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Impact of health on driving for America's older adults: A nationwide, longitudinal study

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ABSTRACT

By 2030, one in every five Americans will be 65 or older. To better serve the mobility needs of a rapidly aging population, a better understanding of older adults' driving behavior is needed. This study explores the impact of health on driving reduction for America's older adults, using a nationwide, longitudinal dataset from the Health and Retirement Study (HRS). I propose two outcome variables: having driven in the past month, and having driven beyond nearby places; and measure health using overall self-rated health status and specific sensory, mobility and physical conditions. Controlling for socio-demographics, residential patterns, personal fixed effects, time fixed effects, and regional fixed effects, I find that older adults with lower self-rated health were less likely to drive or drive beyond nearby places. The magnitudes of such effects vary by race but not by gender. I also identify specific health conditions that could predict driving reduction. The findings imply that in the near future, there will be a large number of older adults suffering from unmet travel demands due to declining health conditions. Hence, planners and policy makers should be proactive in seeking for solutions, including using my findings to identify at-risk older drivers and provide various types of mobility assistance.

1. Introduction

The American population is aging: by 2030, one of every five Americans will be 65 or older (Vespa et al., 2020). Such a trend will considerably change the landscape of passenger transportation in the U. S. In general, people drive less when they age. For instance, the most recent nationwide travel survey in the U.S., the 2017 National Household Travel Survey (NHTS), shows that 91.2% of the respondents 50–59 years old were drivers, and the percentages for those who were 60–69, 70–79 and 80+ were 89.5%, 85.8% and 63.5%, respectively (McGuckin and Fucci, 2018). The previous round of this survey, the 2009 NHTS, shows a similar pattern: the share of drivers for the 50–59, 60–69, 70–79 and 80+ age groups were 93.7%, 91.4%, 83.0% and 61.7%, respectively (Santos et al., 2011). Although older adults drive less when they age, most are not able to use the transit system or the recently popular ride-hailing service to compensate for their reduced driving, due to limited transit access, safety concerns and unfamiliarity of the ride-hailing apps (Kim, 2011; Wasfi et al., 2012; Leistner and Steiner, 2017; Zijlstra et al., 2020). Furthermore, older adults are reluctant to rely heavily on asking family and friends for rides (Nordbakke and Schwanen, 2015).

Thus, most older adults with driving reduction are at risk of having unmet travel demands (Luiu et al., 2017), which will bring about many negative consequences such as reduced social activities and lower quality of life (Lucas, 2012; Metz, 2000). Considering that the currently retiring baby-boomers are the most car-dependent generation to date (Coughlin, 2009), and that most of the suburban older adults will remain living in the suburbs (Binette and Vasold, 2018), the challenge to fulfill older adults' mobility needs will be even greater in the near future. Literature on planning research has called for proactive solutions to be better prepared for this oncoming challenge.

For transportation planners, a better understanding of the factors associated with older adults' driving reduction can help the local governments to better identify at-risk older drivers. Health status is among the strongest predictors of driving reduction. Existing studies, mostly in gerontology and safety sciences, have identified various health conditions associated with driving cessation, namely, completely giving up driving (e.g., Dickerson et al. (2017)). However, limited attention has been given to driving reduction, especially limiting driving within nearby places, which has a greater policy relevance for urban planners. In addition, most of the existing studies on this topic are based on smaller-area or cross-sectional samples, which may suffer from limited external validity or omitted variable biases.

The present study tries to fill these gaps by examining the impact of

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health status on driving reduction using a nationally-representative, longitudinal survey: The Health and Retirement Study (HRS). I focused on the respondents 65 or older regarding their health and driving in 2006, 2008, 2010, 2012 and 2014. I examined two driving reduction variables: having driven in the past month, and having driven beyond nearby places, and applied fixed effects logit regression models to control for individual-specific confounding factors. Specifically, I examine three questions: (a) the relationship between self-rated overall health and the two driving reduction variables; (b) whether the relationships identified in (a) differ with gender and race; (c) the specific physical, sensory and mobility conditions that can predict driving reduction.

The following sections review the relevant literature; introduce the study sample and analytical methods; demonstrate the empirical results; and discuss their implications for practitioners and researchers and concludes.

2. Literature review

2.1. Older adults' driving reduction and mobility options

America's older adults, most of whom live in the suburbs, are expected to "age-in-place", which means they prefer staying in the suburbs rather than moving to central cities (Binette and Vasold, 2018). Most of these suburban older adults are currently drivers (Binette and Vasold, 2018). However, most of them are expected to reduce and eventually forgo driving in the future. Besides the fact that travel demand decreases with age (Siren and Haustein, 2016), there are many other factors associated with older adults' involuntary driving reduction. Such factors include physical limitations (Edwards et al., 2008), use of certain medications (Rosenbloom and Santos, 2014), and reduced confidence in driving (Hassan et al., 2015). Driving reduction includes decreasing frequencies of driving, completely give up driving, and tactical self-regulation such as avoid driving in rush hours (Dickerson et al., 2017; Kostyniuk and Molnar, 2008). Patterns of driving reduction, for both decreasing frequencies and self-regulation, differ by gender. Older women are relatively more likely to have driving reduction, likely due to lower level of confidence (McNamara et al., 2013; Meng and Siren, 2015; Molnar et al., 2014). Driving reduction also differs among race, as Choi et al. (2013) show that African Americans are more likely to cease driving than whites.

Due to the limited supply of alternative travel modes in America's suburbs, older adults who reduce or cease driving may suffer from unmet travel demands (Luiu et al., 2017). Although many older adults express their interests in using transit to compensate reduced driving, most of them are not able to do so due to the low coverage, long waiting time, lack of senior friendly facilities and safety concerns of the current transit system (Kim, 2011; Wasfi et al., 2012). Similarly, the recently emerging ride hailing services (e.g., Uber or Lyft) are not as popular among older adults compared to younger age groups. Although almost two thirds of America's older adults have smartphones (Pew Research Center, 2018), only 29% of them have used ride hailing services (Binette and Vasold, 2018). This is due to older adults' privacy concerns, fear of crime, and unfamiliarity of the ride-hailing apps (Binette and Vasold, 2018; Leistner and Steiner, 2017). Currently, the older adults' most popular alternative mobility option is to ask for rides from family members or friends (Jones et al., 2018). However, around one thirds of such request cannot be met (Luiu et al., 2018). In addition, many older adults feel reluctant to frequently asking for rides, and they end up with "self-censoring" their requests (Nordbakke and Schwanen, 2015). Specifically, their ride requests are mostly for essential needs such as grocery shopping or medical appointments; and their social and leisure trips such as visiting friends or going to cinema are more likely to be censored (Hjorthol, 2013; Nordbakke and Schwanen, 2015). The reduction of such social trips can weaken older adults' social capital and hence decrease their quality of life (Hjorthol, 2013; Mezuk and Rebok, 2008).

2.2. Health predictors of driving reduction

To address the older adults' unmet travel needs, planners and policy makers need to be better in identifying those who are at risk of driving reduction and in need for mobility assistances (Adler and Rottunda, 2006). Health conditions are among the strongest predictors of driving reduction (Haustein and Siren, 2014). Studies connecting health with driving reduction are still limited in the literature of transport policy and urban planning. A closely-related concept, driving cessation, has been of interest in gerontology and safety sciences (Dickerson et al., 2017). Studies have shown that worse self-rated overall health is associated with higher probability of driving cessation (Anstey et al., 2006; Haustein and Siren, 2014). With respect to specific health conditions, Luiu et al. (2017) proposes a framework with three categories of health conditions that could predict driving cessation: sensory, mobility and physical. Specifically, sensory impairments are related to limited eyesight, hearing or cognitive impairments such as memory problems (Hambisa et al., 2021; Marshall, 2008; Seiler et al., 2012); mobility impairments are related to limited physical strength and joint problems (Dickerson et al., 2017; Dugan and Lee, 2013; Kostyniuk and Molnar, 2008); and physical impairments are problems due to other general diseases such as stroke or hypertension (Dickerson et al., 2017; Edwards et al., 2008; Hambisa et al., 2021).

Although evidence regarding associations between older adults' health and driving is emerging, significant questions remain. First, most existing studies focus on driving cessation and tactical self-regulation. Studies focusing on driving reduction, especially on limiting driving within nearby places, are still limited. Such studies could help policy makers and planners to better identify the health conditions with larger mobility and accessibility implications. Second, many existing studies focus on small areas such as a city or a region. Their practical inferences beyond the study areas may be less reliable, making policy makers reluctant to adopt the findings to other regions. Third, the majority of the studies use cross-sectional datasets. These studies may suffer from omitted variable bias, as unobserved personal characteristics may be correlated with both health conditions and driving reduction. It is very difficult for cross-sectional studies to correct for this bias, making the findings less convincing for policy makers.

3. Data and methods

3.1. Data source and study sample

The study sample comes from the Health and Retirement Study (HRS), a nationally-representative survey of Americans who are over 50 years old. The HRS is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan. The HRS is a longitudinal survey that queries the same respondents to collect information on demographics, family structure,

Table 1
Numbers and shares of repeated observations in the study sample (unit: individual).

Number of waves appeared in the study sample	All five waves		2006		2008		2010		2012		2014	
	N	%	N	%	N	%	N	%	N	%	N	%
One wave	2726	17.0%	1299	11.5%	156	1.4%	112	1.0%	122	1.1%	1037	10.5%
Two waves	2624	16.3%	1495	13.2%	1547	13.7%	290	2.7%	1018	9.6%	898	9.1%
Three waves	2350	14.6%	1175	10.4%	1326	11.7%	2212	20.3%	1266	11.9%	1071	10.8%
Four waves	2744	17.1%	1738	15.4%	2674	23.6%	2652	24.4%	2635	24.8%	1277	12.9%
Five waves	5605	34.9%	5605	49.5%	5605	49.6%	5605	51.6%	5605	52.6%	5605	56.7%
Total	16,049		11,312		11,308		10,871		10,646		9888	

personal income and wealth, pensions and insurance policies, retirement plans and health conditions every year from 1992 to 1996, and every two years since then (HRS, 2021). The survey keeps adding younger cohorts across survey years in order to be representative of the 50-and-older population (HRS, 2021).

The dataset used in this study is a subsample of the HRS. It is a longitudinal dataset containing information on health, driving, and socio-economic characteristics of individuals aged 65 or older in five recent waves of HRS: 2006, 2008, 2010, 2012 and 2014. The dataset comes from both the RAND file and the FAT file of the public-use sample of the HRS (HRS, 2021). This dataset is not weighted. It is not a balanced panel, meaning not all individuals were surveyed in all five waves. Some individuals were only covered in a subset of waves, and some "younger" older adults were included in the HRS only in later survey waves. This study sample includes 16,049 individuals. Among these individuals, 83.0% (13,323) were surveyed in at least two waves, and 34.9% (5605) were surveyed in all five waves (Table 1). The total number of person-by-wave observations in this study sample is 54,025. Among these observations, 58% are female, which is comparable with the female share of the 65-or-older in the 2010 census (57%).

3.2. Outcome variables

To examine the relationships between health and driving reduction for older adults, this study aims to explore three questions: (a) do overall health conditions influence older adults' driving, and, if they do, at what magnitude? (b) does the magnitude of such effects differ by gender and race? (c) what specific health conditions predict older adults' driving reduction? To answer these questions, I proposed three sets of fixed effects regression models. Each set of models has two outcome variables: a dummy variable on "having driven in the previous month" that equals one if the respondent had driven in the month prior to the survey, and a dummy variable on "having driven beyond nearby places", which equals one if the respondent was able to drive for trips beyond her/his nearby area. In the HRS survey, all respondents who were 65 or older were asked *"Are you able to drive?"* if the answer was "yes", a follow-up question was posed: *"Have you driven in the past month?"* for those answering "yes" for this follow-up question, another question, "*Do you limit your driving to nearby places, or do you also drive on longer trips?"* was asked. Hence, the respondents with a zero value of the "having driven last month" variable were either not able to drive or were able to drive but chose not to do so; similarly, those with a zero value for the "can drive beyond nearby places" had either not driven in the past month or had driven in the past month but only limit to nearby destinations.

3.3. Exposure variables

The main exposure variables for each set of models are as follows. First, for overall health conditions (Question (a) in Section 3.2), I used a five-category self-rated scale of overall health at the time of survey: "excellent" (reference), "very good", "good", "fair" and "poor" (Anstey et al., 2006; Haustein and Siren, 2014).

Second, for effect differences by gender and race (Question (b)), I introduced models containing overall health and its interaction with gender and race, respectively. The racial profile had four categories: Non-Hispanic white (reference), Non-Hispanic black, Hispanic and other races.

Third, for specific health conditions that predict driving reduction (Question (c)), I followed the framework by Luiu et al. (2017) and proposed six variables on sensory conditions, three variables on mobility conditions and three variables on physical conditions (Dickerson et al., 2017; Dugan and Lee, 2013; Edwards et al., 2008; Hambisa et al., 2021; Kostyniuk and Molnar, 2008; Marshall, 2008; Seiler et al., 2012). The six dummy variables on sensory conditions are: fair or poor self-rated distance vision (yes/no, from a five-category scale of excellent, very good, good, fair or poor), fair or poor self-rated near vision (yes/no), fair or poor self-rated hearing (yes/no), fair or poor self-rated memory (yes/no), having depressive thoughts (yes/no, yes if the depression score [ranges from 0 to 8] is larger than 0[1]), and being diagnosed with psychiatric diseases (yes/no). The three dummy variables on mobility conditions are: difficulties with the activities of daily living (yes/no, yes if having difficulties in either bathing, dressing, eating, bedding or walking), difficulties with activities using large muscles (yes/no, yes if having difficulties in either sitting for 2 h, getting up from a chair, kneeling, or pushing large objects), and having arthritis (yes/no). The four variables on physical conditions are: a factor variable related to whether a person is underweight, overweight or obese (with normal weight as reference), a dummy variable on having high blood pressure (yes/no), a dummy variable on having heart diseases (yes/no), and a dummy variable on history of stroke (yes/no).

3.4. Control variables and fixed effects

With the longitudinal dataset, this study is able to control for individual- and year-fixed effects. The individual fixed effects control for all individual-specific factors not changing over time. For instance, lifestyles and attitudes towards transit ought to be associated with both driving and health, and failing to control for them could bias the regression. Assuming these lifestyles and attitudes were constant across survey years, they are controlled for in the individual fixed effects (Macfarlane et al., 2015). In addition, gender and race of the study

[1] This variable is based on the RwCESD variable of the HRS RAND file (HRS, 2021). This variable measures whether the respondent had experienced the following eight sentiments "for all or most of the time": depression, everything is an effort, sleep is restless, felt alone, felt sad, could not get going, felt happy and enjoyed life. For the first six negative sentiments, the respondent received one point for answering "yes" and zero otherwise; for the last two positive sentiments, the respondent received one point for answering "no" and zero otherwise. Then the RwCESD variable is the summation of these eight sentiment-specific scores, and ranges from 0 to 8 with higher values indicates higher depression risks. This RwCESD variable is different from the typical 20-item Center for Epidemiologic Studies Depression (CESD) Scales (Andersen et al., 1994), where the raw score ranges from 0 to 60. There is no consensus on the "positive/negative" cutoff point for this HRS-specific 8-item CSED scales. Hence, I categorized the respondents with any non-zero values (57.8%) as "yes" for depressive thoughts, as the zero vs. non-zero dichotomy is a natural cutoff point.

Table 2
Descriptive statistics of the study sample, by wave (16,409 individuals across five waves).

Variable	Mean or share, by survey year					
	Total	2006	2008	2010	2012	2014
Driving						
Had driven in previous month	0.736	0.728	0.735	0.733	0.732	0.754
Can drive beyond nearby places	0.474	0.461	0.459	0.476	0.487	0.491
Sociodemographics and residential patterns						
Age (years)	75.6	74.9	75.3	75.8	76.1	75.9
Family below poverty line	0.100	0.091	0.097	0.105	0.108	0.100
Living in a single-family house	0.721	0.714	0.722	0.716	0.718	0.736
Race (%)						
Non-Hispanic white	75.6%	77.2%	76.4%	75.6%	75.2%	73.2%
Non-Hispanic black	13.7%	13.0%	13.5%	13.9%	13.7%	14.6%
Hispanic	8.7%	8.0%	8.2%	8.5%	9.0%	9.8%
Other	2.0%	1.7%	1.9%	2.0%	2.1%	2.4%
Female	0.580	0.573	0.580	0.579	0.583	0.588
Living alone	0.296	0.300	0.300	0.295	0.297	0.286
Employed	0.179	0.183	0.187	0.173	0.172	0.177
Overall health						
Self-rated health (%)						
excellent	7.6%	8.5%	7.4%	7.8%	7.4%	6.8%
very good	27.7%	26.4%	26.9%	28.6%	28.8%	28.0%
good	32.8%	31.6%	32.7%	33.1%	32.5%	34.4%
fair	22.3%	23.3%	22.5%	21.3%	21.8%	22.7%
poor	9.5%	10.3%	10.4%	9.1%	9.5%	8.1%
Specific conditions: sensory						
Fair or poor self-rated distance vision	0.157	0.162	0.153	0.154	0.162	0.156
Fair or poor self-rated near vision	0.198	0.192	0.192	0.196	0.209	0.204
Fair or poor self-rated hearing	0.268	0.276	0.261	0.263	0.275	0.262
Fair or poor self-rated memory	0.329	0.334	0.318	0.318	0.334	0.340
Depressive thoughts	0.578	0.596	0.584	0.573	0.575	0.561
Diagnosed psychiatric diseases	0.166	0.158	0.159	0.168	0.174	0.171
Specific conditions: mobility						
Difficulties in activities of daily living	0.221	0.223	0.217	0.228	0.224	0.215
Difficulties in activities using large muscles	0.680	0.684	0.674	0.691	0.677	0.673
Arthritis	0.695	0.683	0.692	0.699	0.699	0.702
Specific conditions: physical						
Body-mass index (%)						
normal	31.4%	32.9%	31.9%	31.4%	31.0%	29.7%
underweight	2.2%	2.3%	2.2%	2.0%	2.3%	2.2%
overweight	37.4%	37.7%	37.8%	37.2%	37.2%	37.3%
obese	29.0%	27.1%	28.2%	29.4%	29.6%	30.8%
High blood pressure	0.679	0.643	0.670	0.686	0.699	0.704
Heart diseases	0.326	0.322	0.321	0.328	0.333	0.328
Stroke	0.105	0.101	0.103	0.106	0.112	0.100
Number of observations	54,025	11,312	11,308	10,871	10,646	9888

Note: refer to Sections 3.2, 3.3 and 3.4 for the detailed specifications of the variables.

sample have been consistent over the survey years. Hence, they are also controlled for. The year fixed effects control for factors that are consistent across individuals but varying over time. Such factors include national trends of transportation technology, policy and gasoline prices.

Other control variables include dummy variables for the U.S. census divisions where the respondents were located at the time of survey.[2] These census-division fixed effects control for region-specific factors such as culture or economy. In addition, these variables could also help to control for different licensing policies for older drivers across different geographical areas, especially for those who had cross-region moves between survey waves. Ideally, state-specific dummy variables were preferred; however, the public HRS sample does not contain states of residence for confidentiality concerns. Other covariates include socio-economic factors and residential patterns that are theoretically associated with driving, including poverty, being employed, living in a single-family house,[3] living in a single-person household, age and age squared. Unfortunately, I am unable to include more built environment variables because of confidentiality concerns associated with the public HRS sample.

3.5. Statistical modeling

Since the two outcome variables ("having driven in the previous month" and "having driven beyond nearby places") are both binary, I estimated fixed effects logit regression models with the aforementioned outcome, exposure and control variables using Stata 15 (StataCorp, 2015). Note that in such fixed effects logit models, individuals with no variabilities in the outcome variables have no effect on the likelihood functions and are hence ignored by the maximum likelihood estimators

[2] The census divisions are: New England (reference), Middle Atlantic, South Atlantic, East North Central, East South Central, West North Central, West South Central, Mountain, and Pacific. There was another dummy variable for not being in any census divisions (foreign countries or U.S. territories).

[3] As a robustness check, I have re-categorized housing type into a four-factor variable: single-family house, multi-family house, senior housing (including assist living and nursing homes) and others. Models using this variable generate very similar results.

Table 3
Descriptive statistics of the study sample, by outcome variable values (16,409 individuals across five waves).

Variable	Mean or share, by outcome variable values				
	Total	Had driven in previous month		Can drive beyond nearby places	
		Yes	No	Yes	No
Sociodemographics and residential patterns					
Age (years)	75.6	74.0	79.9	73.0	77.9
Family below poverty line	0.100	0.058	0.218	0.035	0.159
Living in a single-family house	0.721	0.775	0.569	0.797	0.653
Race (%)					
Non-Hispanic white	75.6%	80.8%	61.1%	84.0%	68.0%
Non-Hispanic black	13.7%	11.0%	21.3%	8.8%	18.1%
Hispanic	8.7%	6.3%	15.3%	5.4%	11.7%
Other	2.0%	1.9%	2.4%	1.8%	2.2%
Female	0.580	0.520	0.749	0.446	0.701
Living alone	0.296	0.268	0.374	0.215	0.370
Employed	0.179	0.230	0.036	0.286	0.081
Overall health					
Self-rated health (%)					
excellent	7.6%	9.1%	3.4%	11.4%	4.2%
very good	27.7%	32.4%	14.7%	37.4%	18.9%
good	32.8%	34.9%	27.1%	34.5%	31.3%
fair	22.3%	18.4%	33.3%	13.8%	30.1%
poor	9.5%	5.2%	21.5%	2.9%	15.5%
Specific conditions: sensory					
Fair or poor self-rated distance vision	0.157	0.093	0.342	0.061	0.246
Fair or poor self-rated near vision	0.198	0.137	0.373	0.102	0.287
Fair or poor self-rated hearing	0.268	0.235	0.358	0.215	0.315
Fair or poor self-rated memory	0.329	0.297	0.436	0.252	0.405
Depressive thoughts	0.578	0.505	0.782	0.435	0.708
Diagnosed psychiatric diseases	0.166	0.136	0.250	0.112	0.214
Specific conditions: mobility					
Difficulties in activities of daily living	0.221	0.118	0.509	0.075	0.353
Difficulties in activities using large muscles	0.680	0.627	0.826	0.565	0.784
Arthritis	0.695	0.684	0.725	0.652	0.733
Specific conditions: physical					
Body-mass index (%)					
normal	31.4%	29.5%	36.6%	27.8%	34.7%
underweight	2.2%	1.3%	4.7%	0.9%	3.4%
overweight	37.4%	39.9%	30.7%	41.3%	33.9%
obese	29.0%	29.3%	28.0%	30.0%	28.0%
High blood pressure	0.679	0.658	0.738	0.634	0.721
Heart diseases	0.326	0.304	0.389	0.285	0.364
Stroke	0.105	0.069	0.204	0.057	0.148
Number of observations	54,025	39,759	14,266	25,628	28,397

Note: refer to Sections 3.2, 3.3 and 3.4 for the detailed specifications of the variables.

(Feng and Boyle, 2014). In other words, although all individuals enter the fixed effects logit models, only a subsample of individuals (with changes in the outcome variable across survey waves, about 20% of the total) contribute to the model estimations. Nevertheless, this situation only reduces the statistical power of the estimators, but does not create any bias in the estimation (Feng and Boyle, 2014). As a robustness check, I also estimated linear probability models with the same model specifications (with all individuals contributing to the least square estimations), and the main results remain unchanged (results not shown).

Since logit models are non-linear, I use odds ratios when interpreting the regression results. The odds ratio is defined following the equation below:

$$\widehat{odds\ ratio} = \frac{\widehat{P}(y=1|x=1)/\widehat{P}(y=0|x=1)}{\widehat{P}(y=1|x=0)/\widehat{P}(y=0|x=0)} = \exp(\widehat{\beta}), \quad (1)$$

where y is the outcome variable, x is the exposure variable, and $\widehat{\beta}$ is the estimated coefficient of x on y. According to this equation, the odds ratio is the ratio of the odds of y occurring given x equals 1, to the odds of y occurring given x equals 0; and the definition of odds is the ratio of the probability of y happening to that of y not happening, given a specific value of x. The odds ratio for the logit regressions equals the natural exponential of the coefficients of the variable of interest. An odds ratio equal to one means there is no effect of x on y; an odds ratio larger than one means x has a positive effect on y; and an odds ratio smaller than one means x has a negative effect on y.

4. Results

4.1. Descriptive statistics

On average, 74% of the study sample had driven in the previous month of survey, and only 47% of them were able to drive beyond nearby places; these two percentage values were rather consistent across the five waves (Table 2). In each survey year, the respondents were on average in their mid-70s, indicating that the HRS constantly includes new and younger respondents over time. All other average statistics on socio-demographics were fairly constant across the five survey waves: approximately 10% were below the poverty line; 76% of the respondents were non-Hispanic white; approximately 9% were Hispanic and approximately 14% were non-Hispanic black; 58% of the respondents were female; 30% of the respondents were living alone; and 18% of the

Table 4
Tabulations on driving and self-rated overall health.

Variable	Share of "yes", by self-rated overall health					
	Total	Excellent	Very good	Good	Fair	Poor
Had driven in previous month	73.6%	88.2%	86.0%	78.2%	60.6%	40.2%
Can drive beyond nearby places	47.4%	71.0%	64.1%	49.9%	29.2%	14.3%

Note: the tabulations are based on the study sample of 16,409 individuals across five waves.

respondents were employed at the time, either full-time or part-time. In addition, 72% of the respondents were living in single-family houses.

Most of the health variables were also rather constant across the five survey years (Table 2). Approximately one-third of the respondents were in "fair" or "poor" self-rated overall health, and another one-third of them rated their health as "good". In addition, 29% of the respondents were obese; 22% of them had problems in activities of daily living; 68% had problems using large muscles; one third had heart disease; 69% had arthritis; 10% had stroke; 58% had at least some depressive thoughts; one third had memory issues; 17% had psychiatric diseases; 16% had problems with distance vision; 20% had problems with near vision; and 26% had problems with hearing. In contrast, the share of high blood pressure increased from 64% to 70% from 2006 to 2014 – the only health variable that did increase over time in the study sample.

Table 3 shows the descriptive statistics of the study sample by different values of the outcome variables. The average age for those had driven in the previous month is six years lower than those who had not (74.0 vs. 79.9); similarly, the average age for those who were able to drive beyond nearby places is five years older than those who were not (73.0 vs. 77.9). In addition, the overall self-rated health for drivers was better than non-drivers. Specifically, the shares of having "excellent" self-rated overall health among those who had driven in the previous month and those who had not driven in the previous month are 9.1% and 3.4%, respectively; the shares of having "poor" self-rated overall health for those who had driven in the previous month and those who had not driven in the previous month are 5.2% and 21.5%, respectively. Comparing the overall health conditions for those who were able to drive beyond nearby places and those who were unable to drive beyond nearby places yields similar findings. In other words, those who were able to drive beyond nearby places have relatively better overall health conditions.

4.2. *Overall health and driving reduction*

Deteriorating overall health discouraged older adults from driving. As Table 4 indicates, among those rating their overall health as "excellent", 88.2% had driven in the previous month of survey, and 71.0% were able to drive beyond nearby places. In contrast, among those with

Table 5
Fixed effects logit models on the relationship between driving and self-rated overall health.

	(1)	(2)	(3)	(4)
	Had driven in previous month (Y/N)	Had driven in previous month (Y/N)	Can drive beyond nearby places (Y/N)	Can drive beyond nearby places (Y/N)
Self-rated health (categorized)				
excellent	(ref.)		(ref.)	
very good	−0.091		0.009	
	[0.190]		[0.100]	
good	−0.162		−0.280***	
	[0.196]		[0.106]	
fair	−0.625***		−0.646***	
	[0.203]		[0.115]	
poor	−1.184***		−1.279***	
	[0.219]		[0.140]	
With fair or poor self-rated health		−0.622***		
		[0.089]		
With good, fair or poor self-rated health				−0.403***
				[0.055]
Family below poverty line	−0.232*	−0.226*	−0.031	−0.034
	[0.127]	[0.127]	[0.096]	[0.096]
Living in a single-family house	0.236*	0.254**	0.096	0.097
	[0.125]	[0.124]	[0.084]	[0.084]
Living alone	0.389***	0.407***	0.048	0.060
	[0.134]	[0.134]	[0.083]	[0.083]
Employed	1.260***	1.306***	0.417***	0.463***
	[0.208]	[0.208]	[0.080]	[0.079]
Age (year)	1.903***	1.907***	1.420***	1.444***
	[0.197]	[0.197]	[0.113]	[0.112]
Age squared	−0.016***	−0.016***	−0.010***	−0.010***
	[0.001]	[0.001]	[0.001]	[0.001]
Individual fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Census division fixed effects	Yes	Yes	Yes	Yes
N of individuals used in estimation	2575	2575	3998	3998
N of observations used in estimation	10,525	10,525	16,656	16,656
N of individuals in the study sample	16,049	16,049	16,049	16,049
N of observations in the study sample	54,025	54,025	54,025	54,025

Note: Fixed effects logit models of the study sample across five waves. "N of individuals/observations in the study sample" refers to the numbers of individuals/observations enter the fixed effects logit models. "N of individuals/observations used in estimation" refers to the numbers of individuals/observations that actually contribute to the model estimations, i.e. the individuals that has both 1 and 0 values in their outcome variables across different waves. *, ** and *** indicate significance at the 0.1, 0.05 and 0.01 levels, respectively. Standard errors are in brackets.

Table 6
Fixed effects logit models on gender- and race-specific effects of the relationship between driving and self-rated overall health.

	(5) Had driven in previous month (Y/N)	(6) Had driven in previous month (Y/N)	(7) Can drive beyond nearby places (Y/N)	(8) Can drive beyond nearby places (Y/N)
With fair or poor self-rated health	−0.643*** [0.139]	−0.752*** [0.105]		
With good, fair or poor self-rated health			−0.388*** [0.082]	−0.424*** [0.062]
Fair/poor health X female	0.034 [0.180]			
Good/fair/poor health X female			−0.027 [0.111]	
Fair/poor health X race				
non-Hispanic white		(ref.)		
non-Hispanic black		0.541** [0.236]		
Hispanic		0.467 [0.322]		
other races		−0.152 [0.694]		
Good/fair/poor health X race				
non-Hispanic white				(ref.)
non-Hispanic black				0.255 [0.166]
Hispanic				−0.248 [0.237]
other races				0.187 [0.412]
Controls	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Census division fixed effects	Yes	Yes	Yes	Yes
N of individuals used in estimation	2575	2575	3998	3998
N of observations used in estimation	10,525	10,525	16,656	16,656
N of individuals in the study sample	16,049	16,049	16,049	16,049
N of observations in the study sample	54,025	54,025	54,025	54,025

Note: Fixed effects logit models of the study sample across five waves. "Controls" include poverty, employment status, type of house, living alone, age, and age squared. "N of individuals/observations in the study sample" refers to the numbers of individuals/observations enter the fixed effects logit models. "N of individuals/observations used in estimation" refers to the numbers of individuals/observations that actually contribute to the model estimations, i.e. the individuals that has both 1 and 0 values in their outcome variables across different waves. *, ** and *** indicate significance at the 0.1, 0.05 and 0.01 levels, respectively. Standard errors are in brackets.

"poor" self-rated overall health, 40.2% had driven in the previous month of survey, and only 14.3% were able to drive beyond nearby places. The regression models in Table 5 show similar findings after adjusting for covariates and fixed effects. According to Model 1, older adults rating their health as "poor" were less likely to drive in previous month than those rating their health as "excellent" with an odds ratio of 0.306; for the older adults with "fair" self-rated health, the odds ratio was 0.535. In contrast, neither of the coefficients of "very good" and "good" is significant at the 5% level. Model 2 groups the statistically significant categories and shows that older adults in "fair" or "poor" health were less likely to drive than those with "excellent," "very good" or "good" health with an odds ratio of 0.537 (95% confidence interval: 0.451~0.639).

Deteriorating overall health also discouraged older adults from driving beyond nearby places (Table 5). Model 3 shows that older adults with "poor" and "fair" self-rated health were less likely to drive non-nearby trips than those with "excellent" health with odds ratios of 0.278 and 0.524, respectively. In addition, older adults with "good" self-rated health were less likely to be able to drive beyond nearby places than those with "excellent" health with an odds ratio of 0.756; this finding is different from Model 1 where the coefficient of "good" health is insignificant. Model 4 groups the statistically significant "good", "fair" and "poor" health conditions, and shows that older adults in those conditions were less likely to be able to drive beyond nearby places than those with "excellent" or "good" health with an odds ratio of 0.668 (95% confidence interval: 0.600~0.745). A model only grouping "fair" and "poor" health (same as Model 2) shows a significant odds ratio of 0.578 (results not shown).

Models 1–4 also show that the effects of overall health on driving have a larger magnitude than those of many sociodemographic and residential pattern variables (Table 5). Being in poverty was associated with a lower probability of driving in previous month, while living in a single-family house and living alone was associated with a lower probability of driving in previous month. Being employed was associated with higher probability of both driving in previous month and being able to drive beyond nearby places. Being older was associated with a lower probability of driving in previous month as well as being able to drive beyond nearby places. In addition, a positive coefficient for age and a

Table 7
Fixed effects logit models on the relationship between driving and specific health conditions (sensory, mobility and physical).

	(9)	(10)
	Had driven in previous month (Y/N)	Can drive beyond nearby places (Y/N)
Specific conditions: sensory		
Fair or poor self-rated distance vision	−0.275**	−0.246***
	[0.116]	[0.081]
Fair or poor self-rated near vision	−0.058	−0.159**
	[0.106]	[0.068]
Fair or poor self-rated hearing	0.009	−0.009
	[0.112]	[0.070]
Fair or poor self-rated memory	−0.174*	−0.177***
	[0.098]	[0.058]
Depressive thoughts	−0.260***	−0.226***
	[0.093]	[0.051]
Diagnosed psychiatric diseases	−0.092	−0.171
	[0.190]	[0.132]
Specific conditions: mobility		
Difficulties in activities of daily living	−0.796***	−0.601***
	[0.104]	[0.073]
Difficulties in activities using large muscles	−0.293***	−0.196***
	[0.111]	[0.059]
Arthritis	0.028	−0.119
	[0.172]	[0.100]
Specific conditions: physical		
Body-mass index (categorized)		
Normal		
Underweight	−0.136	−0.169
	[0.293]	[0.220]
Overweight	0.267**	0.182**
	[0.135]	[0.085]
Obese	0.486**	0.369***
	[0.192]	[0.117]
High blood pressure	0.374**	0.033
	[0.174]	[0.097]
Heart diseases	−0.228	−0.094
	[0.163]	[0.097]
Stroke	−0.536***	−0.398***
	[0.190]	[0.134]
Controls	Yes	Yes
Individual fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Census division fixed effects	Yes	Yes
N of individuals used in estimation	2110	3730
N of observations used in estimation	8418	15,269
N of individuals in the study sample	16,049	16,049
N of observations in the study sample	54,025	54,025

Note: Fixed effects logit models of the study sample across five waves. "Controls" include poverty, employment status, type of house, living alone, age, and age squared. "N of individuals/observations in the study sample" refers to the numbers of individuals/observations enter the fixed effects logit models. "N of individuals/observations used in estimation" refers to the numbers of individuals/observations that actually contribute to the model estimations, i.e. the individuals that has both 1 and 0 values in their outcome variables across different waves. *, ** and *** indicate significance at the 0.1, 0.05 and 0.01 levels, respectively. Standard errors are in brackets.

negative coefficient for age squared indicate that the magnitude of the associations of age with the two driving variables increased as age increased.

4.3. Gender- and race-specific effects

The impact of overall health status on driving varies by race but does not vary by gender (Table 6). Models 5–8 in Table 6 include interactions of the overall health variable with the variables related to gender and race. The overall health variable groups the overall health categories that are statistically significant in Models 1 and 3 (Table 6): a dummy variable *"with 'fair' or 'poor' self-rated health"* for Models 5–6 (driven in previous month), and a dummy variable *"with 'good', 'fair' or 'poor' self-rated health"* for Models 7–8 (can drive beyond nearby places). The gender variable is a dummy variable on being female, and the race variables are three dummies on non-Hispanic black, Hispanic and other races (with non-Hispanic white as the reference term). Models 5 and 7 show that the effect of overall health on driving does not differ by gender. In contrast, Models 6 shows that the effects of overall health on driving in previous month for non-Hispanic blacks (odds ratio: 0.810) are smaller than those for non-Hispanic whites (odds ratio: 0.471). Model 8 shows that the effect of overall health on being able to drive beyond nearby places does not differ by race.

4.4. Specific health conditions predicting driving reduction

Models 9–10 identify the specific physical, sensory and mobility conditions that can significantly predict driving reduction (Table 7). For sensory conditions, distant vision problems, memory problems and depressive thoughts are significantly associated with lower likelihood of both driving variables, with the caution that the memory problems variable in the "driven in the previous month model" is only significant at a 10% level. Unlike distance vision problems, near vision problems is only associated with lower likelihood of driving beyond nearby places, and is not significantly associated with having driven in the past month. Neither hearing problems nor psychiatric diseases are significantly associated with driving reduction.

For mobility conditions, having difficulties involving any activities in daily living (bathing dressing, eating bedding or walking) is negatively associated with the probability of having driven in the past month as well as having driven to non-nearby places. Similarly, having difficulties in using large muscles (sitting for 2 h, getting up from a chair, kneeling or pushing large objects) is negatively associated with both driving variables. Arthritis is significantly associated with neither driving reduction variables.

For physical conditions, obesity and overweight predict higher probabilities for both having driven in previous month and being able to drive beyond nearby places; and experiencing stroke predict lower probabilities of both driving variables. Hypertension only significantly predicts higher likelihood of driving in the previous month, but is not significantly associated with driving beyond nearby places. Heart diseases is significantly associated with neither driving reduction variables.

5. Discussion

This study finds that deteriorating health conditions discouraged America's older adults from driving, measured by having driven in previous month and being able to drive beyond nearby places. The magnitudes of these two effects are both larger for non-Hispanic whites than non-Hispanic blacks, but do not differ by gender. In addition, this study identifies specific sensory, mobility and physical conditions that predicted lower likelihood of having driven in previous month and being able to drive non-nearby trips.

The significant effects of overall self-rated health on driving are in concordance with many small-area, cross-sectional studies covering health and driving cessation, summarized by Dickerson et al. (2017). Among the older adults with "poor" overall health, 40.2% had driven in the previous month, while only 14.3% were able to drive beyond nearby places. The gap between these two percentages implies that many older adults with poor health conditions were driving by need rather than driving by choice. They limited their driving to nearby places and avoid driving in long distances. Such findings and implications connect with the findings by Nordbakke and Schwanen (2015) that older adults with difficulties in driving will self-sensor their travel demand to focus on daily essential needs such as grocery shopping and doctor's appointments, especially if they do not have good transit access to compensate their unmet travel demands (Kim, 2011; Wasfi et al., 2012).

I did not find significant gender differences in the effects of self-rated overall health on driving. Such results connect with the findings by Rosenbloom and Santos (2014) that the percentage differences in annual vehicle miles traveled (VMT) between those with and without medical conditions are similar for the male and female older adults (both 42%). This study finds a similar pattern using different measurements of driving and controlling for many individual factors. Indeed, empirical evidences show higher shares of older women give up driving than older men, likely due to gender differences in confidence level and life expectancies (Molnar et al., 2014; Meng and Siren, 2015). In addition, female older adults are also more likely to report medical conditions and self-regulate their driving (Rosenbloom and Santos, 2014). My study builds on these facts and shows that when examining the impact of health on driving, gender differences in self-evaluation on health and self-regulation on driving may cancel out, especially when personal characteristics are controlled for.

In contrast, I did find racial differences in the impact of self-rated health on driving. Specifically, the magnitudes of the effects of overall health on driving in previous month for non-Hispanic blacks were significantly smaller than that for non-Hispanic whites. One potential explanation for the racial differences is that minority older adults are less likely to drive than non-Hispanic whites even when they are in good health. In my study sample, 59% of the non-Hispanic blacks had driven in previous month of survey, while the number for non-Hispanic whites was 79%. Studies have demonstrated that residents in minority neighborhoods are more likely to carpool (Shin, 2017), implying closer social ties in these neighborhoods (Portney and Berry, 1997). Nevertheless, further examination of the causes of these racial differences in older adults' health-driving dynamics is beyond the scope of this paper but deserves attention in future studies.

Many of the sensory, mobility and physical health predictors identified in this study have also been reported to be predictive of driving cessation (e.g., Dugan and Lee, 2013; Edwards et al., 2008) and self-regulation in driving for crash prevention (Kostyniuk and Molnar, 2008; Molnar et al., 2014). In addition, the signs and significances of the coefficients of the socio-economic and residential pattern variables all conform with empirical findings in the literature on transport policy and planning, as summarized by Ewing and Cervero (2010).

The findings of this study imply that in the near future, there will be a large number of older adults in the U.S. either severely reduce their driving frequencies or avoid driving in long distance due to declining health conditions. As America's existing transportation system is still dominated by cars and highways, older adults' driving reduction can easily lead to unmet travel demands and lower quality of life (Luiu et al., 2017; Metz, 2000). Additionally, not able to drive beyond nearby areas will harm older adults' social life, as many social trips are long-distance in nature (Leistner and Steiner, 2017; Nordbakke and Schwanen, 2015). Considering the baby-boomer generation's large population size and high car reliance (Coughlin, 2009), such challenges might be in an even greater scale in the next 10–15 years.

Policy makers and planners should be aware of the challenge, and be proactive and innovative in seeking for potential solutions. The findings of this study could help policy makers to better identify the older adults needing mobility assistances. Hence, local governments can prioritize their often-limited financial and labor resources on those at-risk older drivers. Policy makers can also identify potential patrons based on changes in health conditions, if they could work with healthcare providers. After identifying those who needing help, local governments can reach out with them for mobility assistance programs. The assistance could be in different formats, including info sessions for the local paratransit system, vouchers for ride-hailing services, and training programs for smartphone and ride-hailing app usages. Ride-hailing services (e.g. Uber or Lyft) can provide flexible and affordable mobility services to complement the existing paratransit system. Ride-hailing apps have not been a popular option for older adults, partially because older adults have limited experience in using the rail-hailing apps (Freeman et al., 2020; Leistner and Steiner, 2017). Studies show that sufficient outreach and training could make the ride-hailing service better utilized among older adults (Shirgaokar, 2018; Wood et al., 2016), especially for long trips (Leistner and Steiner, 2017).

Besides mobility assistance programs, policy makers should also coordinate with urban planners and designers to retrofit suburban communities to be more age-friendly (Warner and Zhang, 2019), so that older adults could reach sufficient destinations without driving long distances (Buehler and Nobis, 2010). For instance, walking- and cycling-friendly communities with lower road speed limits are expected to improve older adults' traffic safety (Dumbaugh and Zhang, 2013), physical activity (Cheng et al., 2021) and social engagement (Zegras et al., 2012). To plan for such age-friendly communities, more engagement of older adults in the planning process is needed (Warner et al., 2017; Warner and Zhang, 2019). In addition, the mass transit system should also be retrofitted to be more appealing to the older adults. For instance, the bus and transit systems need to be more senior-friendly (Hou et al., 2020; Loukaitou-Sideris et al., 2019); and the paratransit shuttles in suburbs need to be more frequent and more flexible (Alsnih and Hensher, 2003). Hence, they could become a viable alternative than driving if needed for the older adults.

This study has the following limitations, many of which should motivate future research. First, the outcome variable "had driven in previous month" masks more detailed information of driving such as vehicle miles traveled (VMT), trip frequencies or trip-chaining activities. Data with both detailed travel dairies and comprehensive health conditions would help to better examine the health-driving dynamics. Second, the outcome variable "can drive beyond nearby places" is self-reported and may be too subjective. Objective measurements such as limiting driving within a certain distance or a certain period of time will complement this subjective measure. Third, confidentiality concerns prevent the public HRS sample from providing more built environment variables other than housing type. Adding more built environment variables such as residential density or land use mix would make the findings more robust.

6. Conclusions

Using a longitudinal, nationally-representative dataset, this study finds that the declining health is associated with driving reduction for America's older adults. Deteriorating overall health made the older adults less likely to have driven during the previous month of survey, and less likely to be able to drive beyond nearby places. The impact of overall health on driving did not differ by gender but was larger for non-Hispanic whites than non-Hispanic blacks. My findings imply a large challenge for America's existing transport system to meet the increasing mobility needs from the reduced-driving older adults. Hence, policy makers and planners should be proactive in seeking solutions, and be prepared to be more innovative. This study identifies several sensory, mobility and physical conditions that could predict older adults' potential driving reduction. Using these findings, local governments could work with health providers to identify the older adults at risk of driving reduction, and prioritize them on providing various types of mobility assistances.

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