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Classifying Cognitive Decline in Older Drivers from Behavior on Adverse Roads Detected Using Computer Vision

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Abstract

As drivers age, roadway conditions may become more challenging, particularly when normal aging is coupled with cognitive decline. Driving during lower visibility conditions, such as inclement weather, is especially challenging for older drivers due to their sensitivity to glare and reduced visibility. As a result, older drivers may adjust their behavior during adverse weather. This paper explores the differential impacts of weather on older drivers with cognitive decline compared to older drivers with normal cognitive function. Data were from a naturalistic driving study of older drivers in Omaha, Nebraska. Driver speed and weather data were extracted and the correlation between speed compliance, road weather conditions, and the cognitive/neurological status of the drivers was examined. Speed compliance was used as the surrogate safety measure since driving at lower speeds can indicate that the driver is challenged by roadway or environmental conditions and can therefore indicate a risk. The percentage of time during a trip when drivers were 16.1 kph under the speed limit was modeled as the dependent variable using beta regression. The variables that resulted in the best fit model were mild cognitive impairment (MCI), age group, traffic density, and weather. Results indicated that the youngest group of older drivers (young-old) spent less time driving at impeding speeds and had the least variability compared to the other two age groups. The middle group of older drivers (middle-old) had the highest amount of time driving at impeding speeds and had more variability than young-old drivers. The oldest group of older drivers (old-old) were the most likely to drive at impeding speeds and had the most variability. In general, older drivers were more likely to drive at impeding speeds during peak hours than during non-peak hours. Additionally, in most cases, older drivers spent less time below the speed limit when the weather was clear than in adverse conditions. Results indicate that older drivers are impacted by weather conditions, and distinct patterns were noted between older drivers who were cognitively impaired compared to drivers with normal cognition.

Keywords

Traffic Safety, Older Driver, Cognitive Impairment, Machine Learning, Speed

1. Introduction

1.1. Background

With aging, the risk of cognitive and visual decline increases and may impact the ability to drive, increasing the risk of a crash [1] [2]. Identifying specific areas of risk for older drivers can assist roadway agencies in understanding how to better address this driving population. Additionally, measurable differences in driving behaviors may also assist caregivers and medical professionals in identifying cognitive and visual decline as well as provide information for original equipment manufacturers (OEMs) to design supportive in-vehicle technology for older drivers at risk due to cognitive and visual impairments.

Driving at nighttime or during lower visibility conditions, such as inclement weather, can be problematic for all drivers. Approximately 15% of fatal crashes, 19% of injury crashes, and 22% of property damage-only (PDO) crashes occur under adverse weather conditions (such as rain, sleet, snow, or fog) in an average year. This translates to nearly 4,900 fatal crashes, over 301,100 injury crashes, and close to 919,700 PDO crashes annually due to adverse weather [3].

Adverse weather may be particularly challenging for older drivers due to their sensitivity to glare and reduced visibility. A study by the University of Iowa linked citation and crash data and found that drivers 50 years and older had a 21% greater chance of being involved in a crash within 30 days after receiving a traffic-related charge. The study also found that within 30 days of receiving a traffic-related charge, these drivers had an increased risk of being involved in a crash during bad weather [4].

It has been noted in several studies that older drivers adjust their behavior during adverse weather. Several studies have used self-reported studies to assess differences in driving. Sabback and Mann [5] indicated that older drivers alter their driving during seasonal variations in weather conditions. Braitman and McCartt [6] reported that drivers with self-reported memory, vision, or mobility impairments and/or medical conditions (e.g., arthritis or diabetes) were more likely to make fewer trips, travel shorter distances, or avoid driving at night, on Interstates, or in ice or snow. Drivers aged 65 and older were twice as likely to report difficulty leaving home during icy conditions [7]. Older drivers in Maryland reported weather as one of their top driving concerns [8]. A study by Karali *et al.* [9] indicated that older drivers (compared to younger drivers) reported decreased reaction times and more difficulty driving during inclement weather.

In contrast to self-reported studies, naturalistic driving studies (NDS) have indicated different behaviors during adverse weather. A study by Myers *et al.* [10] used NDS data and found that older drivers were more likely to drive than not drive (69% versus 31%) during inclement weather and that 67% drove on days when weather advisories had been issued. Smith *et al.* [11] assessed NDS data and found that older drivers took fewer trips during the winter months (7%) but longer trips during rain events. Crizzle and Myers [12] used NDS data to assess drivers with Parkinson's disease (PD) (median age of 71.6 years) compared to matched controls (median age of 70.6 years). Drivers with PD drove less than the control group in terms of number of trips, distance, and length. They also drove less at night (18.6% versus 27.3%) and during bad weather. Around 32% of drivers with PD did not drive on days with inclement weather, compared to 16% of drivers in the control group. Participants were also questioned about how weather would change their driving behavior. Drivers with PD were more likely to indicate that they would postpone shopping/errand trips (81% versus 60% in the control group) and recreation trips (74% compared to 65% in the control group). However, drivers with PD were less likely to say that they would postpone all trips (including medical) than drivers in the control group (40% versus 50%).

1.2. Project Objectives

The objective of this study was to establish a connection between clinical measures of age-related cognitive decline and driver behaviors under specific weather conditions. The amount of time drivers in a particular age/cognition category drove at speeds lower than the speed limit was assessed using NDS data. In particular, the impact of adverse weather conditions on driver behavior was explored.

Weather was coded using a video-based system that can predict weather-related road surface conditions from NDS video data. In-vehicle cameras were used to collect roadway video data, and a computer vision model was developed for classifying road surface weather conditions.

2. Naturalistic Driving Study Data

This research utilized naturalistic driving data collected from 77 legally licensed, active, older drivers aged between 65 and 90 years old from the Omaha, Nebraska, region. The participant acquisition strategy encompassed community engagement via fliers, local news, and discourse at local senior institutions. The recruitment from the senior demographic was designed to capture a broad spectrum of functional impairments associated with cognitive aging (including neurotypical and impaired drivers) within the study's purview. All participants provided informed consent in line with institutional protocols. All participants met the Nebraska state licensure prerequisites, which mandate a visual acuity superior to

20/40 (corrected or uncorrected). Participants also self-disclosed their medication regimen and medical diagnoses.

Participants were excluded if they reported major confounding medication use (such as stimulants, narcotics, anxiolytics, anticonvulsants, antipsychotics, and other significant psychoactive medication) or significant medical comorbidities (including dementia, sleep disorders, pulmonary disease, congestive heart failure, major psychiatric illness, vestibular disease, alcoholism, or other drug addiction). Visual impairments were permissible provided drivers met state licensure standards. Drivers with physical limitations (for instance, arthritis) were included, given the prevalence of such limitations in older adults. The drivers exhibited a range of age-related dysfunction (from normal to mild cognitive impairment), consistent with typically aging driver cohorts [13] [14].

Data collection was a component of a longitudinal two-year investigation, where each participant was involved in two separate data collection periods of three months each, with a one-year interval in between. The analysis in this study was based on the cross-sectional data collected over the course of a two-year study period that specifically focused on the roadway conditions and driving habits of the drivers.

Participants were required to visit the University of Nebraska Medical Center to undergo clinical and laboratory evaluations at the beginning of the study. The collected data encompassed self-reported demographic information and results from neuropsychological tests relevant to dementia and driving. This assessment incorporated standardized neuropsychological metrics that are widely recognized and utilized in clinical settings for the quantification of cognitive impairment. A comprehensive metric of cognitive functioning, denoted as "COGSTAT," was derived from eight distinct clinical neuropsychological evaluations relevant to aging and driving. These evaluations encompassed areas such as executive functioning, attention, visuospatial skills, episodic and working memory, speed of processing, and attention [15]-[18].

Participants demonstrated a spectrum of cognitive abilities, as would be anticipated in a typically aging older adult population without dementia. One of the assessments of cognitive function was carried out using the Montreal Cognitive Assessment (MoCA). MoCA is a frequently employed screening tool in clinical settings for detecting significant cognitive changes, including age-related cognitive declines and mild cognitive impairment (MCI). It evaluates crucial cognitive domains typically affected by aging, such as memory, visuospatial skills, attention, and executive functions [19].

At the beginning of each three-month phase of the study, the drivers underwent a comprehensive evaluation process. This included standardized self-reported demographic information such as age, gender, racial/ethnic identity, educational background, and socioeconomic status. Additionally, they provided information on their driving behavior, including their primary driving environment, driving experience, and frequency of driving. Health-related data were also collected, encompassing medication usage and medical history.

Each participant's vehicle was instrumented with a custom-built data acquisition system (DAS) developed by the team. The DAS was unobtrusively mounted on the vehicle's windshield next to the rearview mirror in each driver's personal vehicle at the start of each study year. The DAS included a set of sensors that passively collected vehicle parameters every second from when the vehicle's ignition is turned on until it is turned off. Sensors included a Global Positioning System (GPS) unit, accelerometer, video cameras (collecting forward roadway and cabin videos along with cabin audio recordings), and other vehicle sensors that collected speed, throttle, and brake data. Drivers were instructed to drive as they typically would.

The study received approval from the Institutional Review Board (IRB) at the University of Nebraska Medical Center (IRB #0217-15-FB). All individuals involved in the study provided their informed consent prior to participation.

Table 1 summarizes participant information. It should be noted that certain participants did not disclose details regarding their income or employment status, which resulted in a lack of data for these specific individuals.

Table 1. Description of participants.

Variable	Range or Counts	Average	Std. Dev.
Age (years)	Range: 65 - 90	75.4	6.45
Sex	Female: 33 Male: 40		
Race	White: 70 African American: 1 American Indian: 1 Other: 1		
Income	\$0 - \$500,000 Not indicated: 9	\$55,362	\$62,854
Employment	Employed: 22 Retired: 35 Unemployed: 13 Not indicated: 3		
Driving Experience (years)	Range: 40 - 76 Not indicated: 1	58.3	8.13
Weekly Driving	48 - 483 km (30 - 300 miles) Not indicated: 1	164 km (102 miles)	97 km (60.3 miles)

3. Video Analytics to Extract Roadway Surface Conditions

This study also developed an analytical model to extract weather-related roadway surface conditions from the DAS roadway-focused cameras. A detection model using computer vision algorithms was developed to classify the roadway conditions as either clear or adverse (rain, snow) based on the video data collected from the camera sensors (inside the black box) installed in the vehicles.

Previous approaches by other researchers have utilized various image sources, data preprocessing methods, and computer vision techniques. Existing models have mainly focused on three road surface weather conditions: clear, snow, and rain. Conventional convolutional neural network (CNN)-based approaches have included fine-tuned AlexNet, GoogLeNet, and ResNet [20] architecture. The following sections describe the development of the weather detection model for this study.

3.1. Data Preparation for the Vision Model

A total of 651,951 kilometers (405,104 miles) of video was available from the DAS. Although the NDS data collection included any drive taken by the driver during the study period, which could have included out-of-state travel, only driving within the state of Nebraska was included, since roadway characteristics were only available for Nebraska and drivers were more likely to be familiar with these roadways. To streamline processing and analysis, the driving data were partitioned into one-minute segments. A video was extracted for each one-minute segment. Weather conditions were extracted using the roadway-facing video data procured from the DAS. A subset of 1,000 videos was selected for the development of the computer vision model. The distribution of these videos for training, validation, and testing was 600, 200, and 200, respectively. Videos were selected to represent variation across drivers and roadway conditions. The machine vision system categorized roadway surface conditions as clear, snow, rain, or not applicable (NA).

Representative frames for each category are depicted in **Figure 1**. The category "NA" was assigned in scenarios where the roadway was absent from the video more than 80% of the time (e.g., parking lots, driveways) or where the video was blank.

(a) (b) (c) (d) (e)

Figure 1. Sample frames from the DAS forward-facing camera sensor: (a) clear roadway surface, (b) wet roadway surface (rain), (c) snow-covered roadway, (d) blank video (NA), and (e) not roadway related (NA).

Frames were extracted at one per second, which gave a roadway weather condition rating every second. Each input image had dimensions of 960 × 752 × 3 pixels and was cropped to examine only the outward-facing views to detect the roadway surface condition. The cropped frames had dimensions of 600 × 400 × 3 pixels. To align the images with the specifications of the computer vision model, these frames were further reshaped to a square format (224 × 224 × 3). Finally, all of the training frames derived from the 600 video files were inputted into the roadway vision model for the classification of roadway weather conditions.

A trained annotator was utilized to provide a comparison set. The annotator categorized roadway surface conditions using the same four distinct roadway surface categories.

3.2. Roadway Weather Model Architecture

A computer vision-based framework known as a vision transformer (ViT) [21] was employed for the roadway weather classification model. It was trained using processed and labeled image frames extracted from the one-minute driving video data. ViTs have recently gained prominence as a potent tool for image classification tasks. These models leverage self-attention mechanisms [22] to process input images in a highly parallelizable fashion, thereby achieving state-of-the-art performance on various benchmarks. Furthermore, the patching of input images enables ViTs to efficiently learn spatial relations between different image regions, a crucial aspect of precise image classification.

The model's architecture is illustrated in **Figure 2**. The ViT model is primarily composed of an embedding layer and a transformer encoder. The embedding layer maps the input image into a sequence of one-dimensional tokens, which are subsequently processed by the transformer encoder. The standard transformer takes a sequence of one-dimensional token embeddings as input. To accommodate two-dimensional images, the image $x \in \mathrm{R}^{H \times W \times C}$ is reshaped into a sequence of flattened two-dimensional patches $x_p \in \mathrm{R}^{N \times (P^2 \times C)}$, where (H, W) is the resolution of the original image, C is the number of channels, (P, P) is the resolution of each image patch, and $N = HW/P^2$ is the resultant number of patches. Position embeddings (standard learnable one-dimensional embeddings) are added to the patch embeddings to preserve positional information. The resulting sequence of embedding vectors serves as input to the transformer encoder. The transformer encoder consists of a series of transformer blocks (consisting of the multi-head self-attention, norm, and multilayer perceptron [MLP] blocks [22]), each of which applies a self-attention mechanism to the input sequence, followed by a feed-forward network. The output of the final transformer block is a representation of the entire input image, which is used to make a classification prediction.

The prediction process of the ViT model involves passing the output of the final transformer block through a classification head, typically composed of a fully connected layer followed by a softmax activation function. The softmax function's output signifies the probability distribution across the different classes in the classification task.

The training of ViT models from scratch requires the availability of substantial volumes of labeled data, a requirement that can pose significant challenges and demand a considerable amount of time. However, the presence of preprocessed and labeled data can expedite the training process, facilitating the efficient training of ViT models. Recent studies [23]-[25] have demonstrated that standard ViT models, when trained with preprocessed and labeled data, surpass their counterparts trained on raw data, achieving enhanced accuracy across a variety of image classification tasks. This underscores the potential applicability of these models in roadway weather classification tasks.

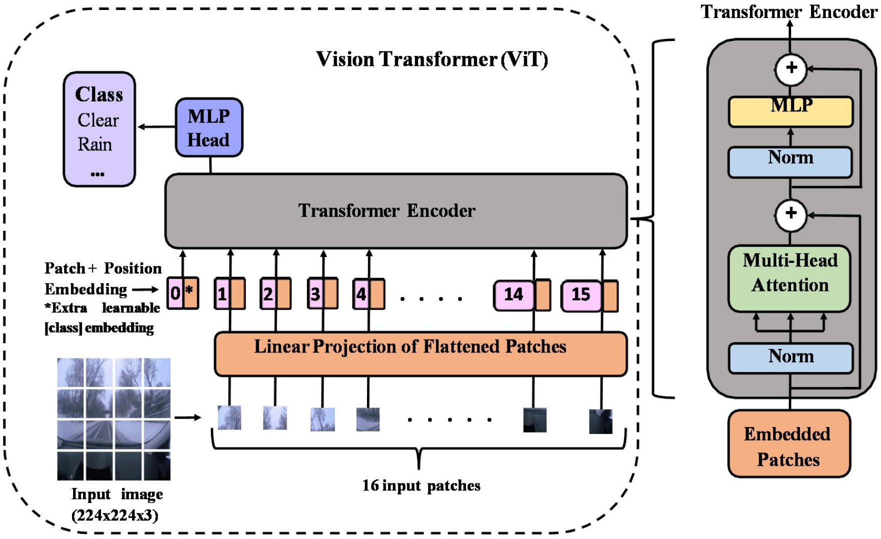

Figure 2. Architecture of the vision transformer model.

3.3. Weather Model Training and Fine-Tuning

The ViT model in this study was trained using the annotated training data. The training procedure incorporated the Adam optimizer [26], with a learning rate set at 0.05 and a batch size of 256. The input images had dimensions of 224 × 224 × 3 pixels. A weight decay of 2×10^{-5} was applied, which was observed to be advantageous for fine-tuning. For the pre-trained backbone, we adopted the ResNet50 architecture [20] and Dual Path Network (DPN92) [27]. The training was conducted over a span of 20 epochs. In our specific context, the Adam optimizer demonstrated superior performance over stochastic gradient descent (SGD) [28] for the residual networks (ResNets). The learning rate was managed by employing a linear warmup and decay strategy, and a momentum of 0.9 was utilized.

The performance of the trained vision model is illustrated by the confusion matrix in Figure 3, where the diagonal entries denote the percentage of correctly predicted samples for each roadway weather class and the off-diagonal entries are the percentage of incorrectly predicted samples. In this matrix, each row represents the instances in an actual class, and each column represents the instances in a predicted class. The matrix is normalized by dividing each row of the confusion matrix by the sum of that row. This gives the proportion of correct predictions for each class, which can be interpreted as the accuracy of the model for each class. The diagonal elements represent the percentage of samples for which the predicted label is equal to the true label, i.e., the percentage of correctly predicted samples (accuracy). It was observed that the model was able to accurately (overall accuracy ~99%) classify the four roadway weather classes based on the input frame. The F1 scores for the clear, rain, snow, and NA classes are 0.983, 0.986, 0.997 and 0.958, respectively. The off-diagonal entries are the percentage of incorrectly predicted samples.

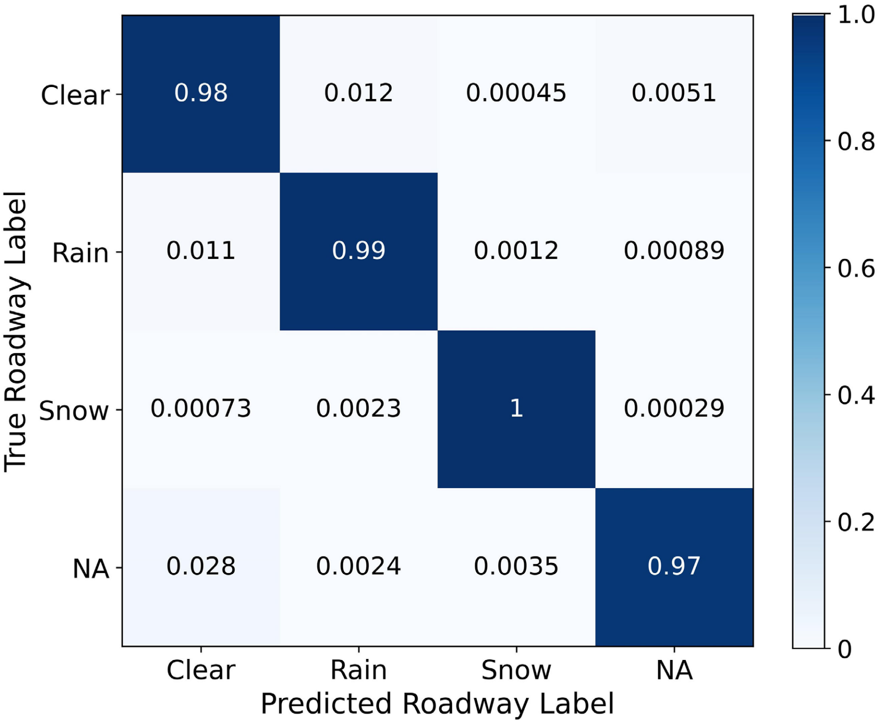

Figure 3. Normalized confusion matrix of the trained ViT model.

The overall accuracy was calculated as the ratio of the total number of correctly predicted samples to the total number of samples, as per equation [1]. Furthermore, to validate the model's predictions, the inference samples were independently evaluated by a separate individual. This cross-checking process involved comparing the model's predictions to the ground-truth labels, thereby providing an additional layer of verification for the model's performance.

$$\text{Model accuracy} = \frac{\sum_1^m \text{correctly predicted samples}}{\text{Total samples}} \tag{1}$$

While transformer-based models typically perform optimally when large training datasets are available, our results suggest the effective utilization of pre-trained image models to train on comparatively smaller or decent-sized video datasets with low resolution.

3.4. Data Quality Analysis

The quality of the driving video data was ensured through a series of filtering steps conducted before further analysis of the driving data. The initial step involved addressing the issue of missing data. Certain video files were found to be corrupted due to various reasons, such as a camera malfunction or blacked-out screen. These defective video files were excluded from our analysis to maintain the integrity of the data. We also observed that for a subset of participants, a significant proportion of their video duration was categorized as "NA." Specifically, for some drivers, more than 50% of their total driving duration over the two-year study period fell into this "NA" category. To maintain the integrity and relevance of our data, we made the decision to exclude these drivers from our analysis. This ensured that our dataset was representative of active driving behavior and conditions, thereby enhancing the validity of our findings.

We also observed instances of poor detection by the vision model, characterized by an average confidence level of less than 0.5 and a majority of frames falling below a threshold value of 0.7. To minimize the noise in our analysis, these frames were discarded. The percentage of these instances of poor detection was very low (<10% of the entire drive duration).

As a result of these data quality measures, seven participants were removed from our analysis based on the aforementioned criteria. Consequently, the total number of participants included in the subsequent analysis was reduced to 70 from the initial count of 77. These data quality measures were implemented to exclude corrupted video files, poor detection frames, and participants with a significant proportion of video classified as "NA" throughout their driving duration. This approach to data quality ensured that the analysis was conducted on accurate, reliable, and representative data, thereby enhancing the validity and robustness of our analysis.

4. Extraction of Driver Variables for Analysis

A set of driver variables was also gathered or extracted from the NDS data. One trip by one driver was modeled as one observation. The analysis explicitly focused on short drives ranging from 0.8 to 16.1 km (0.5 to 10 miles), and some participants only took part in one of the three-month data collection periods. A total of 21,831 trips were included in the analysis, with information aggregated at the trip level. Speed control was used as the dependent variable to assess how weather impacted driving. In terms of safety, it was assumed that driving slower than the posted speed limit or not maintaining speed control poses risks for other drivers. Based on other literature, as described in Section 1, it was assumed that older drivers would be more likely to slow down during weather events and that differential impacts would be present between normal and cognitively impaired drivers, since lack of speed control may also indicate cognitive changes.

Several studies have indicated that impairment is correlated with slower speeds. Wang *et al.* [29] assessed NDS data and found that older drivers with cognitive impairment drove slower than drivers without cognitive impairment, suggesting that impairment was related to speed control. They also found that drivers with visual impairment were less likely to comply with speed limit changes at transition zones. Feng *et al.* [30] also used NDS data to compare speed control between older drivers with suspected mild cognitive impairment and those without cognitive impairment. The metric of interest was speeding, defined as traveling 5 km/h or more over the speed limit for at least one minute. They found no correlation for female drivers except for an increase in speeding events, but the rate of speeding events decreased for older male drivers as age increased.

A description of how data were extracted in this study for each variable is provided below:

Fraction at Impeding Speed (Dependent Variable): This was calculated as the fraction of time the subject spent driving at a speed of 16.1 kph (10 mph) or less below the speed limit. Seconds of driving time spent at traffic intersections or in parking areas were excluded from the calculation. The average amount of time spent driving at impeding speeds was 28.4% (standard deviation = 13.0).

Age Group: Drivers were grouped into three categories based on clinical differences in elderly subjects as they age [31]. The categories included 65 to 73 (young-old), 74 to 79 (middle-old), and 80 to 90 (old-old). The sample size of trips reduced for each group was 7,780 for young-old, 7,718 for middle-old, and 6,333 for old-old.

Gender: Drivers self-categorized as male or female. No participants self-identified as another category.

Cognitive Status: A MoCA score of <26 is the standard cutoff indicating a positive screen for MCI that shows good discrimination based on clinical diagnosis [32]. A threshold of 26 was used in this study to provide comparability to the broader literature. Drivers who screened positive for MCI based on a MoCA score of <26 were classed as MCI.

Traffic Density: Higher volumes of traffic are expected to impact driver speed choice, since as volume increases, a driver is constrained by surrounding vehicles. A measure of traffic density was approximated using peak hour, an indicator of higher volumes. Consequently, if a trip occurred during traditional peak hours (6:00 to 9:00 a.m. or 4:00 to 6:00 p.m.), it was considered "peak"; otherwise, it was considered "off-peak." Only trips on weekdays were included in the analysis.

Weather-Related Roadway Surface Conditions: Weather-related roadway surface conditions were reduced for each trip using the methodology outlined in Section 3. Due to concerns with sample size, the categories of "rain" and "snow" were aggregated into a single category called "adverse." Trips where the weather could not be determined were excluded. The "clear" class was retained as is. A total of 19,609 trips were classified as "clear" and 2,222 were classified as "adverse."

Subjects: A total of 70 subjects were included in the study.

Table 2 summarizes the variables included in the model. As noted above, MCI was modeled using MoCA. Individuals were classified as having MCI if their MoCA score was 25 or lower; otherwise, they were considered normal-aging subjects (MCI = 26+) [32].

Table 2. Description of variables.

Factor	Summaries	
Age (Years)	Mean = 75.61, SD = 6.02	
Gender	Female: 33, Male: 37	
MoCA Score	Mean = 28.8, SD = 2.57	
Cognitive Status	Year 1	Year 2
MCI	26	24
Normal Aging	36	41
Drives per Subject	Mean = 598.1, SD = 272.92	
Percentage Driving at Impeding Speed	Mean = 28.4, SD = 13.0	
Age Group	Year 1	Year 2
Young-Old (65 - 73)	22	19
Middle-Old (74 - 79)	26	24
Old-Old (80 - 90)	14	22

5. Analysis

5.1. Description of Model

The dependent variable for the analysis was the proportion of time driving 16.1 kph (10 mph) or more below the speed limit, which was termed "impeding speed." This was selected as the driving behavior of interest since there is some evidence that older drivers drive slower than younger drivers [33], which may increase risk [34] [35]. It was also assumed that older drivers would slow down disproportionately during adverse weather compared to their younger cohorts. The objective was to examine the impact of weather conditions on how older drivers with varying degrees of cognitive impairment adhere to speed limits. The independent variables were described in the previous section.

The proportion of drivers driving at an impeding speed was modeled with beta regression, a regression model for continuous response variables that are bounded between 0 and 1, similar to proportions or rates. This makes it particularly useful for modeling data that represent percentages. The dependent variable follows a beta distribution, which is flexible enough to model various shapes of data distributions within the (0, 1) interval.

The mean of the response is tied to the linear predictor of the variables through a link function. Standard link functions include the logit, probit, and log-log, which relate the mean of the beta-distributed response variable to the linear predictors. A logit link was used for this analysis, which is defined by

$$logit(\mu_i) = \log \frac{\mu_i}{1-\mu_i}. \tag{2}$$

Since $logit(\mu_i) = \beta_0 + x_1^{(i)}\beta_1 + \cdots + x_K^{(i)}\beta_K = x^{(i)T}\beta,$, t, then

$$\mu_i = \frac{e^{x^{(i)T}\beta}}{1+e^{x^{(i)T}\beta}}. \tag{3}$$

For this analysis, the mgcv package [36] in R [37] was used. Figure and data preparation were done with R packages included in the tidyverse library [38].

Different models were compared with the Bayesian information criterion (BIC), and independent variables with the best fit were selected for the final model. Model fit was accomplished using residual plots and tools, including response versus fitted plots, and by checking the outliers among different subjects.

5.2. Results

The variables included in the final model are shown in **Table 3** with their corresponding 95% confidence intervals. The variables that resulted in the best fit model were MCI, age group, traffic density, and weather. The interpretation used for this model was similar in nature to that used for logistic regression in the absence of a binary variable. The base level for this model was young-old, clear weather conditions, normal traffic density, and no MCI. As noted in the table, interactions are present for all of the relevant dependent variables. **Table 3** presents the model estimates.

Table 3. Beta regression estimates.

Variable	Characteristic	Estimate	95% Confidence Interval	p-Value
(Intercept)		−090	−099, −082	**<0.001**
clear	_Clear_	—	—	
	Adverse	−0.03	−0.10, 0.05	0.480
age_group	_young-old_	—	—	
	middle-old	−0.03	−0.12, 0.05	0.458
	old-old	0.00	−0.10, 0.11	0.932
mci	_NormalAging_	—	—	
	MCI	0.03	−0.04, 0.10	0.372
trafficdensity	_Off-peak_	—	—	
	Peak	0.05	0.02, 0.08	**<0.001**
clear * age_group	_Adverse * middle-old_	0.05	−0.08, 0.17	0.458
	Adverse * old-old	0.06	−0.06, 0.17	0.317
clear * mci	_Adverse * MCI_	0.06	−0.06, 0.19	0.334
age_group * mci	_middle-old * MCI_	−0.04	−0.13, 0.04	0.327
	old-old * MCI	−0.06	−0.14, 0.03	0.182
clear * trafficdensity	_Adverse * Peak_	0.04	−0.05, 0.14	0.380
age_group * trafficdensity	_middle-old * Peak_	0.01	−0.04, 0.06	0.686
	old-old * Peak	−0.07	−0.12, −0.02	**0.011**
mci * trafficdensity	_MCI * Peak_	−0.04	−0.11, 0.03	0.302
clear * age_group * mci	_Adverse * middle-old * MCI_	−0.08	−0.25, 0.10	0.402
	Adverse * old-old * MCI	−0.02	−0.20, 0.15	0.812

Continued

clear * age_group * trafficdensity	*Adverse * middle-old * Peak*	−0.06	−0.22, 0.11	0.503
	*Adverse * old-old * Peak*	0.06	−0.10, 0.22	0.460
clear * mci * trafficdensity	*Adverse * MCI * High*	−0.06	−0.24, 0.12	0.535
age_group * mci * trafficdensity	*middle-old * MCI * Peak*	0.03	−0.05, 0.12	0.441
	*old-old * MCI * Peak*	0.12	0.03, 0.21	**0.012**
clear * age_group * mci * trafficdensity	*Adverse * middle-old * MCI * Peak*	0.23	−0.02, 0.47	**0.075**
	*Adverse * old-old * MCI * Peak*	−0.04	−0.29, 0.22	0.778
s(subj)				**<0.001**

The impact of the interactions is best described graphically, as shown in **Figures 4-6**. As noted in **Figure 4**, the youngest group of older drivers spent less time driving at impeding speeds (25.1% to 26.9%) and had the least variability. The confidence interval range for this group was 2.1% to 4.4%. The middle age group spent the highest amount of time driving at impeding speeds (24.8% to 29.1%) and had more variability than young-old drivers. Their confidence interval ranges were from 3.6% to 5.3%. The oldest age group spent more time driving at impeding speeds (25.2% to 28.0%) and had the most variability. Confidence interval ranges for this group were 4.1% to 5.7%.

In almost all cases, drivers were more likely to drive at impeding speeds during peak hours than during non-peak hours, which is expected since traffic volumes are higher and lead to more interactions between vehicles. Additionally, in general, all categories of older drivers spent less time below the speed limit when the weather-related roadway surface was clear than when it was adverse.

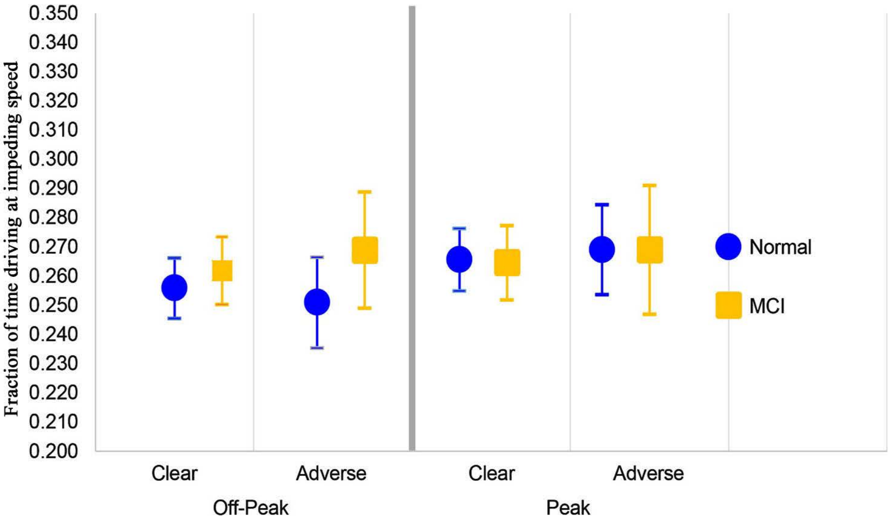

Figure 4. Interaction of cognitive status, traffic condition, and traffic density with a 95% confidence interval for young-old drivers.

Interactions between cognitive status, peak period, and environmental condition for the youngest group of older drivers are shown in **Figure 4**. During peak periods, young-old drivers spent nearly identical amounts of time at impeding speeds regardless of roadway conditions (clear versus adverse) and cognitive function (normal versus MCI). During off-peak periods, drivers with normal cognition were slightly more likely to spend more time driving at impeding speeds when clear conditions were present than when adverse environmental conditions were present (23.5% versus 24.6%). During off-peak times with clear weather, drivers with MCI were slightly more likely to drive at impeding speeds than drivers with normal cognition (25.0% versus 24.6%). The main difference between drivers in terms of cognitive function was noted for off-peak conditions and adverse weather conditions. In this scenario, drivers with MCI spent 24.9% of the time driving below the speed limit while drivers without MCI did so 23.5% of the time.

Results for the middle-old group of drivers are shown in **Figure 5**. As noted in the figure, drivers in this age group generally spent more time at impeding speeds during peak periods than they did during off-peak periods (25.9% to 29.1% compared to 24.8% to 25.4%). During off-peak periods and in clear weather conditions, drivers in this age group with MCI and normal cognition drove similarly. During off-peak periods and in adverse roadway conditions, middle-old drivers with normal cognition spent slightly more time at impeding speeds than those with MCI (22.9% versus 22.6%). Drivers in the middle-old age group showed similar patterns for peak periods and clear weather. When adverse roadway conditions were present during peak periods, drivers in the middle-old group with MCI were more likely to drive at impeding speeds (29.1%) than drivers without MCI (26.3%).

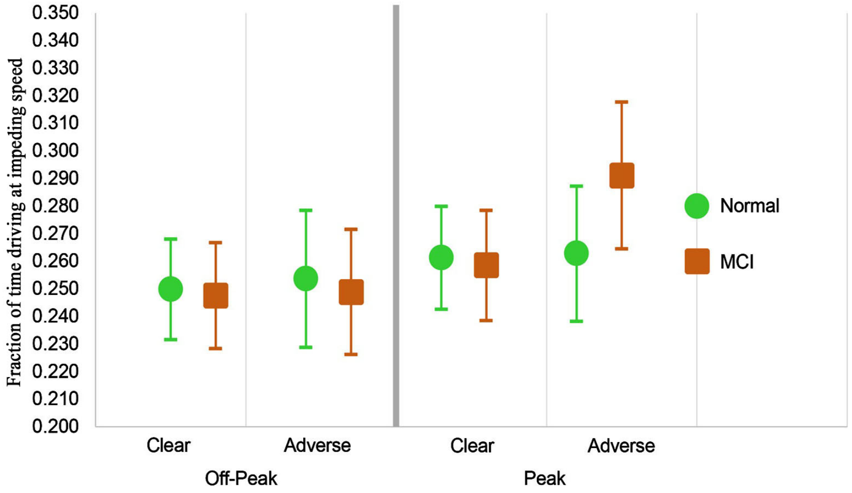

Figure 5. Interaction of cognitive status, traffic condition, and traffic density with a 95% confidence interval for middle-old drivers.

Results for the oldest group of drivers are shown in **Figure 6**. Old-old drivers in general were more likely to drive at impeding speeds during adverse weather-related roadway conditions (26.3% to 28.0%) than during clear weather (25.2% to 26.4%). During off-peak periods and in clear conditions, old-old drivers with MCI were slightly less likely to drive at impeding speeds than those without (23.1% versus 23.5%). However, in adverse roadway conditions during off-peak periods, drivers with MCI were slightly more likely to travel at impeding speeds (26.6% versus 26.3%). During peak periods, old-old drivers with MCI were more likely to travel at impeding speeds than drivers without (26.4% versus 25.4%). In adverse weather-related roadway conditions, no difference was noted between drivers of different cognitive statuses.

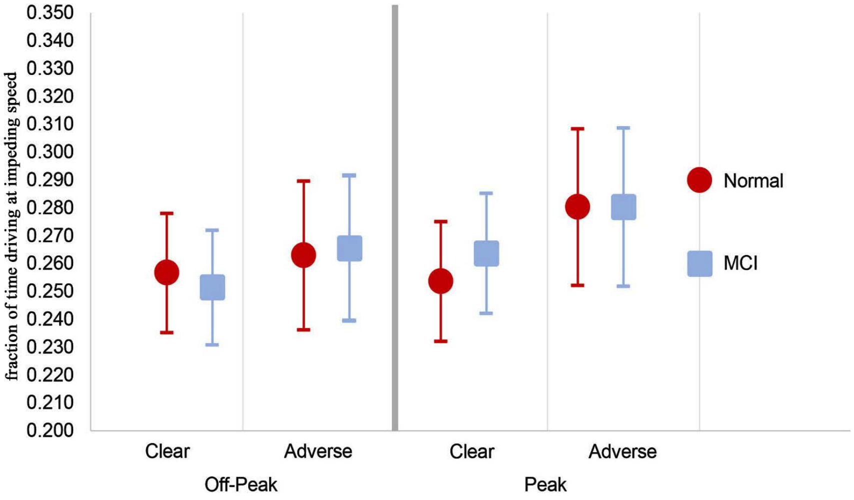

Figure 6. Interaction of cognitive status, traffic condition, and traffic density with a 95% confidence interval for old-old drivers.

6. Discussion

With aging, the risk of age-related cognitive and visual decline increases and may impact the ability to drive, increasing the risk of crashes. Adverse weather may be particularly challenging for older drivers due to their sensitivity to glare and reduced visibility, resulting in changes in driving patterns and behavior during adverse weather.

This paper described the results of a study that assessed how drivers in different age/cognition categories maintained speed control when weather-related roadway conditions were clear or adverse. The percentage of time during a trip when drivers were ≤16.1 kph (10 mph) under the speed limit was modeled using NDS data for a group of drivers aged 65 to 90 in the Omaha, Nebraska, area. Weather-related roadway surface condition was coded using a video-based system that interpreted surface conditions from NDS video data.

The proportion of drivers driving at an impeding speed was modeled using beta regression. The variables that resulted in the best fit model were MCI, age group, traffic density, and weather-related roadway condition. However, interactions among the variables were present. Consequently, results were shown graphically for each age group (young-old, middle-old, and old-old) and for normal drivers versus drivers with MCI by peak period and weather condition. The youngest group of older drivers spent less time driving at impeding speeds (25.1% to 26.9%) and had the least variability compared to the other two age groups. The middle-old group spent more time driving at impeding speeds (24.8% to 29.1%) and had more variability than young-old drivers. The old-old group were the most likely to drive at impeding speeds (25.2% to 28.0%) and had the most variability.

In general, older drivers were more likely to drive at impeding speeds during peak hours than during non-peak hours. This makes sense because traffic volumes during peak periods are higher and drivers are more constrained due to surrounding vehicles. Additionally, in most cases, older drivers spent less time below the speed limit when the weather-related roadway surface was clear than in adverse conditions. Results indicate that older drivers are impacted by weather conditions and that those impacts are differential with progressive age. Further, distinct patterns were noted between older drivers with cognitive impairment and drivers with normal cognition.

Identifying specific areas of risk for older drivers can assist roadway agencies in understanding how to better address the impacts of this driving population. Additionally, measurable differences in driving behaviors may assist caregivers and medical professionals in identifying cognitive and visual decline as well as provide information for OEMs to design supportive in-vehicle technology for older drivers at risk due to cognitive and visual impairments.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Owsley, C. and McGwin, G. (2016) Vision-Targeted Health Related Quality of Life in Older Adults: Patient-Reported Visibility Problems in Low Luminance Activities Are More Likely to Decline than Daytime Activities. *BMC Ophthalmology*, **16**, Article No. 92. https://doi.org/10.1186/s12886-016-0274-5

[2] Merickel, J., High, R., Dawson, J. and Rizzo, M. (2019) Real-World Risk Exposure in Older Drivers with Cognitive and Visual Dysfunction. *Traffic Injury Prevention*, **20**, S110-S115. https://doi.org/10.1080/15389588.2019.1688794

[3] FHWA (2024) How Do Weather Events Impact Roads. Federal Highway Administration.
https://ops.fhwa.dot.gov/weather/q1_roadim-

pact.htm#:~:text=By%20crash%20type%20(not%20shown,from%202%20to%2021%20percent

[4] IPRC (2019) Older Adult Drivers. Injury Prevention Research Center. https://iprc.public-health.uiowa.edu/2019/02/25/older-adult-drivers/

[5] Sabback, F. and Mann, W. (2005) The Influence of Climate and Road Conditions on Driving Patterns in the Elderly Population. *Physical & Occupational Therapy in Geriatrics*, **23**, 64-74. https://doi.org/10.1300/j148v23n02_04

[6] Braitman, K.A. and McCartt, A.T. (2008) Characteristics of Older Drivers Who Self-Limit Their Driving. *Annals of Advances in Automotive Medicine*, **52**, 245-254.

[7] Clarke, P.J., Yan, T., Keusch, F. and Gallagher, N.A. (2015) The Impact of Weather on Mobility and Participation in Older US Adults. *American Journal of Public Health*, **105**, 1489-1494. https://doi.org/10.2105/ajph.2015.302582

[8] Allen, H.K., Beck, K.H. and Zanjani, F. (2019) Driving Concerns among Older Adults: Associations with Driving Skill, Behaviors, and Experiences. *Traffic Injury Prevention*, **20**, 45-51. https://doi.org/10.1080/15389588.2018.1528358

[9] Karali, S., Gyi, D.E. and Mansfield, N.J. (2016) Driving a Better Driving Experience: A Questionnaire Survey of Older Compared with Younger Drivers. *Ergonomics*, **60**, 533-540. https://doi.org/10.1080/00140139.2016.1182648

[10] Myers, A.M., Trang, A. and Crizzle, A.M. (2011) Naturalistic Study of Winter Driving Practices by Older Men and Women: Examination of Weather, Road Conditions, Trip Purposes, and Comfort. *Canadian Journal on Aging/La Revue canadienne du vieillissement*, **30**, 577-589. https://doi.org/10.1017/s0714980811000481

[11] Smith, G.A., Porter, M.M., Cull, A.W., Mazer, B.L., Myers, A.M., Naglie, G., *et al.* (2016) Seasonal and Weather Effects on Older Drivers' Trip Distances. *Canadian Journal on Aging/La Revue canadienne du vieillissement*, **35**, 59-68. https://doi.org/10.1017/s0714980816000040

[12] Crizzle, A.M. and Myers, A.M. (2013) Examination of Naturalistic Driving Practices in Drivers with Parkinson's Disease Compared to Age and Gender-Matched Controls. *Accident Analysis & Prevention*, **50**, 724-731. https://doi.org/10.1016/j.aap.2012.06.025

[13] Ferri, C.P., Prince, M., Brayne, C., Brodaty, H., Fratiglioni, L., Ganguli, M., *et al.* (2005) Global Prevalence of Dementia: A Delphi Consensus Study. *The Lancet*, **366**, 2112-2117. https://doi.org/10.1016/s0140-6736(05)67889-0

[14] Petersen, R.C., Roberts, R.O., Knopman, D.S., Geda, Y.E., Cha, R.H., Pankratz, V.S., *et al.* (2010) Prevalence of Mild Cognitive Impairment Is Higher in Men. *Neurology*, **75**, 889-897. https://doi.org/10.1212/wnl.0b013e3181f11d85

[15] Dawson, J.D., Uc, E.Y., Anderson, S.W., Johnson, A.M. and Rizzo, M. (2010) Neuropsychological Predictors of Driving Errors in Older Adults. *Journal of the American Geriatrics Society*, **58**, 1090-1096. https://doi.org/10.1111/j.1532-5415.2010.02872.x

[16] Uc, E.Y. (2005) Driver Landmark and Traffic Sign Identification in Early Alzheimer's Disease. *Journal of Neurology*, *Neurosurgery & Psychiatry*, **76**, 764-768. https://doi.org/10.1136/jnnp.2004.049338

[17] Aksan, N., Dawson, J.D., Emerson, J.L., Yu, L., Uc, E.Y., Anderson, S.W., *et al.* (2012) Naturalistic Distraction and Driving Safety in Older Drivers. *Human Factors*: *The Journal of the Human Factors and Ergonomics Society*, **55**, 841-853. https://doi.org/10.1177/0018720812465769

[18] Dawson, J.D., Anderson, S.W., Uc, E.Y., Dastrup, E. and Rizzo, M. (2009) Predictors of Driving Safety in Early Alzheimer Disease. *Neurology*, **72**, 521-527.

https://doi.org/10.1212/01.wnl.0000341931.35870.49

[19] Freitas, S., Simões, M.R., Alves, L. and Santana, I. (2013) Montreal Cognitive Assessment: Validation Study for Mild Cognitive Impairment and Alzheimer Disease. *Alzheimer Disease & Associated Disorders*, **27**, 37-43. https://doi.org/10.1097/wad.0b013e3182420bfe

[20] He, K., Zhang, X., Ren, S. and Sun, J. (2016) Deep Residual Learning for Image Recognition. 2016 *IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), Las Vegas, 27-30 June 2016, 770-778. https://doi.org/10.1109/cvpr.2016.90

[21] Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., *et al.* (2021) An Image Is Worth 16x16 Words: Transformers for Image Recognition at Scale. arXiv: 2010.11929. https://doi.org/10.48550/arXiv.2010.11929

[22] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, L. and Polosukhin, I. (2017) Attention Is All You Need. *Proceedings of the* 31*st International Conference on Neural Information Processing Systems*, Long Beach, 4-9 December 2017, 6000-6010.

[23] Touvron, H., Matthieu, C., Douze, M., Massa, F., Sablay-Rolles, A. and Jegou, H. (2021) Training Data-Efficient Image Transformers and Amp; Distillation Through Attention. *Proceedings of the* 38*th International Conference on Machine Learning*, 10347-10357.

[24] Yuan, L., Chen, Y., Wang, T., Yu, W., Shi, Y., Jiang, Z., *et al.* (2021). Tokens-to-Token ViT: Training Vision Transformers from Scratch on ImageNet. 2021 *IEEE/CVF International Conference on Computer Vision* (*ICCV*), Montreal, 10-17 October 2021, 538-547. https://doi.org/10.1109/iccv48922.2021.00060

[25] Foret, P., Kleiner, A., Mobahi, H. and Neyshabur, B. (2021) Sharpness-Aware Minimization for Efficiently Improving Generalization. *International Conference on Learning Representations*, Vienna, 4 May 2021.

[26] Kingma, D. and Ba, J. (2014) Adam: A Method for Stochastic Optimization. *International Conference on Learning Representations*, San Diego, 7-9 May 2015, 1-13.

[27] Chen, Y., Li, J., Xiao, H., Jin, X., Yan, S., and Feng, J. (2017) Dual Path Networks. *Proceedings of the* 31*st International Conference on Neural Information Processing Systems*, Long Beach, 4-9 December 2017, 4470-4478.

[28] Ruder, S. (2017) An Overview of Gradient Descent Optimization Algorithms. arXiv: 1609.04747. https://arxiv.org/abs/1609.04747

[29] Wang, S., Sharma, A., Dawson, J., Rizzo, M. and Merickel, J. (2021) Visual and Cognitive Impairments Differentially Affect Speed Limit Compliance in Older Drivers. *Journal of the American Geriatrics Society*, **69**, 1300-1308. https://doi.org/10.1111/jgs.17008

[30] Feng, Y.R., Meuleners, L., Stevenson, M., Heyworth, J., Murray, K., Fraser, M., *et al.* (2021) The Impact of Cognition and Gender on Speeding Behaviour in Older Drivers with and without Suspected Mild Cognitive Impairment. *Clinical Interventions in Aging*, **16**, 1473-1483. https://doi.org/10.2147/cia.s319129

[31] Lee, S.B., Oh, J.H., Park, J.H., Choi, S.P. and Wee, J.H. (2018) Differences in Youngest-Old, Middle-Old, and Oldest-Old Patients Who Visit the Emergency Department. *Clinical and Experimental Emergency Medicine*, **5**, 249-255. https://doi.org/10.15441/ceem.17.261

[32] Milani, S.A., Marsiske, M., Cottler, L.B., Chen, X. and Striley, C.W. (2018) Optimal Cutoffs for the Montreal Cognitive Assessment Vary by Race and Ethnicity. *Alzheimer's & Dementia*: *Diagnosis*, *Assessment & Disease Monitoring*, **10**, 773-781.

https://doi.org/10.1016/j.dadm.2018.09.003

[33] Doroudgar, S., Chuang, H.M., Perry, P.J., Thomas, K., Bohnert, K. and Canedo, J. (2016) Driving Performance Comparing Older versus Younger Drivers. *Traffic Injury Prevention*, **18**, 41-46. https://doi.org/10.1080/15389588.2016.1194980

[34] Horberry, T., Hartley, L., Gobetti, K., Walker, F., Johnson, B., Gersbach, S., *et al.* (2004) Speed Choice by Drivers: The Issue of Driving Too Slowly. *Ergonomics*, **47**, 1561-1570. https://doi.org/10.1080/00140130412331290925

[35] Joanisse, M., Gagnon, S. and Voloaca, M. (2012) Overly Cautious and Dangerous: An Empirical Evidence of the Older Driver Stereotypes. *Accident Analysis & Prevention*, **45**, 802-810. https://doi.org/10.1016/j.aap.2011.11.002

[36] Wood, S.N. (2017) Generalized Additive Models: An Introduction with R. Chapman and Hall.

[37] The R Core Team (2022) R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing.

[38] Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L., François, R., *et al.* (2019) Welcome to the Tidyverse. *Journal of Open Source Software*, **4**, Article 1686. https://doi.org/10.21105/joss.01686