Assessing Mileage Exposure and Speed Behavior among Older Drivers Based on Crash Involvement Status

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ABSTRACT
Population and crash projections for the year 2030, suggest that drivers age 65 and older will represent one quarter of total population and one quarter of motor vehicle-related fatalities. The full implications of these trends in terms of crash reduction measures such as operator education, self-regulation, and licensing regulations are unknown. However, for any of these crash reduction measures to be effective, it is first imperative to understand and identify older driver behavior (or activity patterns). Only then can data be linked with crash involvements to determine effective countermeasures allowing safe mobility for older persons. This study investigates the driving patterns of seniors who have and who have not experienced a crash during a 14-month study period using the longitudinally collected GPS trip data. This investigation allows for an empirical investigation to determine if older drivers with a recent crash experience drive differently in terms of speed, time of day, or roadway types.

This study found that crash-involved older drivers usually traveled longer distances and traveled at higher speeds than older drivers who were not involved in crashes. While travel on freeways between the two groups showed significant mileage and speed differences, the crash-involved older drivers were more likely to exhibit over-speeding activity at arterials and local roadways than drivers who were not involved in crashes. This study suggests that transportation safety engineers and policy makers should also aim speed campaigns to older drivers. Traditionally, older drivers have not been a target population for these types of campaigns.

INTRODUCTION

The proportion of older individuals is on the rise. In fact, the growth rate of individuals 70 years of age or older is 4% higher than that of the total population in the United States [1]. In 2004, the 65 and older age group represented 9% of the population of the United States consisting of over 26 million people. Older individuals are expected to represent 20% of the population by 2030 [2]. As a result of the growing number of older adults, the proportion of older drivers is also increasing [3]. By the year 2030, individuals 65 years of age and older will represent one quarter of all drivers and account for 25% of all fatal crashes [4]. There is evidence that these older drivers are staying in their cars longer, for example, in the state of South Carolina 90% of all trips made by individuals between the ages of 65 to 84 were made in private vehicles [5].

The increasing number of older drivers on the roadways will be a cause of significant safety problems. Not only will roadways be more congested, but the outcomes of crashes involving seniors are more serious than crashes with younger, healthier drivers. Seniors are simply more medically fragile and therefore more likely to have serious injuries or die from motor vehicle crashes than younger drivers [1, 4]. The highest death rate per mile driven and the highest death rate per crash are associated with drivers 80 years of age and older [6]. Just like novice drivers, older drivers are frequently considered high-risk drivers. Insurance companies recognize the increased risk associated with elderly drivers, as evidenced by increasing insurance rates after age 65 [7] (Figure 1).

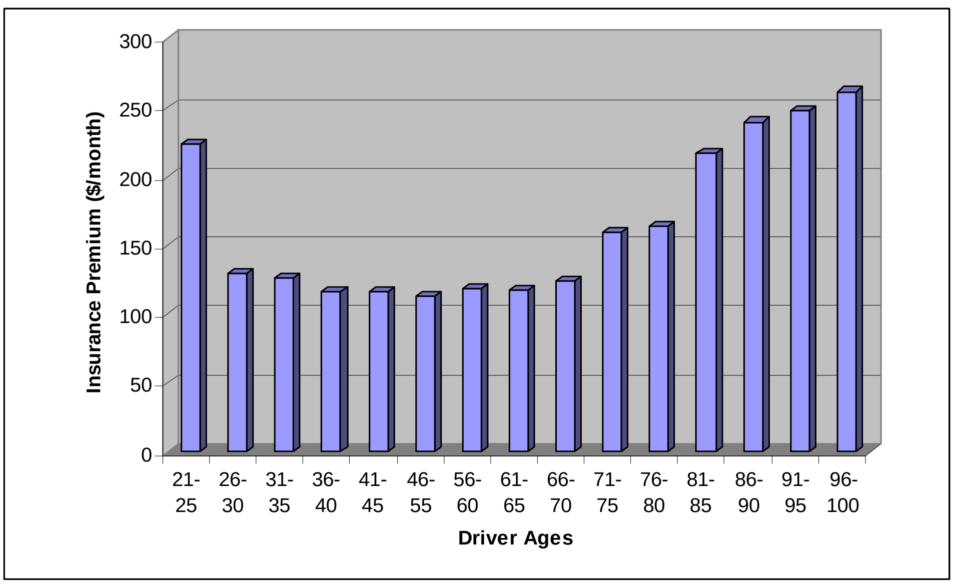

FIGURE 1 Insurance premium by driver age.

One important difference between these at-risk populations is the survival rate of crashes, where young drivers simply survive more crashes than seniors. It is well documented that numerous visual abilities decline with age, including decreases in acuity, contrast sensitivity, depth perception, dynamic visual acuity, night vision, motion perception, useful field of view, cognitive performance, visual field size, and tolerance to glare [8-10]. In addition to reduced visual abilities, general cognitive abilities, and motor skills also decline with age [11]. One example pertinent to driving includes the restriction in the ability to turn one's head. Drivers 70 years of age and older have typically lost about one third of the head movement available in younger drivers [12]. It is important to note that many of these changes occur slowly with little or no conscious awareness to the driver and large individual differences exist.

While older individuals drive less than other age groups, older drivers are involved in a greater proportion of accidents per mile driven than other adult drivers [13]. While it has been well documented that older drivers have an increased proportion of left-hand turn crashes [1, 13] there is also recent evidence that speeding or driving too fast for conditions is also a causal factor in crashes. In a recent analysis for the South Carolina Department of Transportation, driving too fast for conditions / speeding was the second leading causal factor of traffic crashes after driver failure to yield right of way [5]. Traffic speeds depend not only on the driver, but also on the road conditions, traffic density, and time of day. During peak travel conditions, the driver may be in congested traffic and therefore forced to travel at slower speeds due to congestion, while on the other hand a driver may uncomfortably drive over the speed limit due to the surrounding traffic. Only in free flow conditions can the driver choose his or her own speed. Therefore, the type of roadway and time of day must be investigated in regards to the speeds in which older drivers travel. There is also evidence that sometimes older drivers have trouble navigating and maneuvering at the same time and therefore compensate by driving more cautiously and slower [6, 14]. In addition, most previous studies have evaluated driving characteristics of older drivers by comparing with other age driver groups. The current study will investigate the driving behavior activity patterns between seniors who have and who have not experienced a crash during the time frame of the study. This investigation will allow for an empirical investigation to assess if older drivers with a crash experience have differently driven prior to crash involvements in terms of speed, time of day, and roadway types.

DATA COLLECTION PROCESS

Trip Data Collection

Researchers from the DRIVE Atlanta Laboratory at the Georgia Institute of Technology developed a wireless data collection system known as the Georgia Tech Trip Data Collector (GT-TDC). The GT-TDC collects second-by-second vehicle activity data, including vehicle location and speed from an on-board Global Positioning System (GPS) receiver. The GT-TDC also collects ten engine-operating parameters from the onboard diagnostics (OBD-II) system for most post-1996 model year vehicles, and monitors redundant vehicle speed at 4Hz from the vehicle speed sensor (VSS) when available. The second-by-second vehicle operation records are aggregated into trip files, encrypted, and transmitted to the central server system at Georgia Tech using a wireless data transmission system [15]. The GT-TDCs have been installed in over 460 light-duty vehicles in the metro Atlanta region through the Commuter Choice and Value Pricing Insurance Incentive Program (Commute Atlanta program). The Commute Atlanta program has been collecting data continuously since September 2003.

Before GPS and mobile computing were introduced, information on a driver's exposure by facility type and time of travel was difficult or impossible to collect. In the absence of better methods, travel diary surveys and telephone interviews were a popular means for collecting driver behavior data, especially to obtain travel distance and travel duration. One limitation of diaries and interviews is the lack of reliability and validity information. Ogle et al. [16] recently conducted an analysis of the accuracy of household trip reporting by comparing simultaneous GPS-measured trip data in the Commute Atlanta program with trips reported in a standard two-day travel diary survey. A total of 2,292 trips were found from the GPS-measured trip files, but only 1,622 trips were reported by the corresponding two days of travel diaries, with an under-reporting rate of 29.2%. In addition, after comparing trip duration and distance estimates from the both methods, the researchers concluded that the trips reported by the survey diaries produced only 90% of total travel duration and 78% of total distance. When comparing only reported survey trips with corresponding GPS-measure trips, respondents overestimated their travel duration and distance by 15% and 2%, respectively. While the under-reporting and overestimation of trip duration nearly cancel each other out, the total travel distance obtained from the surveys is off by 20% from actual.

Although travel distance and duration could be obtained from the previously described survey methods, a driver’s distance and speed on the certain types of roadways (specific travel routes such as freeways, arterials, or local roads) could not be obtained. Kirk et al. [17] tried a new method for travel data collection. The researchers distributed maps and asked participants to mark their travel route directly on the maps. However, the researchers found that participants were unwilling to follow the project requirements due to safety issues and the additional burden. Unfortunately, they did not implement an alternative data collection method and therefore, the accuracy of this method unknown.

Unlike previous travel survey methods, the GPS-measured travel data provide abundant reliable information which can help to better identify the relationships between driving behavior and crash risk under varying conditions of facility type and time of day. Coupling the detailed travel information with known driver characteristics, operations can then be tied back to a wide variety of socio-demographic parameters. Furthermore, GPS-measured data can be used to identify how driving behaviors change during a trip in response to changes in roadway operating conditions.

Using the GPS technology, this study examines the difference of total travel mileage (exposure) between older drivers who have been involved in crashes during the Commute Atlanta study period and those who have not been involved in crashes. In addition, the researches also investigated the facility-time-specific mileages and speeding behavior of the two older driver groups.

Self-Reported Crash Data

The DRIVE Atlanta Laboratory at the Georgia Institute of Technology (Georgia Tech) developed a wireless data collection system known as the GT Trip Data Collector (GT-TDC). The GT-TDC collects second-by-second vehicle activity data, including vehicle position (latitude and longitude via GPS) and vehicle speed. In addition, the GT-TDC collects ten engine operating parameters from the onboard diagnostics (OBD) system in post-1996 model year vehicles and also monitors vehicle speed at 4Hz from the vehicle speed sensor (VSS). The data are integrated into trip files, encrypted, and transmitted to the central server system at Georgia Tech using a wireless data transmit system via a cellular connection.

The GT-TDCs were installed in about 460 light-duty vehicles through the commuter choice and value pricing insurance incentive (Commute Atlanta) program and have been used to monitor more than 1.3 million light-duty vehicle trips on a second-by-second basis. Thus, research team developed the sampling framework reflecting the distribution of households in the Atlanta region using the random stratified sampling based on household size, income, auto ownership, age, and gender to specially accommodate hypothesis testing within the insurance-based research goal [16].

As one component of the Commute Atlanta Program, a safety-related survey was conducted in November 2004 to obtain the information on participants' involvement in crashes and whether they had received any speeding citations during the study period (about 14 months between September 2003 and November 2004) [16]. The relevant questions in regards to the current project from the survey include the number of crashes during the study period.

From this self-reported survey, researchers were able to categorize drivers into two groups based on their crash involvements over the study period. Among the 234 drivers of all ages who returned the self-reported survey, drivers that shared a vehicle with another household member more than 10 % of the time were excluded because their personal driving trip data could not be adequately distinguished from that of other household members. In addition, some participants had purchased new vehicles and several GT-TDCs had malfunctioned and had to be replaced, and those drivers could not be used for this analysis. After the data cleaning process, the researchers found 167 drivers of all ages who had been continuously monitored through a whole 6-months period (January through June 2004) for which survey data were available. This study focuses only on the unimpaired 24 drivers age 65 and older from those 167 drivers. Nineteen of the older drivers were not involved in crashes (12 males and 7 females), while five older adults were involved in crashes (3 males and 2 females). In addition, 18 older drivers were retired (15 non-crash drivers and 3 crash-drivers), three older drivers had part-time jobs (two non-crash drivers and one crash-drivers), and three older drivers had full-time jobs (two non-crash drivers and one crash-drivers) during the study period.

It is possible that the self-reported number of crashes during the study period could be underestimated since some drivers might not report their crash or simply forget to report minor crashes [18]. However, the self-reported crash data may include minor crashes that cannot be obtained from the official crash report database since motor crashes resulting in minor property damage and occurring at non-public roadways are usually not reported [19]. Researchers compared the crash rates per licensed driver in the 13 county study area in 2002 (11.24%) [16] with the crash rate based on the self-reported crash survey (13.6%), indicating that the crash survey probably did not significantly underestimate the actual results [1].

After splitting the older driver data into two sets (with and without crashes), second-by-second travel data for a six month period (January through June 2004) were extracted from the Commute Atlanta program database. This study estimates disaggregate behavioral exposures, mileage and speeding, and identifies the differences across the two driver-groups (with and without crashes).

[1] The researchers will request crash reports to DMVS in Georgia in order to verify the accuracy of the self-reported crash survey data under contract to participants.

DATA PROCESSING

The Map-Matching Process

To allow analysis of speeding behavior and alter facility specific exposure the driving activity records must be matched to roadway characteristics (facility type, posted speed limit, rural/urban area type). The Commute Atlanta program research team at Georgia Tech developed an automatic map-matching algorithm to combine GPS-based trip data with roadway characteristics (RC) information in the GIS system. The research team determined that the use of two map-matching methods, route method and buffer method, in combination provided the most complete and accurate data for driving activity analysis [16].

The University of Georgia (UGA) GIS Laboratory provided the most recent roadway maps of the 13 counties in the metro Atlanta region [16]. The UGA GIS Laboratory is continuously updating and managing the roadway network maps and roadway characteristics while under contract to Georgia Department of Transportation [16]. After the map-matching process, each GPS data point is associated with the corresponding roadway characteristics such as facility types, number of lanes, and lane width. Finally, those map-matched GPS data profiles are used to examine older drivers driving behavior differentiating crash-involved and drivers who were not involved in crashes.

GPS Data Filtering Using the Kalman Filter

Similar to the map-matching process, to reduce data processing time and to estimate reliable vehicle mileage and speed estimates, this study used an automatic GPS data filtering algorithm by modifying the conventional Kalman filter. This was done because even though the GPS technology provides highly accurate data (with 95% of the data falling within 3 meters of the actual vehicle location), random errors are noted in the data stream [15]. Jun et al.[15] examined four statistical smoothing techniques: the least squares spline approximation method, the kernel-based smoothing technique, the conventional Kalman filter, and the modified Kalman filter. Each method was applied to the instrumented vehicle GPS speed data and evaluated the performance of the algorithms in minimizing the impact of GPS random error on the estimation of speed, acceleration, and distance estimates. The research team evaluated each filtering technique using GPS data gathered between October and November 2004 from seven vehicles which generated 1,702 trips (1,497,066 data points). The modified Kalman filter proved to be the most accurate when comparing GPS speed and distance with data collected directly from the onboard vehicle speed sensor (VSS). While the conventional Kalman filter smooths all GPS data points with the constant rate (one measurement error), the modified Kalman filter selects two GPS measurement errors based on the quality of GPS data points (number of satellites and Position Dilution of Precision (PDOP) value).

DATA ANALYSIS

Test of Difference in Means Using the Wilks' Lambda Test and the Bootstrap Confidence Interval

Based on statistical literature reviews, the central limit theorem can be applied to not-normally distributed samples although the sample size is small [20, 21] Thus, this study used the Wilks' lambda test to verify differences in means of behavior activity metrics (mileage and speed) between the two older driver-groups. The Wilks' lambda test is the popular asymptotic method in discriminant analysis to check the equality of means of groups and is the analog of the F-test for multivariate analysis of variance (ANOVA) [22]. Thus, the Wilks' lambda test examines if the means of behavioral metrics are equal across the two driver-groups (the null hypothesis). However, other statistical references also show that the number of samples needs to be greater than 100 to obtain a satisfactory result if the sample is not normally distributed [20, 23, 24]. In addition, driving behavior activity metrics were not normally distributed (even after log transformation) after testing three nonparametric methods; Jarque-Bera test, Lilliefors test, and Kolmogorov-Smirnov test (KS-test) [25].

Due to the small sample size and non-normal distribution, this study also used an alternative method for the confidence interval estimation (for a means test). A nonparametric bootstrap resampling method was utilized to estimate the confidence intervals of sample means. The bootstrap method employs uniform random sampling with replacement method to create new data sets from the original sample data. Uniform resampling means that each data point has the same probability of being randomly selected. The bootstrap creates new sample data, and from each new bootstrap sample, the empirical distribution can be estimated. Martinez et al. [23] recommended using 1000 iterations of the bootstap reampling process to achieve stability.

Unlike to the bootstrap technique using resampling method, potential driver bias may be more pronounced in the Wilk's lambda method because it relies on the only original sample data collected without examining individual driver effects by pulling and entering their behavioral metrics. Due to the small sample size of drivers who were involved in crashes as well as the characteristics of parametric and non-parametric methods (the Wilks' lambda test and the bootstrap technique, respectively), this study selects behavior activity metrics showing significant differences between the two driver-groups based on results from either the bootstrap technique or the Wilks' Lambda test. This approach reduces the possibility of losing potential metrcis that may happen when relying on only one of methods. From the test result, any significant values less than the certain level such as 0.05 indicate that the means of behavior activity metrics estimated from the two driver-groups are statistically different.

RESULTS

Due to the small sample size and non-normality of the speed and mileage distributions, this study estimated the means derived by the bootstrap method and the confidence intervals to compare whether the mean values of the two driver-groups are different. For all of the following results, researchers conducted tests of the distributions of the parameters to discern whether crash involved older drivers were significantly different from older drivers who were not in crashes. If significant differences were found, individual significance tests of the paired means were also conducted.

Observed Differences in Mileage Exposure by Crash Involvement Status

Six months of continuous longitudinal trip data were used to examine if the total mileage exposure of two groups of older drivers were different. Researchers investigated the disaggregated mileage exposures for trends based on roadway types (where they traveled) and trip times (when they traveled). For the disaggregated exposure analysis, researchers used three roadway types, freeways, arterials, and locals, and six different time frames, AM peak (6 am ~ 9 am), morning time (9 am ~ 12 am), afternoon time (12 pm ~ 5 pm), PM peak (5 pm ~ 8 pm), night-time (8 pm ~ 12 pm), and early morning time (12 am ~ 6 am). The use of these terms is consistent throughout the remainder of the paper[2].

After comparing the means of total travel mileage between crash-involved and non-crash-involved drivers, researchers found that crash-involved older drivers traveled 6,992 miles on average during 6-month period, and drivers who were not involved in crashes traveled 4,359 miles for the same period. This is a difference of 38% (Table 1), which is statistically significant (α = 0.05) about the mean mileage. This result indicates that older drivers who were involved in recent crashes have tended to travel more than the non-involved group.

An analysis of travel mileage by trip-time categories indicated that the distributions of mileage by time period are not significantly different between the two groups. Regardless, the data still provides important information regarding time-based travel trends by older drivers. On average, over 70% of travel by older drivers is undertaken between 9 AM and 5 PM. Less than 5% of travel by older drivers occurs between the hours of 8 PM and 6 AM.

TABLE 1 Time-Specific Mileage and Differences Based on Total Mileage Traveled

	Mean of Travel Mileage (miles/6-months)		Mileage Difference (miles/6-months)	% Difference
	Older Drivers *Not* Involved in Crashes	Older Drivers Involved in Crashes		
Total Distance *	**4358.65**	**6992.48**	**2633.83**	**38**
AM Peak	450.44 (10.33%)	822.48 (11.76%)	372.04	45
Morning	1166.52 (26.76%)	1804.26 (25.80%)	637.74	35
Afternoon	2001.75 (45.93%)	3070.08 (43.91%)	1068.33	35
PM Peak	573.09 (13.15%)	896.62 (12.82%)	323.53	36
Night	154.42 (3.54%)	330.65 (4.73%)	176.24	53
Early Morning	24 (0.55%)	21.62 (0.31%)	-2.38	-11

* indicates a significant mean difference (α = 0.05).

All of the travel undertaken by participants within the 13-county area were matched with roadway characteristics to allow examination of differences in facility-time-specific mileage exposures between the two groups. On average, travel mileage outside of the 13-county area accounted for approximately 20% of total mileage for both groups. The means of total travel mileages inside the 13-county area were 5,563 miles

[2] Readers are cautioned to keep these time-periods in mind when interpreting the results of the study (i.e., results related to night-time should not be misconstrued as the total dark/night period).

for crash-involved older drivers and 3,445 miles for drivers not involved in crashes. This difference is not significant at 0.05 significant level.

Table 2 provides the distributions of older drivers with respect to mean travel mileage by facility type and time of day. There is a significant difference in the distribution of mean mileage within the 13-county area across the three facility groups between the two groups of drivers at the 0.05 significance level. However, there is not a significant difference in the distributions of mileage within the 13-county area between the two older driver-groups when segregated by time of day. The facility-based results show that crash-involved older drivers produce the largest differences in mean mileage (60%) on freeways (1,440 miles/6-months) versus drivers who were not involved in crashes (571 miles/6-months). Thus, indicating that crash-involved older drivers were more likely to undertake freeway trips than drivers who were not involved in crashes. However, further analyses will need to have more information associated with each individual crash event so that crash location (facility type) and time of day can be brought into these types of analyses.

TABLE 2 Facility and Trip Time Mileage Differences within the 13-County Area

	Mean of Travel Mileages (miles/6-months)		Mileage Difference (mile)	% Difference
	Older Drivers *Not* Involved in Crashes	Older Drivers Involved in Crashes		
Roadway Types				
Freeways *	**570.86 (16.70%)**	**1439.46 (25.74%)**	**868.6**	**60**
Arterials	1667.26 (48.78%)	2327.49 (41.62%)	660.23	28
Local Roads	1179.62 (34.51%)	1825.54 (32.64%)	645.92	35
Time of Day (Trip Time)				
AM Peak	366.16 (10.71%)	611.3 (10.93%)	245.14	40
Morning	853.07 (24.96%)	1261.77 (22.56%)	408.7	32
Afternoon	1495.85 (43.77%)	2519.07 (45.04%)	1023.22	41
PM Peak	534.3 (15.63%)	875.53 (15.66%)	341.23	39
Night	152.62 (4.47%)	313.92 (5.61%)	161.3	51
Early Morning	15.74 (0.46%)	10.9 (0.19%)	-4.85	-44

* indicates a significant mean difference (α = 0.05).

Researchers also investigated facility-time-specific mean mileage. While the distribution of mileage by time of day was not significant by itself, the interaction between facility and time of day did provide significant differences in distributions between the two groups of older drivers. The bootstrap confidence interval test showed that only freeway mileages during AM peak, afternoon, and nighttime between the two groups were significantly different (α = 0.05). Larger sample sizes will need to be developed to test this potential effect. Specifically, mileage on freeways during AM peak provided the largest difference (84%) between crash-involved older drivers (253 miles/6-months) and drivers who were not involved in crashes (42 miles/6-months) (Table 3). Crash-involved drivers also traveled much more on freeways (123 miles/6-months) during the night-time (79%) than non-crash-involved drivers (26 miles/6-months). This result may infer that non-crash-involved older drivers in this study are avoiding freeway travel during congested periods and at night. In addition, distributions of facility-time-specific mileages were significantly different.

TABLE 3 Facility-Time-Specific Mileage and Differences within the 13-County Area

Facility	Trip Time	Mean of Travel Mileages: Drivers *Not* Involved in Crashes	Mean of Travel Mileages: Drivers Involved in Crashes	Mileage Difference	% Difference
Freeways	**AM Peak ***	**41.58**	**253.41**	**211.83**	**84**
	Morning	151.74	309.69	157.95	51
	Afternoon *	**245.27**	**490.09**	**244.82**	**50**
	PM Peak	101.63	256.71	155.08	60
	Night *	**26.37**	**122.94**	**96.57**	**79**
	Early Morning	4.28	6.63	2.36	36
Arterials	AM Peak	188.35	183.04	-5.31	-3
	Morning	422.56	519.18	96.63	19
	Afternoon	712.41	1129.77	417.36	37
	PM Peak	255.18	370.15	114.97	31
	Night	81.01	122.01	41.00	34
	Early Morning	7.75	3.33	-4.42	-133
Local	AM Peak	136.23	174.85	38.62	22
	Morning	278.77	432.89	154.12	36
	Afternoon	538.17	899.21	361.04	40
	PM Peak	177.48	248.67	71.19	29
	Night	45.25	68.98	23.73	34
	Early Morning	3.71	0.93	-2.78	-299

* indicates a significant mean difference (α = 0.05).

Observed Differences in Speed Exposure by Crash Involvement Status

In addition to the mileage exposure difference analyses, researchers also examined differences of facility-time-specific speed behavior between the two groups because older drivers usually require longer reaction and perception-response times than other age drivers and high speeding decreases physical capability of older drivers [11]. When studying central values of speeding behavior, it is important to consider the effects of stop delays and slow moving traffic on overall speeding pattern. Thus, average running speeds (excluding all speeds less than 5 mph) were used to examine the speeding behavior differences between the two groups of older drivers [16]. As shown in Figure 2, crash-involved older drivers tended to travel at higher speeds on each facility type and time of day (a surrogate for traffic flow and speeds) than drivers who were not involved in crashes. Average running speeds of crash-involved older drivers during nighttime and early morning[3] on freeways showed that their speeding behaviors were significantly different from older drivers who were not involved in crashes. However, speeds on arterials and local roadways did not provide any significant differences based on the average running speed patterns (α = 0.05).

[3] In fact, exposures of older drivers during early morning period were very rare, so the comparisons of this time period were excluded.

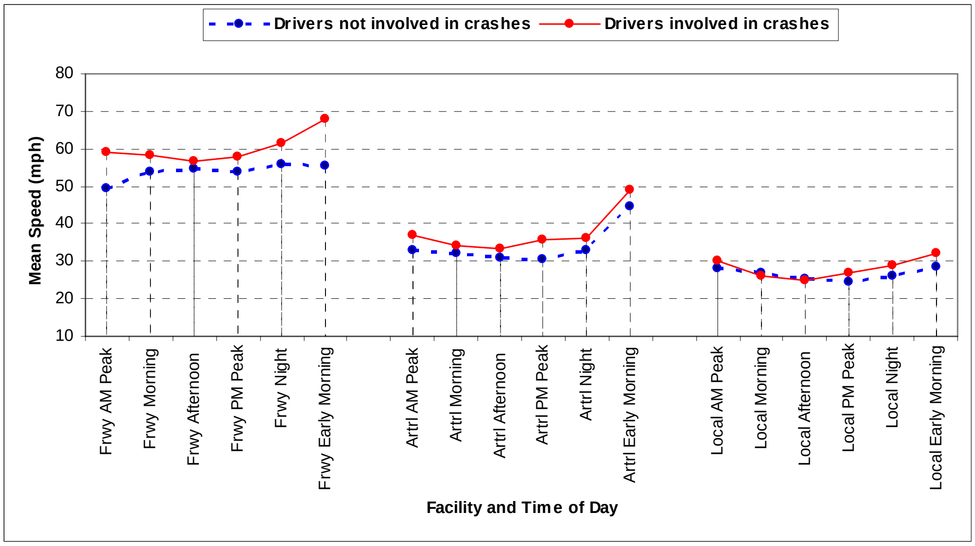

FIGURE 2 Comparisons of average running speeds by time and facility type.

When investigating facility-time-specific average running speeds (Table 4), speeds on freeways during AM peak except early morning provided the largest difference (16%) between crash-involved older drivers (59 mph) and non-crash-involved drivers (50 mph), but it did not show statistically significant difference due to the large variation of non-crash older drivers. Crash-involved drivers were also traveled at much higher speeds on freeways (61 mph) during nighttime free flow conditions than non-crash-involved drivers (56 mph). These analyses will need to be refined to ensure that the actual onroad operating speeds during the peak periods are directly accounted for in the analyses, before solid conclusions can be drawn. That is, different freeway segments operate under different congestion levels during the morning and evening peak periods.

TABLE 4 Difference in Average Running Speeds between the Two Older Driver-Groups

Facility	Trip Time	Drivers who *were not involved* in crashes		Drivers who *were involved* in crashes		Speed Difference	% Difference
		Mean	Std. deviation	Mean	Std. deviation		
Freeways	AM Peak	49.61	15.69	58.90	5.92	9.29	16
	Morning	53.97	10.56	58.31	4.77	4.35	7
	Afternoon	54.86	8.12	56.56	4.98	1.7	3
	PM Peak	54.02	9.37	57.83	4.57	3.81	7
	Night *	**55.78**	**6.74**	**61.45**	**2.91**	**5.67**	**9**
	Early Morning *	**55.33**	**3.18**	**67.90**	**2.26**	**12.57**	**19**
Arterials	AM Peak	32.73	8.30	36.86	5.08	4.13	11
	Morning	32.26	5.94	34.04	5.16	1.79	5
	Afternoon	31.02	4.41	33.46	5.16	2.44	7
	PM Peak	30.39	5.88	35.55	6.19	5.16	15
	Night	33.00	5.40	35.98	5.51	2.98	8
	Early Morning	44.64	6.89	49.07	1.76	4.44	9

Locals	AM Peak	28.29	5.73	30.31	3.21	2.02	7
	Morning	26.81	4.58	26.08	2.54	-0.73	-3
	Afternoon	25.13	4.46	25.03	2.06	-0.09	0
	PM Peak	24.53	5.41	26.92	4.14	2.39	9
	Night	25.97	5.34	28.86	6.49	2.88	10
	Early Morning	28.69	6.55	32.23	13.21	3.54	11

* indicates a significant mean difference (α = 0.05).

In addition to the average running speed differences showing normal speed patterns, this study also examined differences in facility-time-specific speeding behavior between the two groups. For the purposes of these analyses, the researchers classified the 'elevated speed risk' threshold as being the speed at which a citation can be issued in Georgia, which is the posted speed limit plus 10 mph [16]. This study also tested other thresholds such as just the post speed limit, the posted speed limit + 15 mph, and the posted speed limit + 20 mph, but better results could not be obtained. Significant differences were found at arterials during PM peak, morning, and nighttime and at the local roadways during peak hours and morning (Table 5).

TABLE 5 Difference in Frequency of 10 mph Over-Speeding per Mile Traveled

Facility	Trip Time	Drivers who *were not involved* in crashes		Drivers *who were involved* in crashes		% Difference
		Mean	Std. deviation	Mean	Std. deviation	
Freeways	AM Peak	8.78	9.70	10.06	5.38	0.13
	Morning	12.03	10.38	14.82	9.23	0.19
	Afternoon	8.81	7.21	14.39	6.92	0.39
	PM Peak	6.57	5.82	10.30	6.19	0.36
	Night	8.84	6.62	8.44	4.39	-0.05
	Early Morning	2.97	6.91	15.78	21.55	0.81
Arterials	AM Peak	4.95	9.37	7.53	5.58	0.34
	Morning **	**3.51**	**3.81**	**8.58**	**8.53**	**0.59**
	Afternoon	3.64	5.50	8.56	7.90	0.57
	PM Peak **	**2.97**	**3.77**	**6.84**	**6.15**	**0.57**
	Night *	**3.26**	**3.90**	**10.90**	**10.68**	**0.70**
	Early Morning	11.76	12.03	32.47	29.75	0.64
Locals	**AM Peak ***	**3.23**	**2.95**	**7.36**	**3.71**	**0.56**
	Morning **	**3.11**	**2.49**	**6.66**	**6.99**	**0.53**
	Afternoon	3.00	2.10	4.72	3.28	0.36
	PM Peak *	**2.51**	**1.86**	**5.29**	**4.07**	**0.52**
	Night	3.29	3.27	5.19	3.59	0.37
	Early Morning	4.30	8.11	9.82	18.80	0.56

* indicates a significant mean difference (α = 0.05).
** indicates a significant mean difference (α = 0.1).

CONCLUSIONS AND STUDY LIMITATIONS

This study evaluated the driving behaviors of older individuals who had recently experienced a crash in comparison to older individuals who had not experienced a crash. Each participant drove his or her own vehicle in an urban setting for a 6-month period of time. Participants were categorized into the "crash" group or the "no crash" group by a self-report survey at the end of data collection. The primary variables of investigation include mileage traveled, roadway traveled, time of day, and speed.

This study found that, overall, crash-involved older drivers usually traveled longer distances and traveled at higher speeds than older drivers who were not involved in crashes. Driving activities between the two groups showed two significant differences, indicating that (1) crash-involved older drivers were more likely to use freeway for trips than drivers who were not involved in crashes and (2) crash-involved older drivers drove at faster speeds than older drivers who were not involved in crashes. The distributions of mileages by facility types between two driver groups were significantly different while the distributions of mileage by time period were not different.

There has been a long standing belief that older drivers choose not to drive at night. Only 5% of the mileage traveled in this study occurred at night. This may be a result of reduced visual abilities, increased glare sensitivity, or simply that seniors do not have the need or desire to be away from home late in the day.

This study is an observational research evaluating naturalistic driving patterns by crash involvement status. In the experimental design research, researchers can recruit large number of drivers, crash-involved and non-crash-involved drivers, and evaluate their driving behavior patterns. However, those driving behavior patterns may not represent a normal driving behavior since drivers may modify their driving behavior patterns after being involved in a crash. The observational research like this study tries to randomly recruit participants and observe their normal driving behavior activity patterns and crash involvements. Thus, this observational study has relatively a small sample size regarding crash-involved drivers. This study collected crash data from the participants during the 14-months period. However, due to the rare event characteristics of crash involvements, this study employed the small sample size (only five older drivers) for drivers who were involved in crashes. Further studies with larger sample data are needed to better determine whether there are differences between by facility-based mileage, speeding, crash risk with both older drivers and drivers of all ages.

This study suggests that transportation safety engineers and policy makers should aim anti-speeding campaigns to drivers of all ages. These findings should be incorporated into education campaigns and driver evaluation or monitoring programs since this study found that crash-involved older drivers traveled longer and at high speed than non-crash-involved older drivers although older drivers traveled lower distance and at low speeds than other age drivers. If driving behaviors of older drivers are regularly monitored and evaluated with other drivers of the same age group, older drivers will be able to recognize and modify their driving activities linked with potential crash involvement. Future research needs to compare the driving habits of healthy and impaired older drivers to the entire driving population in both urban and rural settings.

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