Using the New SHRP2 Naturalistic Driving Study Safety Databases to Examine Safety Concerns for Older Drivers

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16. Abstract

Older drivers, age 65 and over, in the New England region have higher rates of crashes of crash-related fatalities than middle-age drivers, and are especially over-represented in crashes occurring during left turns at signalized intersections. This study sought to learn more about the factors behind this trend, utilizing information from the SHRP2 (the second Strategic Highway Research Program) naturalistic driving study (NDS), and to assess the usefulness of NDS data for examining such research questions. Data were received NDS data for all trips with a driver age 65 and above, including signalized intersections with a crash or near crash event, as well as a sample of random baseline (non-eventful) trips. In the dataset, most of the older driver crashes were minor, with the most common crashes (over 70%) involved vehicles hitting a curb or leaving the roadway. Most of the statistical significant variables impacting whether an older driver crashed were related to their health and to visual and cognitive factors, which impact their ability to monitor oncoming traffic and to identify when there is a sufficient gap to safely make the turn. Training for older drivers to help them negotiate signalized intersections and left turns has shown to be beneficial by helping them adjust to their age-related limitations. The findings of this study, and the statistical significance of the results, were limited somewhat by the small number of crashes in the dataset.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.

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ABSTRACT

Older drivers, age 65 and over, in the New England region have higher rates of crashes and of crash-related fatalities than middle-age drivers. Older drivers are especially over-represented in crashes occurring during left turns at signalized intersections. This study was proposed to better understand factors contributing to this trend, utilizing information collected through the SHRP2 (the second Strategic Highway Research Program) naturalistic driving study (NDS). The study was also designed as a proof of concept project for assessing the usefulness of the NDS data for examining such research questions. The researchers received NDS data for all trips with a driver age 65 and above, including signalized intersections with a crash or near crash event, as well as a sample of random baseline (non-eventful) trips. The researchers found that 81 percent of the left-turn intersection crashes occurred at 4-way intersections and 15 percent occurred at T-intersections. In the dataset, most of the older driver crashes were minor, with the most common crashes (over 70%) involved vehicles hitting a curb or leaving the roadway. The data were analyzed through regression and machine learning models. The analysis showed that most of the statistical significant variables impacting whether an older driver crashed were related to their health and to visual and cognitive factors, which impact their ability to monitor oncoming traffic and to identify, in the case of permissive left turns, when there is a sufficient gap to safely make the turn. Training for older drivers to help them negotiate signalized intersections and left turns has shown to be beneficial. The findings of this study, and the statistical significance of the results, were limited somewhat by the small number of crashes in the dataset.

INTRODUCTION

Older drivers, age 65 and over, in the U.S. and particularly in the New England region have higher rates of crashes and of crash-related fatalities than middle-age drivers (*1-3*). Older drivers are also over-represented in crashes occurring during left turns, including at both signalized intersections (*4*). This study was proposed to find out more about the contributing factors behind this trend, utilizing information collected through the SHRP2 (the second Strategic Highway Research Program) study on naturalistic driving. There has been considerable past research documenting the challenges faced by older drivers, including while negotiating left turns at signalized intersections, but until SHRP2, there was little naturalistic data on this topic. The objective of this study is to use the SHRP2 Naturalistic Driving Study (NDS) data to learn more about the safety issues for older drivers when turning left at signalized intersections, using analysis methods that were not possible or were not feasible before the SHRP2 NDS data became available. The goal is then to leverage the knowledge and insights gained through this study to help design countermeasures for improving intersection safety or training to educate older drivers on critical intersection behaviors for safety. The population of older drivers is expected to grow significantly in the coming decades. It is important to drivers to be able to maintain their independence and ability to drive safely as they age, and important that roadways and intersections be safe for these drivers, and all drivers, as well. This study seeks to provide information that may help.

BACKGROUND

The aging U.S. population poses large challenges for roadway safety. In 2014, drivers age 65 and older accounted for 17 percent of all traffic fatalities (*1*). Since 2004, this age group has continued to have higher rates of traffic fatalities than most other age groups. For example, the fatal vehicle crash rate per 100 million miles driven is 1.8 for drivers overall, but rises substantially for older adults: to 2.1 (driver age 70-74), 2.7 (age 75-79), 4.2 (age 80-84), and 8.8 (age 85 & above) (*2*). This trend partly reflects the fact that older drivers are more likely to be severely injured or die in a crash due to their greater frailty compared to younger drivers (*3*-*6*).

Age 65 and over drivers in the New England states account for about 4 percent of the total traffic fatalities (*7*). This age group is also overrepresented in New England for signalized intersection crashes, particularly ones involving left-turn maneuvers.

Analysis of crash data reveals that crashes involving drivers age 65 or older often occur at intersections, accounting for 37 percent of total crashes for this age group. Intersections top the list of different crash types for drivers aged 70 and older (*8*). For drivers 80 years old and above, intersection crashes account for 47 percent of all crashes (*2*). In comparison, 25 percent of the crashes among drivers age 30 to 59 are at intersections.

A number of studies have shown that older drivers are much more likely to crash at intersections than middle-aged drivers (*4*, *9, 10*) and to have more fatal crashes at intersections. The relative risk of an intersection fatal crash for drivers aged 85 and older is 10.6 times that of drivers aged 40-49 (*11*). The likelihood of traffic violations at intersections is also much higher for older drivers than it is for middle-aged drivers (*12*).

Older drivers themselves perceive making left turns onto divided highways as more difficult than other turning movements at intersections (*13*). Older drivers' crash involvement is higher at intersections, especially when making left turns, in part due to their failure to yield the right of way to opposing traffic (*14*).

Past studies have suggested a number of potential, different explanations of why older are more prone to crashes while turning left at intersections. The explanations include age and decline-related factors regarding the following important skills for driving:

- Ability to multi-task (*15, 16*)
- Working memory capacity (*17*);
- Lack of distractibility (*18-22*)
- Decision-making abilities (*14*, *23-25*)
- Attentional field of view (*26-27*);
- Ability to detect changes in visual scenes (*28-35)*
- Vision (*18*, *27*, *35-40*)
- Flexibility (*41-47*)

These declines in cognitive, sensory and physical abilities may interact and influence safe driving behavior for older drivers, particularly at intersections (*43, 48*). Specifically, at an intersection, the driver might have to identify an intersection sign (sensory), regulate the speed of their vehicle (psychomotor), scan appropriately for hazards (cognitive) and potentially execute head movements (physical). Also specifically during left-turns at intersections, diminishing ability to share attention and to turn the steering wheel sharply enough can compromise the ability of aging drivers to navigate safely through the intersection (*49*).

To date, older drivers’ interactions with the road, vehicle, and environment have been difficult to study. Establishing older driver gap-acceptance behavior during left-turn maneuvers with video has not been done because the cost of collecting appropriate data at a sufficient number of intersections with various geometric designs would be quite high (*50*). While data are available from driving simulator or recruited-driver studies, the observations made of drivers’ behaviors during such studies are not of truly naturalistic behavior, since drivers are aware of the presence of an observer. A review of the published research to date showed that the majority of current findings regarding older drivers have been identified and validated in controlled laboratory systems (in a driving simulator, cave etc.) or via field studies (open road, closed loop, operational tests etc.).

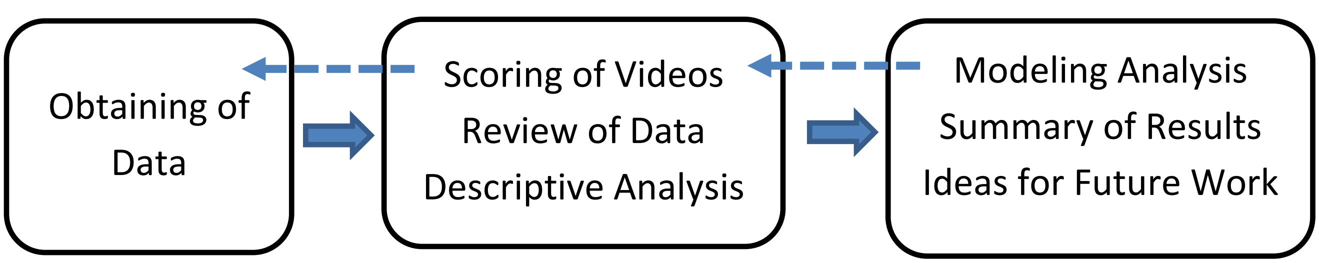
The SHRP2 Naturalistic Driving Study (NDS) addressed the driver's interactions with their vehicle, traffic environment, roadway characteristics, and traffic control devices (*52*, *53*). SHRP2 provides one of the first opportunities to study naturalistic data and observe drivers' behavioral patterns in a comprehensive way. Previous naturalistic studies, including the 100-Car Study (*54*), have been of smaller scale. The SHRP2 NDS included 3,400 driving participants from six metropolitan areas across the country, participating and the NDS data provide a high level of ecological validity. Each participant's car was outfitted with multiple video cameras and sensors to collect data on their driving over a one-to two-year period. The NDS data contain a relatively greater proportion of younger and older drivers than the national driver population databases. The data include: weather and lighting conditions; signal indications at specific times; the presence of oncoming and opposing left-turn vehicles, the presence of leading and following vehicles; vehicle speed, acceleration, and braking; vehicle controls, lane position; forward radar. Above all, video samples of the forward driving scene provide start and end time of each gap rejected or accepted by the turning driver. The NDS data also include extensive surveys and screenings of participants, including regarding the following: demographics; driving history, behaviors, and attitudes towards risks while driving; knowledge of driving regulations; medical conditions that could impact driving; sleep patterns; testing regarding vision, strength, and cognitive abilities.

NDS data have been used previously by researchers to learn more about the safety impacts of left-turn lane offsets at intersections (*50*). To our knowledge, ours is the first study with the NDS data to focus on left turns at signalized intersections and older drivers. The UMass research was designed, in part, as a proof of concept project to assess the usefulness of the NDS data for better understanding older adults' driving behaviors and challenges with left turns at signalized intersections. One goal was also to then be able to take the information and insights gained through analyzing data from the NDS data and use it to develop potential options for improving driver safety for signalized intersection left turns.

METHODOLOGY AND PROCEDURES

Figure 1graphically summarizes the steps of this research study, from first requesting and obtaining the data through the data analysis and summarizing of results. The steps of the study are discussed further below, in this and the following sections.

Figure 1: Overview of Study Process



NDS Data Request

One of the first steps of this research project involved obtaining the SHRP2 NDS data that UMass needed for its analysis. The full NDS dataset is housed at the Virginia Tech Transportation Institute (VTTI). A sample of the data can be seen and queried through the SHPR2 online database Insight (https://insight.shrp2nds.us) though it cannot be downloaded in dis-aggregated form.

The data associated with specific drivers and their vehicles were collected with the drivers' consent. Nonetheless, protective measures are still in place to protect the anonymity of the NDS data and the driver participants. To qualify for access to the Insight database and query tools, researchers must show proof that they have completed training on human subject research ethics. After that, to obtain access to disaggregated data on different groups of drivers, for example teen drivers or drivers age 85 and older, or to data that is not available through Insight, researchers must provide VTTI with details about the driver population(s) and questions they are interested in studying using the SHPR2 data. Once a researcher has a clear idea about the scope of their data request, including the key variables and the sample size, VTTI asks that researcher to apply for a data use license (DUL) for accessing the data. The DUL form asks for details on the information being sought including the population being studied, the sample size, and the specific tables and variables being requested. The DUL form also asked about the security plan for the data, including who will have access to the data, how other access will be restricted, and whether the researchers have already obtained Institutional Review Board (IRB) review and approval, or a waiver indicating no IRB approval was necessary, from their home institution's IRB for their study. Getting IRB approval or a waiver is required before VTTI will share the data requested in the DUL.

The UMass researchers conducted queries on the NDS datasets using the Insight web site to help inform their data request to VTTI. Originally, the UMass team was going to limit its request to trips involving drivers age 65 or over making a left turn at a signalized intersection, including those trips with crashes, near crashes, and those without. However, the Insight queries showed that there were fewer such trips than the researchers had expected. As a result, the researchers decided to request data on all trips made by a driver age 65 or over which involved a signalized intersection and during which a crash or near crash occurred. This included trips whether the driver was turning left, turning right, or going straight through the intersection. The researchers also asked for a sample of intersection trips with this age group with no crash or near-crash. Also requested was a comparison sample of trips with signalized intersections by drivers 30 to 49 years old, including those with a crash, near-crash, or no crash event (baseline). Signalized intersections were defined as those for which the "Traffic Control" in the NDS data Events Details table was marked as "Traffic signal."

SHRP2's baseline dataset was created at VTTI. As described by the VTTI researchers (*51*), the objective of the baseline sample are to provide sufficient information to help answer a variety of research questions related to: (a) exposure: the prevalence of factors under normal driving conditions (i.e. analyzing the baseline file by itself) and (b): risk evaluation: the base for evaluating the relative risk of factors (i.e. comparing crash and/or near crash events to the baselines). The VTTI researchers applied analytical algorithms to over 5 million SHRP2 trip files to identify crashes, near crashes, and baseline events. The baselines were designed to reflect "normal driving" and typical driving behaviors across the sample. "The baselines were chosen via random sample stratified by participant and time driven, from the trips for each driver. All participants were included in the sample regardless of whether they were involved in a crash or near-crash. A minimum of one baseline was included for each driver in the study. Time driving was operationally defined to include only driving speeds above 5 mph." (*51*).

Data Variables

The UMass research team focused its data request to VTTI on variables in the main categories: driver characteristics, trip details, and vehicle characteristics (Table 1).

Table 1: SHPR2 NDS Data Requested

Driver Characteristics	Trip Details	Vehicle Characteristics
Age Gender Driving History Driving Knowledge Driving Behavior Medical Conditions Sleep Habits Visual Abilities Cognitive Abilities	Time of Day Trip Duration Speed Acceleration Braking Steering Event Data Video	Year Classification Mileage

Most of the requested data were collected through the questionnaires given to the SHRP2 participants at the start of their enrollment in the SHRP2 study, including the following:

- Driver Demographics Questionnaire, asked about individual and family demographics.
- Driver History Questionnaire, included questions on the amount of driving experience, crashes, traffic violations, and driver training.
- Driving Behavior Questionnaire, asked about how frequently participants had committed different described driving errors or violations (e.g., running a red light).
- Medical Conditions and Medications Questionnaire, contained a list of medical conditions and asked which applied to participant. It also asked for details on current medications and dosages.
- Sleep Habits Questionnaire, included questions regarding participants' sleep habits and patterns, and level of fatigue.

Each of the above questionnaires had participants self-report their responses. For the Driving Knowledge Questionnaire, participants were asked questions from a number of state department of motor vehicle driving knowledge tests.

Participants were also given a battery of visual tests, including regarding peripheral vision and field of view, as well as cognitive tests. One test was the clock-drawing test which is used to screen for dementia and other neurological issues.

Details on the vehicle itself (model of vehicle, vehicle age, mileage, features) were gathered during the installation of the in-vehicle sensors and cameras for the study. The vehicle trip and time series data (speed, acceleration, yaw, and pedal brake status) were collected primarily through sensors installed in participants' vehicles.

Event data were requested for all trips in the received dataset, including the trips with crashes or near crashes, plus a sample of the baseline trips. In the SHRP2 datasets, crashes are defined as "any contact that the subject vehicle has with an object either moving or fixed, at any speed." Crashes can include "non-premediated departures of the roadway where at least one tire leaves the paved or intended travel surface of the road." Near crashes are defined as "any circumstance that requires a rapid evasive maneuver by the subject vehicle or any other vehicle, pedestrian, cyclist, or animal to avoid a crash." Non-subject conflicts are defined as "any incident that gets captured on video (near-crash or crash) that does not involve the subject driver. The UMass researchers received data on severity of crashes, on the vehicle positions and maneuvers just before and just after crashes, and on driver behaviors during events. The researchers requested that VTTI provide forward video and time series data for a 2.5-minute period. For trips in which a crash or near-crash occurred, the 2.5-minute period included 2 minutes before that event and 30 seconds after the event. For baseline trips, we requested a time period that went from two minutes before entering the signalized intersection (crossing the stop line) until the vehicle exited the intersection (for turning vehicles, this was when the vehicle straightened out again post-turn; for non-turning vehicles, this was when the vehicle crossed the stop line (or equivalent) at the far end of the intersection). The 2 minute period before the event was helpful because it allowed sufficient time to observe the drivers approaching the signalized intersections and any queues they had to wait in before going through the intersection.

The forward videos came from a dashboard camera looking out the front windshield and away from the car. The videos didn't include any view of the driver, and the videos were additionally redacted by VTTI to maintain the anonymity of other drivers and vehicles appearing in the videos and of the geographic location where the videos were recorded. Initially, some of the videos received by UMass ended before the participant vehicles had completed going through the intersection. This happened when there was a long waiting time at the intersection before the vehicle started turning. Upon UMass' request, VTTI sent UMass additional video footage for those trips, to cover the time through the end of the intersection.

None of the data received by the UMass team contained personal identifiers of participants. The data tables provided to UMass did include randomized IDs, such as for participants, trips, and events, to facilitate the linking of the different types of data during the analysis part of the study.

Video Scoring

The UMass researchers developed a scoring rubric for coding the dash camera videos. The rubric focused on the characteristics of the signalized intersection and the traffic environment as participants approached and went the intersection. The details of the rubric are listed in Table 2.

Table 2: UMass Rubric for Scoring the NDS Video Data

Field	**Value(s)**			
Initials_of_Scorer	Scorer Initials			
File_ID	Trip_ID; Unique identifier for each vehicle trip			
	0	**1**	**2**	**3**
Day_Night	Trip after dark	Trip during daylight hours		
Weather	Clear	Not clear (rain, sleet fog)		
Intersection Type	T-intersection	4-way intersection	Other	
Dedicated Left Turn Lane at Intersection	0: No	1: Yes		
Wait at Intersection due to Queue or Traffic Signal	No Wait	Wait		
Signalized Intersection (This should always be 1)	Not a signalized intersection	Signalized intersection		
Opposing Lanes Present	No	Yes		
Oncoming Traffic Obscured	No oncoming traffic or oncoming traffic not obscured	Oncoming traffic obscured		
Vehicle Movement	No turn	Left turn	Right turn	
Traffic Signal Obscured	Not obscured	Obscured		
Traffic Signal State (at time of turn/going through intersection)	No signal	Green	Yellow	Red
Traffic Signal Turn Indicator (for turns)	No signal	Circular signal	Flashing signal	Arrow, not flashing

Table 2: UMass Rubric for Scoring the NDS Video Data (continued)

Field	Value(s)			
	0	1	2	3
Turn Phasing for direction of turn	Not applicable/ no turn	Permissive (should yield)	Protected (have right of way)	
Gap Decision Required	No gap decision required	Gap decision Required		
Lead Vehicle to Follow through Intersection	No lead vehicle to follow through intersection	Lead vehicle present		
Time stamp of entering the intersection (in ms, truncated to the nearest 0.1 sec)	Time at which the vehicle passed the stop line to entered the intersection			
Time stop of exiting the intersection ((in ms, truncated to the nearest 0.1 sec)	Time at which the vehicle completed the intersection; for turning vehicles, this is when the vehicle has straightened out again post-turn; for vehicles going straight through the intersection, this is when the vehicle passed the stop line (or equivalent) at the far end of the intersection			

The videos were viewed and scored by trained scorers. The video scoring values were recorded using Qualtrics software. The scorers consisted of the study researchers and undergraduate and graduate students. Each video was scored at least once, and about 20 percent of the video were scored two times using different scorers to verify the scoring. An estimated 70 percent of the videos including a left-turn at a signalized intersection were scored multiple times to check the scoring, and record additional details such as the presence of signage or pavement markings for the left turn lanes. The scorers met to review discuss videos for which there were questions regarding the correct scoring values.

Initial Data Analysis

For the initial data analysis, the researchers used descriptive statistics for get an overview of the NDS data received by VTTI, and to examine correlations between different driver and intersection characteristics and the occurrence of crashes and near crashes.

Machine Learning Algorithms

The researchers also used machine learning models to analyze the received data and to predict which factors are most significant for classifying drivers and predicting drivers' risks of crashing. With machine learning, computer systems use algorithms and mathematical models to progressively improve their performance on specific tasks. The core objective with machine learning is to be able to generalize from previous data experience, and to build algorithms that can receive input data and use statistical analysis to accurately predict an output while updating outputs as new data becomes available. For the current work, the researchers used supervised machine learning. Supervised learning algorithm build mathematical models of a set of example data, known as training data, which contains both the inputs and the desired outputs.

Three different types of models and machine learning algorithms were utilized in this study: Logistics Regression, Support Vector Machine and Random Forest. The details of these algorithms are discussed in length below:

Logistic Regression Algorithms

Logistic Regression is a supervised machine learning class of algorithms. In supervised learning, there are one or more independent variables that determine the outcome. The outcome is measured with a dichotomous variable, in which there are only two possible outcomes. The goal of the logistic regression is to find the best fitting model to describe the relationship between the dichotomous characteristic of interest (dependent variable = response or outcome variable) and a set of independent (predictor or explanatory) variables. Logistic regression generates the coefficients (and its standard errors and significance levels) of a formula to predict a *logit transformation* of the probability of presence of the characteristic of interest:

$$logit(p) = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \ldots + b_kX_k$$

Logistic regression equation

Where *p* is the probability of presence of the characteristic of interest. The logit transformation is defined as the logged odds:

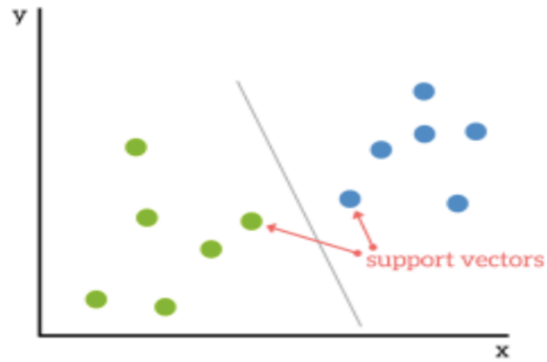
$$logit(p) = \ln\left(\frac{p}{1-p}\right)$$

Rather than choosing parameters that minimize the sum of squared errors, estimation in logistic regression chooses parameters that maximize the likelihood of observing the sample values (*55*). An example of a logistic regression algorithm model would be one that seeks to estimate whether a driver will crash or not crash (the dichotomous vehicle) given certain driver behavior and health characteristics.

Support Vector Machine Algorithms

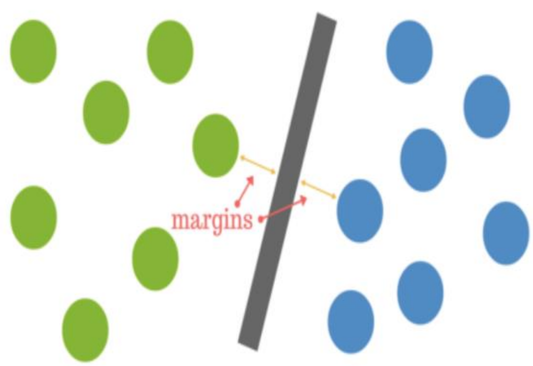
A Support Vector Machine (SVM) algorithm is a supervised machine learning algorithm that can be employed for both classification and regression purposes. SVM algorithms are based on the idea of finding a hyperplane that best divides a dataset into classes. Support Vector are the data points nearest to the hyperplane (Figure 2), the points of a dataset that, if removed would alter the position of the dividing hyperplane. Because of this, they can be considered the critical elements of a dataset.

Figure 2: Support Vector Machine Highlighting Support Vector



To find the best hyperplane, we segregate the classes within the data. The distance between the hyperplane and the nearest data point from either set is known as the margin as shown in Figure 3. The goal is to choose a hyperplane with the greatest possible margin between the hyperplane and any point within the training set, giving a greater chance of new data being classified correctly (*56*).

Figure 3: Support Vector Machine Highlighting the Margins



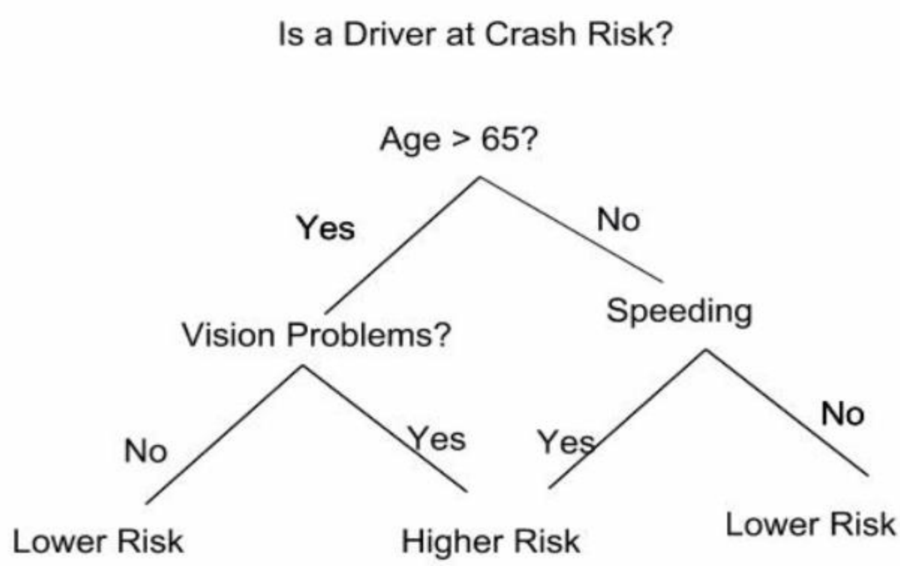
An example of a Support Vector Machine (SVM) approach: for drivers are approaching an intersection we want be able to identify whether they will drive safety through the intersection or not. Using examples from collected data, we separate out the cases where drivers drove safety through the intersection and when they did not, in order to learn what are the most critical factors for determining one outcome or another. An SVM algorithm builds a model based on that training data that seeks to separate the data points for each outcome as much as possible from the other, in different classes, and then assigns new example to one class or the other.

Decision Tree Algorithms

Decision Trees are a non-parametric supervised learning method used for classification and regression. Decision Trees learn from data to approximate a sine curve with a set of if-then-else decision rules. The deeper the tree, the more complex the decision rules and the fitter the model.

Decision Trees build classification or regression models in the form of a tree structure. They break down a dataset into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed. The final result is a tree with decision nodes and leaf nodes. A decision node has two or more branches. Each leaf node represents a classification or decision. The topmost decision node in a tree that corresponds to the best predictor called the root node (*57*). To understand Decision Trees better, Figure 4 shows an example problem, to find out if the person has a higher or lower crash risk.

Figure 4: Simple Decision Tree



Random Forest Algorithm

The Random Forest algorithm belongs to the ensemble algorithm family. An ensemble algorithm consists of aggregating multiple outputs made by a diverse set of predictors to obtain better results. Ensemble methods utilize the output of set of weak predictors to create a strong predictor. The purpose of using ensemble methods is to average out the outcome of individual predictions by diversifying the set of predictors, which then lowers the variance, to arrive at a powerful prediction model that reduces overfitting in training set. Random Forest utilizes decision tree classifier as a weak predictor to create an ensemble model. Random Forest models are trained via the bagging method. In the bagging method, each model is trained on a randomly sampled subset of training data and the output is generated by aggregating the predictions (*58*).

ANALYSIS AND RESULTS

Descriptive Statistics and Data Summary

As discussed earlier, in the UMass researchers' data request to VTTI, we asked for driver and vehicle characteristics, and time series and video data, for the following trips in the NDS dataset available from VTTI:

a) All trips for drivers age 65 and over involving signalized intersections, including crash, near-crash trips.
b) A sample of baseline trips (no crashes or near crashes) for drivers age 65 and over involving signalized intersections
c) A sample of trips for drivers age 30-49 including a signalized intersection, and either a crashes, near crash, or baseline event, for comparison to (a) and (b).

Dataset Received by UMass Amherst

In the spring of 2018, UMass received the SHRP2 data it requested from VTTI. The received data included a total of 884 trips (Table 4) for 586 individual drivers (Table 3). Each trip included at least one signalized intersection, at which the driver would be turning left, turning right or going straight through the intersection.

Of the 586 drivers in the dataset received by UMass, 59 percent were 65 years of age or older. Overall, 46 percent were female and 54 percent male. Among the older drivers, 44 percent were female and 56 percent were male. For the older drivers, the data received represent all the drivers age 65 & over in the available NDS data who drove through a signalized intersection. For the 30-49 year old drivers, the received data are a sample of the drivers in that age cohort with a trip through a signalized intersection.

Table 3: NDS Data Received from VTTI, Individual Drivers

	Drivers Age 30-49	**Drivers 65 & over**	**Total**
Female	116	152	268
Male	125	193	318
Total	241	345	586

Crashes and near crashes comprised 9 percent and 34 percent respectively of the total number of events; almost all of the rest were for baseline events. An estimated 68 percent of the crashes in the received data and 53 percent of the near crashes involved a driver age 65 or above. The determination of which events were crashes, near crashes, or non-subject conflicts was made by the researchers at VTTI.

Table 4: NDS Data Received from VTTI, Events

Event	Drivers Age 30-49	Drivers 65 & over	Total
Crash	**26**	**55**	**81**
Near Crash	**140**	**156**	**296**
Baseline	200	299	499
Non-Subject Conflict	4	4	8
Total	370	514	884

Left Turn Trip Data Only

The left turn data were separated out from the main dataset after the completion of the video scoring which helped identify during which trips drivers turned left at signalized intersection, turned right, or went straight. Table 5 summarizes the crashes, near crashes, and baseline events for left turns for drivers in both the older and younger cohorts. There were a total of 39 crashes and 118 near crashes during trips with left turns at signalized intersections in the dataset received by UMass. For the trips with left turns for drivers age 65 and over, 13 percent involved a crash and 36 percent involved a near crash. Overall, the older driver group accounted for 60 percent of the left-turn trips, including 67 percent of the crashes, and 61 percent of the near crashes.

Table 5: NDS Data Received from VTTI, Left Turns at Signalized Intersections

Event	Driver Age 30-49	Driver Age 65 & over	Total
Crash	**13**	**26**	**39**
Near Crash	46	72	118
Baseline	75	102	177
Non-Subject Conflict	0	2	2
Total	134	202	336

Crashes and Crash Severity

In terms of crash severity, there were 4 crashes categorized as “most severe,” equal to 12 percent of the total crashes. All of the most severe crashes involved drivers age 65 and over. A most severe crash is defined as any crash that involves an injury requiring doctor follow-up, an airbag deployment, or vehicle towing afterwards. Four crashes (75% of them with older drivers) were considered “Police Reportable” meaning that they were smaller crashes than the “most severe,” but they still involved property damage of at least $1,500, or the hitting of a traffic sign or large animal. There were 14 “minor crashes,” 71 percent with older drivers. Minor crashes are defined as those crashes that are less severe than reportable crashes. Minor crashes including physical contact with another object with minimal damage. The most common type of crash overall was “Tire strike, low risk” which can occur if a driver clips a curb during a turn. For drivers 65 and over, 73 percent of the recorded crashes were minor crashes (38%) or low-risk tire strikes (35%).

Table 6: Left Turns at Signalized Intersections, Crash Severity of Recorded Crashes

Crash Severity	Driver Age 30-49	Driver Age 65 & over	Total
I – Most Severe	0	4	4
II – Police Reportable	1	3	4
III – Minor	4	10	14
IV – Tire strike, low risk	8	9	17
Total	13	26	39

Of the left-turn crashes among both age cohorts, it is estimated that 64 percent of the crashes occurred at intersections with protected left-turn lanes, where drivers didn’t need to yield to any oncoming traffic. Thirty percent of the crashes occurred during a permissive turn phase, where the turning drivers should yield to oncoming traffic and wait for a gap before turning. For the final two crashes, the video scorers couldn’t determine if the traffic signal was in a permissive or protected phase from the video. For the drivers age 65 and over, 16 crashes (62%) of the crashes occurred at intersections with protected left-turn lanes.

Table 7: Overall Left Turn Crashes at Signalized Intersections, by Turn Phase & Driver Age

	Driver Age 30-49		Driver Age 65 & over		Total	
	Crash Count	% of Trips*	Crash Count	% of Trips*	Crash Count	% of Trips*
Permissive Turn	3	7.8%	**9**	**12.7%**	**12**	**11.0%**
Protected Turn	9	11.3%	**16**	**14.2%**	**25**	**12.9%**
Not clear from video	1		1		**2**	
Total	13	10.8%	**26**	**13.8%**	**39**	**12.6%**

**Percentage of trips by driver age, in the SHRP2 dataset provided to UMass by VTTI*

Looking at the crashes by intersection type and turn phase for the drivers age 65 and over (Table 8), 81 percent of the crashes occurred at signalized 4-way intersections and 12 percent occurred at signalized T-intersections. There was also a small number of crashes for other types of signalized intersections.

For both 4-way intersections and T-intersections, crashes were more common when there was a protected turn lane than when there was not. The researchers found there could be a few explanations for this result, including that the 4-way intersections were often larger and more complicated than the T-intersections, and many times had more than 1 lane for turning left. With multiple turn lanes, one potential explanation for minor crashes in those locations could that drivers were not staying in their lane as they turned. Another potential explanation could be that drivers were not being as vigilant while turning during a protected left turn, compared to a permissive left turn, because they have the right-of-way and did not have to worry about oncoming traffic.

Table 8: Left Turn Crash Severity at Signalized Intersections, by Intersection Type & Turn Phase, for Drivers age 65 & over

	T-intersection		**4-way intersection**		**Other Intersection Types**
Crash Severity	**Permissive Turn**	**Protected Turn**	**Permissive Turn**	**Protected Turn**	
I – Most Severe	0	1	2	0	1
II – Police Reportable	0	1	0	1	1
III – Minor	0	0	4	6	0
IV – Tire strike, low risk	0	1	2	6	0
Total	**0**	**3**	**8**	**13**	**2**
Total by Intersection Type*	**3**		**21**		**2**

Two crashes occurred at different types of intersection than a T-intersection or 4-way.

For the 30-49 year old drivers, 84 percent of the crashes occurred with 4-way intersections, including all of the minor crashes and 88 percent of the tire strike crashes. There was only one police reportable crash for this age group; it occurred at a T-intersection and it was not clear from the video whether the turn was made during a protected or permissive phase.

After the initial video scoring, the researchers went back to the videos to find out more details about the crash events. These additional details are shared in Table 9 and Table 10. Reviewing the videos showed that some of the most severe and police reportable crashes were not the driver's fault. For the minor crashes, the majority of the crashes involved the driver misjudging the edge of the road and curb locations as they were turning. This occurred with both with daytime and nighttime driving.

Table 9: Details on Most Severe, Police Reportable Crashes & Minor Crashes that Occurred with Left-Turning Drivers (Age 65 & Over) at Signalized Intersections

(Unless otherwise noted, the crashes occurred during daylight hours & in clear weather conditions.)

	Crash Severity	Driver Age & Gender	Intersection Type	Description
1	I – Most Severe	75-79, Male	T-intersection	Not driver's fault. Hit by another driver running a red light.
2	I – Most Severe	70-74, Female	4-way	Not driver's fault. Driver was rear-ended while in queue at traffic light waiting to turn.
3	I – Most Severe	70-74, Female	4-way	Permissive turn, driver turned when the light was red & hit oncoming car.
4	I – Most Severe	65-69, Female	Other	Driver ran a red light & hit pickup truck turning in front of them. Crash occurred at nearby intersection after the left turn.
5	II – Police Reportable	65-69, Female	T-intersection	Not driver's fault. Was rear-ended by another driver. Crash occurred after the left turn.
6	II – Police Reportable	75-79, Male	4-way	This driver rear-ended the car ahead of them in the queue. Permissive turn. Car ahead started to go, but had to wait for a gap.
7	II – Police Reportable	75-79, Female	4-way	Not driver's fault. Rainy conditions. Driver got rear-ended while waiting in queue to turn left.
8	III – Minor	65-69, Female	4-way	Dedicated left turn lane. Permissive turn. Driver hit inside curb as she started to make the turn.
9	III – Minor	70-74, Female	4-way	Nighttime. Dedicated left turn lane. Driver hit the inside curb as she started to make the turn.
10	III – Minor	75-79, Male	4-way	Nighttime. 4-way intersection with two dedicated left turn lanes. Driver hit median on the street he turned onto.
11	III – Minor	80-84, Female	4-way	No other traffic presence, and no wait at turn. Driver hit the outside curb at the end of the turn.
12	III – Minor	80-84, Female	4-way	Not driver's fault. Driver got rear-ended at the light after braking when vehicle ahead stopped.
13	III – Minor	80-84, Female	4-way	Rainy conditions. Dedicated left turn lane. Driver hit the median on the street she turned onto.
14	III – Minor	80-84, Female	4-way	Twilight. Driver didn't have to stop or wait before turning. Dedicated turn lane. Driver hit the outside curb at the end of the turn.
15	III – Minor	80-84, Male	4-way	4-way intersection with dedicated left turn lane. Driver hit outside curb on turn & went onto sidewalk.
16	III – Minor	80-84, Male	4-way	4-way intersection with dedicated left turn lane. Driver hit the median on the street he turned onto.
17	III – Minor	80-84, Male	4-way	4-way intersection with dedicated left turn lane. Driver hit the median on the street he turned onto.

Table 10: Details on Police Reportable Crashes & Minor Crashes that Occurred with Left-Turning Drivers (Age 30-49 Sample) at Signalized Intersections

(Unless otherwise noted, the crashes occurred during daylight hours & in clear weather conditions.) There were no crashes rated as "Most Severe."

	Crash Severity	Driver Age & Gender	Intersection Type	Description
1	II – Police Reportable	30-34, Female	T-intersection	Driver wanted to go straight, not left, but was in the left turn lane; the driver switched lanes & was hit by approaching car in adjacent lane.
2	III – Minor	35-39, Female	4-way	Crash happened after the left turn. Driver rear-ended the car ahead of them; didn't slow down before the crash.
3	III – Minor	45-49, Female	4-way	Nighttime. Dedicated left turn lane. Cut corner on turn & went over left edge of road.
4	III – Minor	40-44, Male	4-way	Not driver's fault. Twilight. Driver vehicle was rear-ended while in queue at traffic light waiting to turn. Intersection had two dedicated left turn lanes.
5	III – Minor	35-39, Male	4-way	Rainy. Dedicated left turn lane. Crossed yellow line approaching the turn, ran red light & hit the median on entering street.

Vision and Medical Data

The UMass researchers looked at the vision and medical data of the drivers who had left-turn crashes or near crashes at signalized intersections. Table 11 shows the medical, and vision and cognitive testing variables with the strongest correlations for crashes and near crashes, from all the pre-study screening and questionnaire data collected on participants. Results of the medical conditions questionnaire (self-reported by participants) were available for most but not all drivers.

The researchers found the strongest correlation of left-turn crashes with drivers who had visual search challenges, or spatial-cognitive challenges as measured by the clock drawing test. As shown in Table 11, an estimated 83 percent of drivers, including 87 percent of drivers age 65 and above, who had left-turn crashes at signalized intersections were considered to have a least a mild impairment in their visual search abilities. Impairment was assessed by measuring the time it took for participants to complete two visual search tasks. Similarly, on the clock drawing test (participants were shown a circle & asked to draw & make the circle look like the face of a clock set to a specific time), 83 percent of drivers with left-turn crashes, including 96 percent of drivers age 65 and over, made at least minor errors on the task.

Table 11: Visual Challenges or Medical Conditions Impacting Participant Drivers with Left Turn Crashes & Near Crashes at Signalized Intersection
Percentage with Impairments/Conditions by Age Group

	Crashes			Near Crashes		
	Age 30-49	**Age 65+**	**Total**	**Age 30-49**	**Age 65+**	**Total**
Visual Search Impairment(mild or more)	76.9%	87.0%	83.3%	52.9%	95.4%	80.8%
Visual Field of View Impairment (mild or more)	7.7%	56.5%	38.9%	2.9%	55.4%	37.4%
Clock Drawing Test Errors (minor or more)	61.5%	95.7%	83.3%	70.6%	84.4%	78.8%
Nervous System/Sleep Conditions	38.5%	34.8%	36.1%	32.4%	23.1%	26.3%
Psychiatric Conditions	23.1%	65.2%	50.0%	2.9%	15.4%	11.1%

Lower correlations were found between the left-turn crashes and near crashes and other pre-study participant screening variables, including impairment of visual field of view (57% of the crashes with drivers age 65 & over), psychiatric conditions (65%) and nervous system and sleep conditions (35% of crashes). The assessment of visual field of view was based on a timed divided attention task where participants had to identify the location of both a central visual target and a peripheral target. Nervous system and sleep conditions were self-reported by participants, and included such health issues as multiple sclerosis, Parkinson's disease, epilepsy, migraines, narcolepsy, insomnia, and sleep apnea, among others. Psychiatric conditions were also self-reported, and included depression, anxiety or panic attacks, bipolar disorder, psychotic disorders, and attention deficit hyperactivity disorder (ADHD).

With Table 11, in some cases the percentages of drivers with certain types of impairments or conditions are higher for drivers with near crashes than for drivers with crashes. This may seem somewhat counter-intuitive. However, it can be explained by thinking about the degree of impairment, since that is not noted in the table. Also with the categories of health conditions, some conditions can have a bigger impact on driving and likelihood of crashing, though in the table they are grouped together.

Of the various other variables in the pre-study screenings and questionnaires, the researchers found none which have anything more than very minor correlations with left turn crashes at signalized intersections.

These findings are explored further in the discussion in the next section on the regression models used in the researchers' analysis.

Machine Learning Models and Regression Models

A number of machine learning models were developed and evaluated to predict crash risks for left turns at signalized intersections. The models employed the NDS data received from VTTI, and the results of the scoring of the NDS vehicle dashboard camera videos conducted at UMass. The best performing of the tested models are discussed in this section. Many other models were tried and did not perform as well.

Two metrics for evaluating the machine learning models are training accuracy and validation accuracy.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

Training Accuracy: Training accuracy is the percentage of times a machine learning model predicted the training data correctly for the total number of data points.

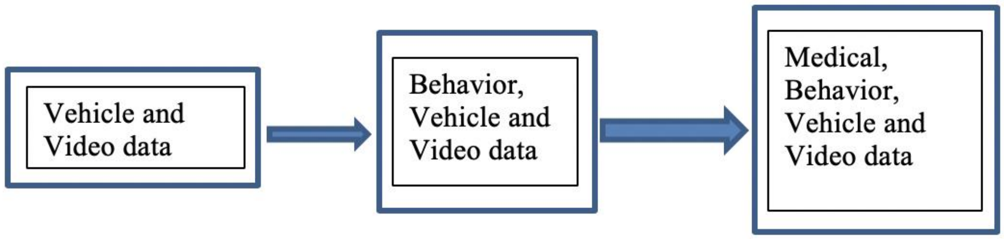
Validation Accuracy. Some data are kept unseen by each machine learning model during training and then those data are used with the trained model to check the performance of the model after training is complete. Validation accuracy is the percentage of times that the trained model accurately predicted the unseen data for the total number of unseen data points.

Results

Three different types of machine learning algorithms - Logistics Regression, Support Vector Machine and Random Forest - were used for the different classification tasks. The variables from the two types of data (NDS data and video scoring results) were formatted and normalized before being used in the machine learning models. The learning/hyper parameter for the machine learning algorithm was found using the Grid Search (*59*). The best variables were selected using the univariate feature selection method. Univariate feature selection works by selecting best features/variables based on univariate statistical tests. ANOVA (Analysis of variance) F-values were used for the univariate statistical test and the k variable with highest F-values was selected to be passed through the machine learning models.

Figure 5 shows the input data evolution in the machine learning models. Initially, the focus in the models was on the NDS vehicle time series data (such as speed and acceleration; hereafter referred to as vehicle data) and the video scoring data. In the next phase, the driver behavior data from NDS participant questionnaires were incorporated into the models, and then the medical data were incorporated as well. Vehicle speed and acceleration were examined at 0.1 sec intervals from the time vehicles entered the intersection (passed the stop line) until they completed the intersection (finished the turn and straightened the vehicle if turning; passed the stop line on the far side of the intersection if going straight).

Figure 5: Input Data for Different Machine Learning Models



Predicting Crash Risk (Trips with Crash/Near- Crash Compared to Baseline Trips)

Table 12 shows the results of three Machine Learning Models for predicting drivers' crash risk when including both crashes and near crashes as the crash event. These models considered all the drivers in the dataset that UMass obtained from VTTI, both the 30-49 year old drivers and those 65 and above. The first logistic regression model was trained with the best 15 variables selected using the univariate feature selection method from among the video scoring data and all

Table 12: Machine Learning Model for Predicting Crash Risk (Crash and Near Crashes both included as "Crashes")

Significant Variables (P-values)	R-Squared & Adj. R-Squared	Inputs	Model	Performance
Day/Night (0.013) Intersection Type (0.006) Signal State (0.012) SD (Standard Deviation) of Acceleration (0.0001)	0.640/ 0.620	Medical, Behavior, Video & Vehicle Data (15 Variables)	Logistic Regression	Training Accuracy: 70.4% Validation Accuracy: **73.7%**
Day/Night (0.006) Intersection Type (0.025) Leading Vehicle (0.031) SD of Acceleration (0.002)	0.653/ 0.619	Vehicle & Video Data (All Variables)	Logistic Regression	Training Accuracy: 76.8% Validation Accuracy: **76.4%**
Day/Night (0.006) Intersection Type (0.02) SD of Acceleration (0.002)	0.631/ 0.617	Vehicle & Video Data (10 best variables)	Support Vector Machine	Training Accuracy: 77.7% Validation Accuracy: **78.2%**

Significant Variables, and R-Square and Adjusted R-Square values were extracted from OLS models and are independent of the Machine Learning Models.

the medical, behavior, and vehicle NDS data the researchers examined. The model achieved training accuracy of 70 percent and validation accuracy of 74 percent. The best model for predicting the crash risk (shaded in Table 12) was found to be the Support Vector Machine model with 10 vehicle and video scoring variables as inputs. This model achieved training accuracy of 78 percent and validation accuracy of 78 percent. Ordinary Least Squares (OLS) models were used to find the statistically significant variables. The OLS models showed that only variables from video scoring and vehicle data were significant and medical and all behavior data variables were not significant

Predicting Crash Risk (Trips with Crashes Compared to Baseline Trips, Near Crashes Excluded)

Table 13: Machine Learning Model for Predicting Crash Risk (Near Crashes not included under "Crashes")

Significant Variables (P-values)	**R-Squared/ Adj. R-Squared**	**Input**	**Model**	**Performance**
Day/Night (0.003) Clear/Inclement Weather (0.011) Opposing Lane Present (0.019) SD of Acceleration (0.001)	0.494/ 0.411	Vehicle and Video Data (All Variables)	Logistic Regression	Training Accuracy: 89.8% Validation Accuracy: **82.7%**
Nervous System/Sleep Condition (0.009) Limited Flexibility (0.025) Severe Arthritis (0.003)	0.321/ 0.257	Medical Data (All Variables)	Random Forest	Training Accuracy: 82.1% Validation Accuracy: **86.8%**
Day/Night (0.001) Clear/Inclement Weather (0.001) SD of Acceleration (0.001) Nervous System/Sleep Condition (0.011)	0.499/ 0.452	Medical, Behavior, Video and Vehicle Data (15 Variables)	Support Vector Machine	Training Accuracy: 83.7% Validation Accuracy: **94.3%**

Significant Variables, and R-Square and Adjusted R-Square values are extracted from OLS models and are independent of Machine Learning Models.

Table 13 shows the results of three Machine Learning Models for predicting drivers' crash risk when not near crashes are not included as a crash event. The first logistic regression model was trained with video scoring and vehicle data. The model achieved training accuracy of 90 percent and validation accuracy of 83 percent. The best model for predicting the crash risk was found to be the Support Vector Machine Model with the best 15 variables selected using the univariate feature selection method from the medical, behavior, video scoring and vehicle data. This model achieved training accuracy of 84 percent and validation accuracy of 94 percent. OLS models again were used to find the statistically significant variables. As the OLS results show, some variables from each data category (video scoring, vehicle, medical, and behavior data) were statistically significant in the OLS models.

Predicting Age (Older Drivers Compared to Younger Drivers)

Table 14 shows the results of three Machine Learning Models for predicting if drivers are 65 years old or above, or in the comparison cohort of drivers age 30 to 49. The researchers only received NDS data from VTTI for drivers in these two age groups. The best model for classifying drivers as older or younger was found to be the logistic regression model with the best 15 variables selected using the univariate feature selection method from the medical, behavior, video scoring and vehicle data. This model achieved training accuracy of 81 percent and validation accuracy of 79 percent. OLS models were used to find the statistically significant variables. The OLS models showed that variables from all four types of data (video scoring, vehicle, medical and behavior data) were significant. Some of the statistically significant variables are related to hearing problems, impaired visual search abilities and field of view, and heart and psychiatric health issues.

Table 14: Machine Learning Models for Predicting if Driver is Older (age 65+) or Younger (30-49)

Significant Variables (P-values)	R-Squared & Adj. R-Squared	Input	Model	Performance
Gap Decision (0.039) Average Speed (0.001) Maximum Speed (0.001)	0.666/ 0.635	Vehicle & Video Data (All Variable)	Random Forest	Training Accuracy: 77.6% Validation Accuracy**: 66.3%**
Hearing Issues (0.001) Heart Conditions (0.004) Psychiatric Conditions (0.001) Impaired Visual Search (0.001) Impaired Field of View (0.044) Clock Drawing Test (0.001)	0.710/ 0.700	Medical Data (10 Variables)	Random Forest	Training Accuracy: 87.8% Validation Accuracy: **77.9%**
Hearing Issues (0.001) Heart Conditions (0.001) Psychiatric Conditions (0.001) Impaired Visual Search (0.001) Quality of Sleep (0.002)	0.703/ 0.686	Medical, Behavior, Video & Vehicle Data (15 Variables)	Logistic Regression	Training Accuracy: 80.8% Validation Accuracy: **79.1%**

Significant Variables, and R-Square and Adjusted R-Square values are extracted from OLS models and are independent of Machine Learning Models.

Predicting Crash Risk for Older Drivers (Crash Compared to No Crash)

Table 15 summarizes the results of three Machine Learning Models for predicting older drivers' risk of crashing. The best model for predicting the crash risk for older driver was found to be the Random Forest Model with the best 15 variables chosen using the univariate feature selection method, from the medical, behavior, video scoring and vehicle data. This model has validation accuracy of 83 percent. OLS models were used to find the statistically significant variables. Here, the OLS models showed that the most of statistical significant variables were health variables such as the presence of nervous system/sleep conditions or arthritis, and visual and cognitive factors, such as having to monitor oncoming traffic and wait for a sufficient gap in traffic before turning.

Table 15: Machine Learning Models to predict if Older Driver is at Risk of Crashing

Significant Variables (P-values)	**R-Squared and Adj. R-Squared**	**Input**	**Model**	**Performance**
Heart Conditions (0.007) Nervous System/Steep Conditions (0.001) Severe Arthritis (0.006) Impaired Visual Search (0.004) Multiple Med. Conditions (0.05)	0.749/ 0.652	Medical Data (All Variables)	Support Vector Machine	Training Accuracy: 91.9% Validation Accuracy: **70.6%**
Nervous System/Sleep Conditions (0.001) Severe Arthritis (0.049) Impaired Field of View (0.038)	0.730/ 0.669	Medical, Behavior, Video and Vehicle Data (10 Variables)	Logistic Regression	Training Accuracy: 83.8% Validation Accuracy: **76.5%**
Gap Decision (0.037) Nervous System/Sleep Conditions (0.003) Severe Arthritis (0.052)	0.803/ 0.728	Medical, Behavior, Video and Vehicle Data (15 Variables)	Random Forest	Training Accuracy: 100.0% Validation Accuracy: **83.0%**

Significant Variables, and R-Square and Adjusted R-Square values are extracted from OLS models and are independent of Machine Learning Models.

The results shared in the section reflect the best of the machine learning and OLS models that the UMass researcher team ran to understand more about factors that make some drivers more likely to crash at during left turn maneuvers than others. Some of the model results may have been affected by the small number of left turn signalized intersection crashes for the older driver cohort in the NDS data that the researchers received for the study. Particularly, regarding the impacts of certain behaviors or medical conditions that were not very common, the results may have been impacted by the small number of left-turning participants in the dataset with those conditions, including for crashes and baseline trips.

DISCUSSION

The UMass research study was designed, in part, as a proof of concept project to assess the usefulness of the NDS data for understanding older adults' driving behaviors and challenges with left turns at signalized intersections. Older drivers are especially over-represented in crashes occurring during left turns at signalized intersections, and this study sought to find out more about the reasons for this trend.

The NDS data that UMass received from VTTI provided helpful generally for learning more about the driving behaviors of drivers age 65 and over and their primary risk factors while making left turns at signalized intersections. As discussed earlier, for their analyses, the UMass researchers examined the NDS data on events for crashes and near-crashes, the vehicle trip data including speed and acceleration, and the results of the pre-study questionnaires and screening. The UMass research team also scored video footage from the vehicle dashboard cameras to learn more about drivers' left turns at signalized intersections and the intersections themselves.

For their analysis, the UMass researchers relied on standard regression techniques, but also applied machine learning algorithms and models to see what else might be learned through such an approach. Numerous regression and machine learning models were developed to understand more about the characteristics of drivers who are most likely to have a crash or near crash while turning left at a signalized intersection.

One of the models focused on the drivers age 65 and over, and on identifying the factors that may most influence whether the driver may have a crash at a signalized intersection while turning left. The analysis showed that most of the statistical significant variables for this are related to the drivers' health and to visual and cognitive factors. Important health factors include whether they have arthritis, nervous system conditions, or sleep ailments such as sleep apnea that affect the quality of their sleep. Visual and cognitive factors affect their ability to monitor oncoming traffic and to identify, in the case of permissive left turns, when there is a sufficient gap to safely make the left turn.

In the dataset, the most common types of crash for older drivers making a left turn at a signalized intersection involved them hitting a curb or leaving the roadway, this accounted for more than 70 percent of the older driver left-turn crashes at signalized intersections. There were also a small number of more serious crashes during which older drivers ran a red light or failed to yield to oncoming traffic during a permissive left-turn. Previous studies have shown that older drivers are less likely than middle age drivers to glance towards cross-traffic when they enter a signalized four-way intersection and less likely as well to glance towards opposing traffic while making a left-turn at a signalized intersection (*60*). Past research (*61*) has also found that older drivers have more confusion than younger drivers regarding the differences between permissive and protected left-turn signalizations at intersections, and that even younger drivers often lack a full understanding. Training may help with this, as might more signage at intersections to indicate that left-turning vehicles need to yield during the permissive turn phase. When the UMass researchers reviewed the NDS videos involving left turns, few of the intersections were found to have such signage.

Of benefit to older drivers may also be training to help with visual scanning at intersections, including signalized intersections and during turning movements. In this study, the researchers found that an estimated 87 percent of drivers age 65 and above, who had left-turn crashes at signalized intersections has at least a mild impairment in their visual search abilities, and as noted earlier, at intersections, older drivers have been found to scan for other vehicles less frequently. One effective way to train older drivers is through active training in which they are asked to drive (either on-road or in a simulated environment such as a driving simulator) and then receive feedback on their driving. Active training has been shown to be more effective with older drivers than more passive training such as watching a presentation or hearing a classroom lecture that's not interactive and does not include feedback (*62, 63*).

The main limitation of this study was that there were only a relatively small number of events and trips with older drivers turning left at signalized intersections, and a small number of crashes, so some of the results may not be fully generalizable, and some results may be skewed by the small dataset. In the NDS dataset that UMass obtained from VTTI, there were only 26 crashes and 72 near crashes recorded for left turns at signalized intersections involving older drivers. Additionally, as noted earlier, of those 26 crashes, most were minor crashes involving a car hitting a curb or leaving the roadway.

When proposing this study, the researchers were interested in studying older driver behavior if possible for specific situations such as signalized intersections with offset turn lanes, and with both permissive and protected turn phases. The Technical Advisory Committee for this study consisted mainly of department of transportation representatives for the New England states, similarly had interest in learning more about how intersection configurations and infrastructure may contribute to making intersections safer or less safe especially for older drivers. In this case, the NDS data were found to be insufficient to study such questions in depth. In the researchers' final meeting with the committee, there was discussion about how useful SHRP2 and the NDS data may be answering questions about roadway infrastructure and what scale of data may be needed for the SHRP2 data to help address such questions and better understand the impacts of infrastructure on safety. No conclusions were drawn about this. Some of the committee members indicated that the NDS data and studies such as this one can still be useful to their state DOTs even if there are limited statistically significant results.

There was also discussion about how SHRP2 is focused on driver behaviors and is a not a crash database but designed to complement existing crash databases. There is rich data to be mined in

SHRP2, even if it cannot answer some crash and infrastructure questions. The naturalistic data collected through the SHRP2 study is important for traffic safety and older research, providing information on driving behavior beyond what can be gained in a driving simulator or other controlled environment. This project was useful as a proof of concept to test using the NDS data for a specific research question and for familiarizing the researchers and the technical advisory committee with the data and its strengths and limitations. Beyond this project, the UMass researchers expect to continue to work with NDS and other SHPR2 data, exploring and analyzing it further, including as additional NDS data is released and shared with researchers. The researchers may also look further at how their findings on the primary factors for older driver left-turn signalized intersection crashes compare to the results of other studies using other data sources.

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