has focused on situating the current findings into the existing literature, and considering the potential underlying reasons for these findings. It is also important, however, to consider the expected *consequences* of the transportation environment's influence on driving reduction and cessation. Previous research has established that driving limitations are associated with loss of independence, increases in depressive symptoms, and strained social networks (Choi & DiNitto, 2015; Davey, 2007; Eby et al., 2009; Mezuk & Rebok, 2008), so anything that delays driving reduction or cessation could be seen as protective and valuable. As such, living in a less congested or roadway dense environment where people can continue to drive longer could be seen as a way to remain actively engaged in life for a longer period of time.

On the other hand, living in a simpler transportation environment could also increase the risk of injury or death, both to the older driver and others on the roadway, if a higher percentage of people driving in such areas have lost their ability to safely drive. As noted earlier, there are differences in driving cessation among people who live in urban and rural areas (Hanson & Hildebrand, 2011; Johnson, 2002). If a rural transportation environment can be thought of as generally less congested and simpler, then older adults may continue driving longer than they should. Involvement in a motor vehicle crash is an important predictor of driving reduction and cessation (Charlton et al., 2006; Stutts, Wilkins, Reinfurt, Rodgman, & Van Heusen-Causey, 2001). Although having fewer opportunities for crashes or near-crashes in such environments is beneficial, the lack of stimuli to engender driving cessation could result in a more catastrophic crash when one does occur. Additionally, this research found that men are more affected by the transportation environment than are women. It is already known that men continue driving longer than women, even given the same health conditions, relationship status, and other factors (e.g., Gwyther & Holland, 2012). Living in a less congested and roadway dense environment could potentially exacerbate the injury risk associated with this difference if men continue to drive in such environments. This issue highlights the public health challenge faced by older adults and their families when their ability to safely drive declines – weighing the risk of injury against the reduced quality of life associated with driving reduction and cessation.

Individual and interpersonal predictors

Individual- and interpersonal-level factors like age, gender, education, race, relationship status, household size, health, and vision have all been identified in previous research as potentially important predictors of driving reduction and cessation (Bauer, Rottunda, & Adler, 2003; Braitman & Williams, 2011; Choi, Mezuk, et al., 2012; Donorfio, D'Ambrosio, Coughlin, & Mohyde, 2008; Dugan & Lee, 2013; Freeman et al., 2005; Freund & Szinovacz, 2002; Kulikov, 2010; Raitanen, Törmäkangas, Mollenkopf, & Marcellini, 2003; Rosenbloom, 2010; Siren & Meng, 2013). In addition, driving reduction and cessation is known to be associated with depressive symptoms (Fonda et al., 2001). Many of the previous findings related to those factors were replicated here, with a few differences and additions, which are discussed in this section.

In general, these findings lend support to the previous body of work in this area, but with a nationally-representative sample, longitudinal panel data, and different approaches to the operationalization of key constructs. Previous research that has examined race, for example, has often looked only at Whites versus non-Whites (Choi, Mezuk, et al., 2012; Dugan & Lee, 2013). The same is true for household size. This variable has typically been defined simply as living alone or not living alone (Donorfio et al., 2008; Raitanen et al., 2003). The additional breadth of these variables used in the current study allows for a deeper understanding of their predictive usefulness.

Indeed, household size was an important predictor of driving cessation that was consistent across all of the different models. For every additional person in one's household, the odds of driving cessation increased by 34% (UMR) to 43% (GIS). This effect was consistent for men and women, and within the racial groups. It is likely that living with more people makes it easier to give up driving, because as each additional person represents another individual who can help share the transportation burden. A larger household size also means that there are more people who might notice a decline in one's ability to safely drive, a role often fulfilled by family or others in the household (Perkinson et al., 2005). These factors may make it more likely for the older person to recognize their driving declines, as well as accept driving cessation. Those who live alone may have no choice but to continue driving, even if they recognize that it may no longer be safe to do so. An interesting analysis for future research would be to examine household size categorically. As noted, other research has studied the effect of living alone or not (Donorfio et al., 2008), and the current study examined this factor as a continuous variable. It is likely that having another person in one's household explains a large portion of this effect, but it would be interesting to explore how much difference is made by each additional person, which coding this variable categorically would allow.

Two interpersonal-level variables that have not been explored in previous research were included here: number of living children and having a friend in the neighborhood. Qualitative research has focused on the role played by adult children of older drivers. That work has found that conversations about driving reduction and cessation often occur with one's adult children (Bauer et al., 2003; Connell et al., 2012; Kostyniuk, Molnar, & Eby, 2009; Rosenbloom, 2010). Given what is known about this process, it was quite surprising that the number of living children was not predictive of driving reduction or cessation. In the non-interacted models, it only had a significant effect (and it was small, OR=1.03, $p<0.05$) on driving cessation, and only in the UMR sample. Within the stratified models, this factor was also mostly non-significant; driving reduction among the Other race was the only group for which this was a significant and substantial predictor (OR=1.24, $p<0.01$). It may be that the *number* of living children, as operationalized here, is not the aspect of this issue that truly underlies decisions about driving reduction and cessation. The more important factors to consider may be about closeness of the relationship, or about frequency of contact – issues that were not accounted for in this research.

Having a friend in one's neighborhood was not significantly predictive of driving reduction, but was a very important predictor of driving cessation. Having a friend in one's neighborhood reduced the odds of driving cessation by 23% (GIS sample; 22% in the UMR sample). It may be that the close proximity of a friend makes older adults loath to give up driving completely, and thus reduce contact with that friend. It could also be that close contact with a friend keeps older adults more engaged in life, and positively affects their health and well-being, which would allow them to continue driving longer. This finding presents another opportunity to explore in future research.

An interesting difference noted in this research, compared to previous work, is the effect of driving reduction and cessation on depressive symptoms. Although both were significantly predictive of this outcome, and those relationships have been previously established, this research found that driving reduction was a stronger predictor of depressive symptoms than driving cessation. Several studies have previously examined these factors, but most have not included both in the same study. Fonda et al. (2001) studied both factors, and found that restricting one's driving was a risk factor for developing depressive symptoms, but driving cessation was an even bigger risk. Given that driving cessation has much more serious consequences, those previous findings logically follow. Counter-intuitively, the final non-interacted models in the current study suggested that not restricting one's driving reduces the rate of depressive symptoms by 18%, while not giving up driving reduced the rate by only 7%.

In terms of explaining this puzzling finding, it could be that when an older adult recognizes that they must begin to limit their driving, this realization serves as a warning sign about potential declines to come, and consequently acts as a trigger for depressive symptoms. Compared to driving cessation, refraining from taking long trips probably begins when a person is still relatively healthy and actively engaged in life, and thus may represent the first big lifestyle comprise.

Alternatively, another explanation may be related to the covariates included in these two models. Consider that by the time one has to give up driving, the health declines and other changes one has undergone may actually be better predictors of depression than the act of quitting driving. If that is the case, the covariates included in these models (e.g., health declines, relationship status, etc.) may better account for onset of depressive symptoms (explain more of the variance) for someone who engages in driving cessation, than someone who is only limiting their driving. Both models included all of the same covariates, and accounted for differences in demographics, health, and social support. Interestingly, the weighted mean number of depressive symptoms by subgroup also supports this idea. Those who had stopped driving completely had the highest number of depressive symptoms, followed by those who limited their driving; those who did not engage in driving limitation had the smallest number of depressive symptoms. Given that this bivariate analysis supported the common sense understanding of these relationships, but the multivariate analyses did not, it is likely that the explanation indeed lies with the higher proportion of variance being explained by the covariates.

A final possible explanation for this finding may be that the sample changed with each of these predictors. As noted earlier, the driving limitation question was only asked of those who report that they can still drive, so this finding could be related to differences in the respondents included with each question. Regardless of the underlying reason, these mixed results suggest that future research is needed to better understand these complicated relationships.

As discussed, most previous research in this area has examined individual- and interpersonal-level factors as standalone predictors, and identified their direction of influence (e.g., worse health and female gender lead to increased risk of driving reduction and cessation). Only a few studies have used interactions or stratified models to examine differences in the relationship between these factors and driving limitations by gender or race, as was done in the current study.

Being married or partnered, for example, was only protective against driving reduction and cessation for men. This finding was also observed by Choi et al. (2012). Why this difference exists, however, remains a question for future research. It could be that traditional gender roles or driving history compel men to serve as the "transportation provider" when they are involved in a relationship (Connell et al., 2012). Hakamies-Blomqvist and Siren (2003) suggest that this might be the case, which could result in men continuing to drive longer than they should. On the other hand, being in a relationship may allow for sharing driving responsibilities. This would spread the driving load and reduce the likelihood of an event like a crash, which often precedes a major driving change (Charlton et al., 2006). It is unclear, however, why that would affect men and not women. A more likely explanation may lie with previous research that has shown a "copiloting" phenomenon among older drivers. Having a passenger in the car who can help with navigation and attentional requirements significantly reduces crash risk (Braitman, Chaudhary, & McCartt, 2014). Given that men are more often the drivers when they travel with women (Rosenbloom & Herbel, 2009; Siren & Hakamies-Blomqvist, 2006), relationship status would have more of an effect on men than women.

Age alone was a highly significant predictor of both driving reduction and cessation for both men and women. Interestingly, after controlling for the other predictors in the model, age affected women more than men. Health also affected both men and women, but had a significantly larger effect on driving reduction in men. These findings support previous research related to gender differences, and specifically support the idea that women may limit or stop driving earlier than is medically necessary (Siren et al., 2004). Women seem to be more affected by age alone, while men respond to a health decline by adjusting their driving behavior.

Choi and colleagues (2012) found that education differentially predicted driving cessation among men and women. In their study, increased educational attainment significantly increased the odds of driving cessation among men, and significantly decreased them among women. The results here differ from those findings. The interaction terms between education and gender were not significant for either driving reduction or cessation, and increased education was significantly protective against driving reduction for both genders, and marginally protective against driving cessation for women. The odds ratios for this factor were also much larger (1.40 for men, 0.90 for women) in the study by Choi et al., (2012). It could be that the additional predictors included in the current study account for the variance explained by educational attainment in the previous work, but given these mixed findings, the role of education in these behaviors merits additional study.

Racial differences were also observed between the individual- and interpersonal-level predictors and the driving behaviors. Being married or partnered, for example, was most protective against driving reduction for Whites and Hispanics, compared to the other races. In the stratified models, relationship status was not significantly predictive for African Americans at all, and there were mixed results between the subsample (UMR) and full sample (GIS) for those of Other race. There were also mixed results related to driving cessation. One finding that was consistent throughout the models was that relationship status significantly affected these behaviors among Whites, but did not significantly affect African Americans. For driving reduction, the odds ratios for non-married Whites were much higher than for non-married

African Americans. For driving cessation, however, the odds ratios were similar for both groups, but there was more variance in the estimates for African Americans. This suggests a true difference in driving reduction between these groups, but the reasons for this difference are unclear. Marriage may compel Whites to continue to take long trips (the driving reduction variable assessed in this study) even after experiencing health declines and other problems. Alternatively, African Americans may take fewer long trips than Whites in general, which could be reflected in this difference.

Vision declines negatively affected all participants' driving ability, but White respondents' engagement in driving reduction and cessation was affected more than that of other groups. This difference may reflect differential access to resources. For example, African Americans and Hispanics generally have less accumulated wealth than Whites (Gittleman & Wolff, 2004; Killewald, 2013). This disparity would likely result in fewer financial resources to pay for alternative transportation, and fewer community resources dedicated to that purpose. If that is the case, Whites could more easily reduce or stop driving in response to a decline in their vision, where non-Whites may have no choice but to continue driving.

A significant interaction between age and race was observed when driving cessation was regressed on these factors in the UMR sample. The stratified models showed that Whites, African Americans, and Hispanics were all significantly affected by age. However, driving cessation among Whites was influenced significantly more by age than among African Americans. This finding partially supports previous research that has also identified a significant interaction among these factors. Increasing age predicted driving cessation among Whites, but not among non-Whites in the study by Choi et al. (2012).

Race also significantly interacted with a few other factors in the models. One's number of living children had a small but significant effect on driving reduction among African Americans and those of Other race, but not among Whites. Also, having a friend in the neighborhood reduced the odds of driving cessation significantly more for Whites compared to those of Other race. However, all of these were relatively small effects, and were not consistent between the UMR and full samples. As such, their importance remains unclear. Collectively, these findings suggest that driving reduction and cessation of Whites and non-Whites differ based upon several individual- and interpersonal-level factors. Future research should attempt to identify the reasons for these differences, and could potentially study social support, driving needs, or driving history differences between these groups as potential explanations.

Implications

The influence of the transportation environment identified in this study has implications for policy, community, interpersonal, and individual-level interventions. Indeed, the incorporation of predictors from multiple levels of the *Social Ecological Model* has resulted in implications and a need for future research at multiple SEM levels.

As mentioned previously, higher levels of congestion and roadway density reduce older adults' ability to drive without restriction and hasten driving cessation. There are several implications of this finding. The first obvious response would be to adjust funding and city design policies in order to reduce roadway congestion; in effect, build more roads with more lanes of travel. Although this approach is likely to reduce congestion and allow older people to continue driving longer, this is probably not a practical solution, and may miss the most important point. The vast majority of trips are taken for a specific purpose, rather than just driving enjoyment (Santos et al., 2011). People need access to certain things, want to visit friends, or have to get to work. As such, a better solution would be to change policies such that more of the things to which people want or need access are available in closer proximity. As described earlier, mixed-use zoning laws are a good example of such a policy change. These laws allow for a given neighborhood to have retail and commercial businesses in close proximity to denser residential areas (American Planning Association, 2013; FindLaw, 2014), which reduces the need to travel. Although it is likely that such an area would have more congested roadways, overall there would be less need to drive. Continuing to drive for a longer portion of one's life is important because it allows older adults to remain engaged in productive activities into older adulthood (Curl et al., 2014). Moreover, increased engagement in activities is related to better quality of life and lower rates of depression (Potocnik & Sonnentag, 2013).

Increasing the availability of quality public transportation is another solution that could potentially mitigate some of this problem. For a number of reasons, it is likely that driving will always be important in the US. The country is extremely large geographically, with the population spread throughout, which makes expanding public transit to all areas expensive and impractical. There is also a long history of a "driving culture" in the US (Moeckli & Lee, 2007), which is unlikely to quickly change. As discussed earlier, public transportation is primarily only available in large cities. All of these reasons make driving a practical and popular choice for everyone, and older adults are no different. However, where public transportation does exist, older adults do use it, even those who can no longer drive. Estimates suggest that older non-drivers take 310 million trips per year on public transportation (Bailey, 2004).

It is not enough to simply have a public transportation system, however, and expect people to switch from driving to using that system when they get older, particularly given the strong preference people have for driving (Coughlin, 2001). Just like anything, using a public transportation system takes practice or training. Indeed, there is evidence that completing a transit training program increases use of public transportation (Stepaniuk, Tuokko, McGee, Garrett, & Benner, 2008). Additionally, if better public transportation systems were available wherever they are practical, the increased use throughout people's lifespan would likely make these more acceptable options for older people who struggle to safely drive. Finally, it is likely that increased public transportation would ease traffic congestion for everyone (Anderson, 2013), which would also allow older people to continue driving longer.

These results also have implications for how older individuals plan their future. There is a strong preference among older adults toward "aging in place," a term that refers to older people remaining independent and in their own homes and communities for as long as possible (Benefield & Holtzclaw, 2014). Given this preference, the built environment within which one lives should be an important consideration for people who prefer to age in place. A more congested driving environment would likely result in giving up driving earlier, and may hasten a loss of independence. On the other hand, if older people in such an environment have better access to alternative forms of transportation – whether that means rides from nearby friends and family, public transportation, or paratransit – the location may be well-suited to aging in place. Regardless, this research suggests that the transportation environment of a community is something older adults should consider to successfully age in place, in addition to their home and social environments.

As discussed, people often consider where they want to live when they retire (aging in place), they plan for their medical care during retirement (Jacobson, Huang, & Neuman, 2014), and they plan their finances for the later stages of their life (Copeland, 2013). This research also suggests that driving and mobility issues should become a regular part of more general retirement and life planning. Planning and having discussions with family members about transportation needs before driving becomes problematic is likely to reduce the potential trauma associated with role loss, complication of interpersonal relationships, and increased isolation often associated with this change (Musselwhite & Shergold, 2012). As noted earlier, these conversations often occur following a crash or near-miss, which is already a stressful situation. Planning ahead for how these needs will be met is likely to allow people to more readily accept reductions in their driving ability when they become necessary, particularly if they have already moved to a community more supportive of older adults' mobility needs.

These results also have implications for identifying potential individuals at risk and for informing interventions. It is well established that age, health, vision, and gender all affect driving reduction and cessation. Those results were echoed in the current research, and continue to suggest potential points of intervention. For example, given the influence of age, vision, and health in this process, health care providers who have contact with older adults remain a potentially key point of contact. There is evidence that physician warnings are an effective way to reduce crash-related injuries, but such warnings may also increase depression and can negatively affect patient-provider relationships (Redelmeier, Yarnell, Thiruchelvam, & Tibshirani, 2012). Vision care providers are also likely to have contact with older adults who may be experiencing driving problems, particularly if the problem is vision-related. Many of these providers report that they discuss driving issues with their patients, but they also note concerns about the potential for liability issues, wonder whether this is the responsibility of a vision care provider, and worry about the negative implications for the patient-provider relationship (Leinberger, Janz, Musch, Niziol, & Gillespie, 2013; Musch, Janz, Leinberger, Niziol, & Gillespie, 2013).

Interventions and policy changes could be developed to increase health care providers' ability to discuss these issues with their older patients. A guide has already been created to help providers more fully understand this topic, recognize warning signs, and provide such counseling, but it is long and complex (Wang, Kosinski, Schwarzberg, & Shanklin, 2003). To increase providers' self-efficacy to discuss driving problems with their patients, training sessions on this topic could be developed and planned to coincide with major medical conferences, for example. Policies could also be implemented to allay fears related to damaging the patient-provider relationship and for legal liability. These concerns arise especially when locales require physicians to report older adults to driver licensing authorities if they have a certain condition (Porter, Marshall, & Bédard, 2013; Redelmeier et al., 2012). Mandatory reporting requirements differ between countries and US states (Wang et al., 2003), so making these laws more consistent would help everyone involved. Adding insurance reimbursement for health care providers to have these discussions, and enacting laws to protect providers from civil liability related to this issue would also likely increase provider involvement.

Social support-related factors like relationship status, having a nearby friend, and household size can also inform intervention design and identify target populations. Based on the results of the current study, as well as previous work, it is clear that social support plays a key role in driving reduction and cessation. It is likely that instrumental (e.g., providing rides), informational (e.g., evaluating driving), and emotional social support affect older adults who are struggling to safely drive or who have given up driving. Researchers and practitioners have already begun to develop interventions targeted toward older adults facing driving cessation and their partners or caregivers (Dobbs et al., 2009). This work has shown promise, and continuing to focus on the complicated interpersonal communication and relationships involved in driving reduction and cessation is critical. The social support aspects of driving reduction and cessation also represent an opportunity for interventions aimed at improving the life of both the older adult and his or her caregiver. Previous research has found that *providing* social support is associated with increases in positive affect and overall well-being (Siedlecki, Salthouse, Oishi, & Jeswani, 2013; Thomas, 2009). Interventions could focus on maximizing the positives related to this transition, like an increased sense of well-being among the transportation provider or the potential for additional time spent together while helping to meet the mobility needs of another.

Future research

The most important need for future research is to examine the reasons that underlie the findings from this study. As described throughout the discussion, the influence of the transportation environment and individual- and interpersonal-level factors on driving reduction and cessation has been established, but *why* these relationships exist remains unclear. For many of the findings, there were several potential explanations, but the causal pathways were unclear. Future research is needed to better inform the development of policy and other programs designed to help older adults transition from driving to other approaches to mobility. If we understood more about why people change their driving behavior in response to the environment, or why not being in a married/partnered relationship leads to driving limitations among men only, for example, we could create interventions that were as responsive to unmet needs as possible.

Another important avenue of future research is to examine differences in health, driving behaviors, and quality of life, based on measures of accessibility, rather than just mobility. The earlier discussion of the key differences between these two metrics suggested that studying accessibility may add a new perspective to the relationships described in this manuscript, given that most people drive in order to access things and other people, rather than just for enjoyment.

To date, very little work has examined differences in driving reduction and cessation by race and other subgroups. Virtually all of the previous research on aging and driving has been conducted primarily with White participants, but is considered generalizable to everyone. The scope of potential subgroup differences in driving behaviors remains largely unknown, and the current research, as well as work by Choi and colleagues (2012), suggests that future work should continue to identify and explain those differences.

Finally, in the aging field there is a concept known as *successful aging*. Researchers define this term in different ways, but it generally includes staying relatively healthy, maintaining cognitive and physical functioning, and remaining actively engaged with life (Rowe & Kahn, 1997). Other research suggests that this concept should also include an individual's own assessment of how successfully they have aged (Cernin, Lysack, & Lichtenberg, 2011; Gwee et al., 2014; Strawbridge, Wallhagen, & Cohen, 2002), and that it should take a life course perspective (Stowe & Cooney, 2014). In considering each of these aspects of successful aging, there are many obvious connections to driving and transportation, but very little research has considered how these areas relate to each other (Bartley & O'Neill, 2010). For example, it is typically a health decline or deterioration in cognitive or physical functioning that leads to driving problems. In the US, driving your own car is how people remain actively engaged with different aspects of their life. They drive themselves to see friends, to do their shopping, and to go to church. Future research should apply a successful aging perspective to the issue of older drivers to more clearly link the broader gerontological literature to the work on driving reduction and cessation.

Strengths

There are several strengths and unique contributions related to this research. This study was the first to examine the role of the transportation environment on driving reduction, driving cessation, and onset of depressive symptoms. Given that driving behaviors occur while interacting directly with the physical environment, understanding the role played by the environment in these relationships is vital. Another strength of this research was that established theories (the *Social Ecological Model* and *Social Determinants of Health Theory*) were used to inform hypotheses and predict relationships. As noted earlier, exploring the influence of multilevel factors on each other is the best way to truly understand the context within which decisions are made, and in which health-related behaviors are engaged. This research did that, using established ecological theories as a guide.

The data and analyses used in this study are also key strengths of this work. Longitudinal data allowed for respondents to be followed prospectively over time for a 12-year period. Because of this, analyses could account for changes in a given environment over time (e.g., as congestion increased within a region over the years), as well as when a person moved from one location to another. The HRS sample is also large and nationally-representative. This allowed for adequate power to examine complex relationships simultaneously, including the interactions, while controlling for the important known predictors. In addition to the HRS data, GIS-based calculations were made for every zip code in the US. As such, the results using the GIS-based variables can be generalized to the US population, and those using UMR variables are representative of people who live in urban areas.

A final strength of this work is that it explored differences within subgroups of interest defined by gender and race. These analyses examined potential gender and racial differences in not only the transportation environment, but in all other factors included in the models. Previous research has documented that men and women respond differently to a decline in their driving ability, but most of that work has only noted these differences. Almost no research has explored differences in these factors by race. The interacted and stratified models included in this research begin to provide an explanation for some of the known differences between groups and to identify new differences, all of which will deepen our understanding and identify potential points of intervention to address the mobility needs of growing numbers of older drivers.

Limitations

There are some important limitations to this research that must be acknowledged. As noted earlier, the variables used to assess driving reduction and cessation were not ideal, but have been used for this purpose in multiple other studies and are considered acceptable. Ideally, a measure of driving reduction would assess additional avoidance behaviors like driving during rush hour, at night, and in inclement weather. A more robust measure of driving cessation would ask respondents about their actual driving behavior, rather than their ability to drive.

The available categories for assessing differences by race and ethnicity were somewhat limited. Specifically, only four categories were available. Although this *was* an improvement over previous research, both the Hispanic and Other race categories were not very nuanced (e.g., no differentiation between those of Mexican, Cuban, etc. descent in the Hispanic category or between any groups in the Other category). In addition, data from the UMR were only available at the Census Urban Area level. Although the 101 urban areas represent a large portion of the US population (and the HRS sample), those variables were not available for all respondents. Consequently, some respondents (those who live in less populated or rural areas) did not have information available about that aspect of their transportation environment. On the other hand, the GIS variables were available for the entire sample.

The roadway density variable was also somewhat limited. The GIS data did not include the number of lanes of travel, so the count of roadway miles used to create this variable was not as precise as it could have been. An ideal measure of roadway density would include both of these factors (miles of roadway and lanes). Given that this was a highly significant predictor throughout the study, however, it is likely that a more nuanced version of this factor would only increase its predictive value. Additionally, each of the variables used in this study to represent the transportation environment focus on mobility, which does not account for proximity or connectivity, the two other components included in the conceptualization of accessibility (Grengs et al., 2010). As discussed earlier, accessibility would more closely capture people's ability to access the things they need and want.

It should also be noted that no data were available to account for differences in access to paratransit – an umbrella term for transportation services provided specifically for older adults, usually at the neighborhood or community-level. Finally, the survival analyses did not include respondents who reported that they were already unable to drive during their first eligible wave (left-censored respondents). As noted earlier, those respondents were older; had less education; were more likely to be female, non-White, and non-married; and had worse health and vision. Given that these factors are all known to predict higher odds of driving cessation, it is likely that the results noted in the current study would be strengthened if those respondents could have been included. The differences between the included respondents and those who were left-censored also suggest that HRS, and other studies that assess driving reduction and cessation, should begin asking people about their driving behaviors much earlier than age 65.

Summary and Conclusion

This research explored a broad spectrum of factors related to driving reduction and cessation among older adults. Given the scope of this work, it is useful to briefly review the most important findings. The key research questions assessed the influence of the transportation environment, a community-level factor, on individuals' driving reduction and cessation. This research found that as roadway congestion increased, the odds of engaging in driving reduction and cessation also increased, even after controlling for individual- and interpersonal-level factors like demographics, social support, and health. Likewise, increases in roadway density also predicted higher odds of driving reduction and cessation. The transportation environment affected men more than women in this process, and affected Whites and Hispanics more than African Americans and those in the Other racial category.

In addition, the transportation environment, driving reduction, and driving cessation significantly affected depressive symptoms. As the transportation environment became more congested, the rate of depressive symptoms decreased. The rate of depressive symptoms increased for those who limited their driving and those who had stopped driving completely.

There were also several findings worth emphasizing among the individual- and interpersonal-level factors. Because of the large sample size in the current study, most of the covariates included in the models were statistically significant; however, not all are equally meaningful. Relationship status, for example, was a highly significant predictor of driving reduction and cessation, particularly for men. Being married or partnered was significantly protective against driving reduction and cessation for men, but less so for women. Having a friend living nearby was protective against driving cessation, but had no effect on driving reduction. Likewise, household size was one of the most consistent and strongest predictors of driving cessation, but had little effect on driving reduction. The number of living children one has was generally not significantly predictive of driving reduction or cessation, nor was having a relative living in the neighborhood. These findings were surprising given the importance of other social support-related variables in the current study, and from findings of previous research that has established adult children as key stakeholders in this process.

Collectively, these findings highlight the importance of understanding and designing interventions that focus on all levels of the *Social Ecological Model*, and do so in an integrated fashion. Individual- and interpersonal-level predictors of driving reduction and cessation remain important. Going forward, however, factors in the social and physical environment must also be considered. Increasing the focus on higher-level factors is also consistent with the core tenets of public health. For example, changes in social policies and those that affect the physical environment would create population-level changes from an upstream perspective, rather than relying on individuals to change their behavior. Some of the interventions described earlier also take a proactive and preventative approach to this problem, rather than the reactive way these problems are often currently managed. Given the existing US transportation system and the aging of our population, this issue will remain critical to public health, both in terms of safety and quality of life.

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