Identification of Risk Factors for Severe Younger and Older Driver Crashes in Massachusetts

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ABSTRACT
Systemic safety analysis is a comprehensive and proactive approach to identifying and addressing high-risk roadway features and crash types that contribute to severe crashes. The Massachusetts Department of Transportation (MassDOT) identified 14 emphasis areas for systemic improvement, including younger and older driver crashes. Research was undertaken to conduct separate comprehensive analyses of fatal and serious injury crashes involving younger and older drivers, using a systemic safety approach to develop risk factors and identify critical locations within the state. The study utilized crash, roadway, driver's license, citation, healthy aging, and environmental justice data from various sources. Negative binomial regression models were developed to relate crash frequency with town-specific traffic, behavior, and site characteristics, considering exposure and spatial variance. The findings highlighted the significance of multiple risk factors contributing to severe crash frequency. For younger drivers, the presence of young drivers in the town, risk-taking behaviors such as unbelted and impaired driving, and infrastructure characteristics, particularly high-speed facilities and underinvested infrastructure, were key contributors to crash frequency. Older drivers' crash frequency was influenced by the presence of older drivers, healthy aging indicators, risk-taking behaviors, and high-speed facilities. Based on the model results, risk scores were developed for each variable in the model and applied to each town. The towns were ranked using percentile ranking to classify them into primary and secondary risk categories. The towns identified in the primary risk category (top 5 percentile-18 towns) captured approximately 14 percent of severe younger driver crashes and 15 percent of severe older driver crashes.

Keywords: younger driver, older driver, risk factor, crash analysis, systemic safety analysis

INTRODUCTION

The Highway Safety Improvement Program (HSIP) is a core Federal-aid highway program with a focus on reducing fatalities and serious injuries on all public roads (*1*). The legislation recognizes that a State's HSIP should identify safety improvement projects not solely based on crash history but also on crash potential. The Bipartisan Infrastructure Law (BIL) places significant importance on systemic safety improvements as part of the safety management process, making such improvements eligible for HSIP projects. This systemic approach to safety focuses on implementing widely adopted improvements that target high-risk roadway features associated with focused severe crash types (e.g., roadway departure, distracted, and pedestrian) (*1*). This approach offers a more comprehensive method for safety planning and implementation, which supplements and complements traditional site analysis. Furthermore, it allows agencies to expand their traffic safety initiatives while accounting for both risk factors and crash history when determining suitable locations for cost-effective safety enhancements.

To inform risk-based network screening in their IMPACT tool (*2*), the Massachusetts Department of Transportation (MassDOT) identified focus crash types, facility types, and risk factors for the Massachusetts Strategic Highway Safety Plan (SHSP) Emphasis Areas. MassDOT identified a total of 14 emphasis areas based on a number of factors including crash frequency and severity (*2*). Two of these emphasis areas are crashes involving younger and older drivers.

Younger and older driver crashes are a nationwide concern, accounting for 9 percent and 17 percent of total traffic fatalities in 2021, respectively. Younger drivers (aged 16-19 years) have a fatal crash rate per mile driven approximately three times higher than the rate for drivers aged 20 and over (*3*). A total of 3,051 fatal crashes involved younger drivers in 2021. In Massachusetts only in 2022, approximately 21,000 crashes involved younger drivers, which resulted in 54 fatal crashes and 300 serious injury crashes (*2*). Crashes involving older drivers pose a higher risk than younger drivers. Between 2000 and 2017, there were 110,422 drivers aged 65 and above involved in fatal crashes, and out of these drivers, 61.4% lost their lives (*4*). In 2021, individuals aged 65 and older who were killed in traffic crashes resulted in a total of 9,102 fatalities (*5*). In Massachusetts in 2022, over 24,000 crashes involved drivers aged 65 and older, which resulted in 99 fatal crashes and 448 serious injury crashes (*2*).

Several prior studies have evaluated factors impacting younger and older driver crashes (*6*–*8*). Potential factors behind younger driver crashes include inexperience, risk-taking behavior, high-speed facilities, and challenging driving conditions (*9*). On the other hand, older driver crashes are influenced more by a combination of age-related factors and medical conditions that affect driving ability and survivability of the crashes (*6*, *7*).

There is the potential to implement systemic improvement strategies that prioritize countermeasure programs focused on enhancing driver behavior; however, it is essential to identify focus crash types and critical locations within the study area. MassDOT aimed to use this analysis to produce results that would aid in prioritizing targeted education programs. Given that educational programs in Massachusetts are administered at the municipal level, targeting towns and cities, a study was designed to perform a systemic analysis for both younger and older driver crashes at the town level. Again, the systemic approach focuses on crashes with higher severity. To this end, research was undertaken to evaluate severe crashes (i.e., fatal injury or suspected serious injury) involving younger and older drivers. The analysis guided the development of risk scores that can be applied to identify towns with a greater need.

To achieve the objectives, the study first identified overrepresented crash attributes (i.e., functional class, number of lanes, speed limits, distraction, and action prior to a crash) in younger and older driver crash databases. This was followed by developing separate safety performance functions (SPF) for each focused crash type. The findings from the model results were utilized to develop risk scores for the variables impacting younger and older driver crashes. Subsequently, the risk scores were applied to 350 towns in Massachusetts, identifying towns with a greater risk. Finally, the findings were validated by comparing them with the severe crash frequency of the identified towns.

LITERATURE REVIEW

There are different sets of factors that impact younger and older driver crashes. An analysis of the second Strategic Highway Research Program's Naturalistic Driving Study data identified several situations that may be particularly risky for younger drivers (*10*). These include crashes on local/collector and non-interstate/freeway arterial roads, on two-lane roadways, and at stop signs. Crashes occurring between 6 a.m. and 6 p.m. and during daylight hours were risky situations for young driver crashes. Additionally, situations involving initial impacts to the right sides of vehicles were found to be common, as well as misjudging the timing of left turns, running stop signs, or stop lights among young driver crashes. An analysis of young driver crashes in Louisiana identified driving violation, distraction, presence of a passenger, time of crash, and driver protection system as the top ten predominant factors in multiple young driver groups (*11*). Another study identified driving violations, use of electronic devices and cellphones while driving, non-use of driver protection systems, and nighttime driving to be highly correlated with young driver crashes (*12*).

Several studies also evaluated older driver crashes. Qi et al. (*6*) evaluated older population severe crash data from Illinois and identified several geometric and demographic characteristics associated with high crash risk. The factors identified in this study include traffic control devices, vehicle defects, lighting and surface conditions, roadway alignment, household income, physician care availability, minority and uninsured populations, and prescription drug use. Alrumaidhi and Rakha (*7*) analyzed crash severity among elderly drivers in Virginia using Multilevel Ordinal Logistic Regression and identified two-way roads and high-speed facilities to experience more of these crashes. Different risk-taking behaviors, including not wearing a seatbelt and distractions, were also found to impact severe crashes. Doulabi and Hassan (*8*) evaluated roadway-, vehicle-, environment-, and driver-related factors impacting severe older driver crashes in Louisiana using logistic regression analysis. Results indicate that road characteristics (such as crash location, road type, road alignment, and highway type), driving maneuvers (prior movement and lane departure), and driver characteristics (driver condition and gender) are significant factors affecting crash severity for older drivers.

However, none of the studies discussed in this section focused on systemic safety analysis. Systemic analysis is a proactive safety approach focusing on the evaluation of an entire roadway network using a specific set of criteria. This approach evaluates aggregated crash history to identify high-risk roadway characteristics, instead of site analysis. The Federal Highway Administration (FHWA)'s Systemic Safety Project Selection Tool highlights systemic safety examples from five States and outlines the steps and risk factors agencies can apply when performing systemic analysis (*1*). FHWA's guide cites several methods for selecting risk factors including analyzing exposure or using crash modification factors (CMFs). National Cooperative Highway Research Program (NCHRP) Report 955 also outlined several analysis techniques and data needs for systemic safety analysis for different focus crashes (*13*). Agencies across the United States have also been integrating systemic elements into their safety programs (*14–16*). Efforts have ranged from systemic analysis on a city-wide or Statewide scale to identifying crash locations with high-risk factors.

DATA COLLECTION

Data for this study were primarily shared by MassDOT, while additional data were collected from various MassDOT-maintained sources. In Massachusetts, all roads and geographic areas are covered by town jurisdictions. For the purpose of this study, data were aggregated at the city and town level using ArcGIS. Due to limitations with crash data acquisition, the City of Boston was excluded from the analysis following a discussion with MassDOT officials. The following subsections present the sources of various data utilized in this study.

Crash Data

Younger and older driver crashes by town were collected using the MassDOT IMPACT Test of Proportions tool (*17*). A total of five years of crash data from 2017 to 2021 were collected, combined, and then joined at the town-level. As the systemic approach focuses on severe crashes, the authors limited the crashes to those in which the maximum injury severity reported was a fatal injury or suspected serious injury (KA on the KABCO scale).

Roadway Data

Massachusetts statewide Road Inventory data for 2021 were downloaded from MassDOT Open Data Portal (*18*). Based on discussions with MassDOT, the roadway data were filtered in ArcGIS using mileage counted (equal to 1), jurisdiction (not equal to null), and facility type (less than 7) to identify unique segments that were counted for the Highway Performance Monitoring System (HPMS). Filtering the roadway inventory in this way prevented potential double-counting of mileage and VMT for divided roads and roads with overlapping route numbers. The authors aggregated the segment-level roadway data at the town-level, including summing total centerline miles and centerline miles for each Federal Functional Class.

Driver License Data

MassDOT provided driver license data by age, town, and zip code for 2021. Spatial analysis tool in ArcGIS was utilized to assign driver license zip codes to the relevant town, joining the driver license totals by age. Additionally, the proportion of drivers that fell within the young and older driver query definition for each town was calculated.

Educational Institution Location Data

Primary and secondary school location data were extracted from the Massachusetts Bureau of Geographic Information (MassGIS) open data portal (*19*). College and university location data were separately extracted from the MassGIS open data portal (*19*). Although these data contain several categories of trade schools and other atypical technical training institutions, the study only included "Colleges, universities, and professional schools," "Fine arts schools," "Junior colleges," and "Other technical and trade schools" for the purpose of this analysis.

Traffic Citation Data

Traffic citation count data by town for a five-year period between 2015 and 2019 were shared by MassDOT. These data included total citations, as well as subsets of counts for speeding-, seat belt-, impaired driving-, and distraction-related traffic citations. Since yearly citation data for the study period (2017-21) was not available, the number of annual citations was estimated and utilized based on the available five-year citation data for different types.

Healthy Aging Data

MassDOT and the University of Massachusetts at Boston provided Healthy Aging Data which provided information related to seniors at the town level. Data elements included the proportion of persons aged 65 or older with self-reported cognitive, mobility, or independence challenges as well as counts of assisted living, home health providers, senior care providers, and nonmedical care providers in the town. Communities are then assigned a "healthy aging score" based on the aggregated individual measures.

Environmental Justice Data

MassGIS developed a GIS layer based on 2010 United States Census data for three indicators of high environmental justice (EJ) need neighborhoods (*20*):

- Proportion of non-white population (EJ-M): Block groups with a proportion of non-white population greater than 25 percent are flagged in this category.
- Limited English proficiency (LEP) households (EJ-E): Block groups with a proportion of limited English-speaking households greater than 25 percent are flagged in this category.
- Median household income (EJ-I): Block groups with a median household income below $40,673 are flagged in this category.

EJ data were incorporated by indicating which indicators are present within a town or city.

Additional Data

Several additional data sources were integrated into the data set, including census and American Community Survey (ACS) data, public health data from the Massachusetts Department of Public Health (DPH), and seatbelt use survey data at the county level from MassDOT. Most of the towns in Massachusetts had available seatbelt survey data; however, for the missing towns, survey data from the respective county were utilized instead.

TARGET CRASH ATTRIBUTE SUMMARY

Severe (KA) younger and older driver crash data were first analyzed to identify overrepresented crash attributes. To do that, KA younger and older driver crashes were compared to all KA crashes in the State using the MassDOT IMPACT "Test of Proportions" tool (*17*). Where the proportion for a given attribute is statistically larger than the proportion for the comparison group, that attribute is flagged as a potential risk factor. Statistical overrepresentation is checked by building 95 percent confidence intervals around the proportion using sampling errors. Table 1 summarizes notable overrepresentations found in the analysis for both younger and older driver crashes.

Between 2017 and 2021, Massachusetts experienced a total of 1,539 severe crashes involving younger drivers, accounting for 11.9% of all severe crashes. It is notable that a large proportion of younger driver crashes involved more than one motor vehicle. These incidents also correlate with more severe crashes that involved angle or rear-end collisions at four-way intersections, T-intersections, or driveways. Local streets, undivided two-way roads, streets with rolling terrain, streets with no access control, streets with no right shoulder and median, as well as streets under the jurisdiction of a city or town, have a statistically disproportionate number of crashes involving young drivers. Aggressive driving behaviors that include disregarding traffic signs, signals, road markings, distractions, failing to yield right of way, following too closely, and inattention were statistically disproportionate in younger driver crashes. While the majority of the drivers were not distracted, there were drivers disproportionately distracted by external distractions outside the vehicle and other activities (searching, eating, personal hygiene, etc.).

Similarly, Massachusetts experienced a total of 2,391 severe crashes involving older drivers between 2017 and 2021, accounting for 18.5% of all severe crashes. A large proportion of older driver crashes occurred on arterial roadways with no access control. These crashes were also overrepresented on undivided two-way roads and at four-way or T-intersections. Several of these results are correlated with the driving patterns of older drivers – such as preferring to drive during the day on dry pavement. Additionally, the overrepresentation points to the vulnerability of older drivers and vehicle occupants, with elevated severe crash proportions in multi-vehicle angle, head-on, and rear-end crashes. Similarly, these crashes are overrepresented on relatively lower speed facilities (35-40 mph), indicating their vulnerability even in low-energy collisions. Driver contributing factors are overrepresented by older driver-specific traits including illness, inattention, and failure to yield right of way. The majority of the older divers were found to be not distracted.

While these are notable results providing important information on younger and older driver crashes, they should not restrict conducting in-depth analysis to identify factors impacting these focused crash types.

Table 1 Summary of Significant Overrepresentations in Various Crash Attributes

Crash Field	Crash Attribute	Percent of Younger Driver KA Crashes	Percent of All KA Crashes	Percent of Older Driver KA Crashes	Percent of All KA Crashes
Access Control	No access control	82.20%	71.31%	83.20%	79.20%
County Name	Middlesex	18.24%	13.18%	-	-
	Barnstable	-	-	7.00%	4.60%
Curb	Both Sides	41.19%	34.05%	-	-
First Harmful Event	Collision with motor vehicle in traffic	60.75%	35.28%	60.50%	46.30%
First Harmful Event Location	Roadway	-	-	81.10%	73.00%
Manner of Collision	Angle	31.45%	14.52%	30.00%	22.70%
	Rear-end	15.41%	7.41%	15.60%	13.10%
	Head-on	-	-	15.00%	11.00%
Federal Functional Class	Local	14.40%	10.79%	-	-
	Minor Arterial	-	-	33.10%	30.20%
	Principal Arterial – Other	-	-	32.20%	27.80%
Jurisdiction	City or Town accepted road	62.96%	50.03%	-	-
Trafficway Description	Two-way, not divided	64.78%	54.23%	64.60%	60.20%
Operation	Two-way traffic	-	-	92.90%	91.00%
Total Lanes	2	-	-	71.30%	67.50%
Speed Limit	35 MPH	-	-	13.70%	10.80%
	40 MPH	-	-	10.80%	8.40%
Median Type	None	79.12%	68.05%	79.70%	75.80%
Right Shoulder Type-linked	No Shoulder	49.43%	39.94%	-	-
Terrain Type	Rolling	8.24%	5.42%	-	-

Crash Field	Crash Attribute	Percent of Younger Driver KA Crashes	Percent of All KA Crashes	Percent of Older Driver KA Crashes	Percent of All KA Crashes
Roadway Junction Type	Four-way intersection	18.87%	10.20%	18.90%	16.00%
	Driveway	2.26%	0.99%	-	-
	T-intersection	18.11%	10.90%	18.80%	15.70%
Traffic Control Device Type	Stop signs	15.09%	6.06%	13.50%	10.40%
	Traffic control signal	13.14%	8.69%	-	-
Driver Contributing Circumstances	Disregarded traffic signs, signals, road markings	3.50%	1.90%	-	-
	Distracted	1.63%	0.63%		
	Failed to yield right of way	8.67%	3.32%	9.50%	6.50%
	Followed too closely	2.37%	0.52%		
	Inattention	6.84%	2.65%	7.40%	6.00%
	Illness	-	-	2.70%	1.20%
	No improper driving	-	-	34.80%	29.50%
Driver Distracted By	External distraction (outside the vehicle)	1.54%	0.60%	-	-
	Other activity (searching, eating, personal hygiene, etc.)	2.76%	1.52%	-	-
	Not Distracted	43.72%	32.66%	49.10%	42.80%
Weekday	Thursday	-	-	16.40%	13.70%
Light Condition	Daylight	56.60%	46.36%	77.60%	57.80%
Vehicle Configuration	Passenger car	63.23%	52.31%	-	-
Road Surface Condition	Dry	-	-	83.30%	79.40%

STATISTICAL METHODOLOGY

As discussed earlier, the systemic analysis was performed at the town-level due to the intended municipal-level countermeasure programs. A series of negative binomial regression (NBR) models were estimated to relate crash frequency with town-specific traffic, behavior, and site characteristics. The NBR model is a generalized form of Poisson regression model (*21*). In a Poisson regression model, the probability of town *i*, experiencing y_i younger or older driver crashes during a specific time period is given as shown in Equation (1).

$$P(y_i) = \frac{e^{-\lambda}\lambda_i^{y_i}}{y_i!} \quad \text{Eq. (1)}$$

Where, λ_i is the average number of younger or older driver crashes for town *i* with similar characteristics. The Poisson parameter, λ_i, can be calculated as shown in Equation (2).

$$\lambda_i = EXP(\beta X_i) \qquad \text{Eq. (2)}$$

Where X_i is the vector of explanatory variables and β is a vector of parameters to be estimated that quantify the effect of these variables.

One of the limitations of the Poisson model is that it assumes the mean and variance of the expected crash counts are equal. This assumption is, however, often not satisfied by crash data, which tend to be overdispersed (i.e., variance is greater than conditional mean). The NBR model can accommodate overdispersion by including a gamma-distributed error term, as shown in Equation (3).

$$\lambda_i = EXP(\beta X_i + \varepsilon_i) \qquad \text{Eq. (3)}$$

The term, $EXP(\varepsilon_i)$, is gamma-distributed with mean and variance equal to 1 and α, respectively, where α is the overdispersion parameter. As stated previously, the analysis period was from 2017-2021 which results in repeated observations of each town. This may result in correlations among crash count observations across different years due to site-specific factors that are not incorporated in the model (*21*). To account for these correlations, the crash counts were aggregated across all years for town, thereby eliminating any repetition in the data. Again, each town has a different total centerline mileage. To account for that, the natural log of the product of five years of data and total centerline mileage in the town was used as an offset variable in the NBR model. This introduced an implicit assumption that crashes increase proportionately with number of years and centerline mileage. The analysis included 350 towns from 13 different Metropolitan Planning Organizations (MPOs), which results in repeated observations for each MPO. To account for that, MPO was added as a random parameter in the younger driver crash model, which transforms the negative binomial model to:

$$\lambda_i = EXP(\beta X_{ij} + \varepsilon_{ij})EXP(\eta_j) \qquad \text{Eq. (4)}$$

where, η_j is a random effect for observation group j.

RESULTS AND DISCUSSION

The subsequent sections provide an overview of the data summary for the variables included in the final models for both younger and older driver crashes. Following this, the findings from the models pertaining to younger and older driver crashes are discussed. Note that, before including any variables in the negative binomial, a correlation matrix of input variables was developed. Highly correlated variables are indicators of potential complications in the model development process and hence discarded.

Data Summary

The descriptive statistics (minimum, maximum, mean, and standard deviation) of the dependent variables (younger or older driver severe crashes) and independent variables are presented in Tables 2 and 3 for younger and older driver crashes, respectively. For the binary variables, the mean value indicates the proportion of data when the variable is true. A total of 1,539 younger driver KA crashes and 2,391 older driver KA crashes were included from 350 towns in Massachusetts during the five-year analysis period.

Table 2 Descriptive Statistics-Younger Driver Crashes

Variables	Minimum	Maximum	Mean	Standard Deviation
Severe (KA) younger driver crashes	0	67	4.397	6.969
Natural log of population aged 15-24 in the town	0	10.463	6.883	1.487
Indicator the town is an EJ-E community.	0	1	0.074	0.263
Indicator the town is not an EJ-I community.	0	1	0.403	0.491
Average number of vehicles per household in the town.	1.027	2.487	1.942	0.235
Indicator the proportion of centerline mileage that is interstate, freeway, or expressway is greater than 0.025.	0	1	0.529	0.500
Indicator the annual unbelted citations per centerline mile in the town is greater than 1.0.	0	1	0.306	0.461
Indicator the annual impaired driving citations per centerline mile in the town is greater than 1.5	0	1	0.091	0.289
Percent of drivers belted in the survey is 85 percent or less.	0	1	0.897	0.304
Proportion of licensed drivers aged 16 to 21 in the town.	0.007	0.173	0.073	0.026

Table 3 Descriptive Statistics-Older Driver Crashes

Variables	Minimum	Maximum	Mean	Standard Deviation
Severe (KA) older driver crashes	0	83	6.831	9.394
Proportion of mileage that is interstate, freeway, or expressway	0	0.237	0.036	0.039
The number of senior care providers in the town is more than 0.	0	1	0.689	0.464
Annual impaired driving citations per centerline mile in the town is greater than 0.5.	0	1	0.674	0.469
Annual speeding citations per mile in the town is greater than 3.	0	1	0.537	0.499
Natural log of persons aged 65 or older in the town.	2.890	10.134	7.377	1.226
2 or fewer assisted living facilities in the town	0	1	0.911	0.285

The percentage of persons aged 65 or older with self-reported cognitive issues	0	0.240	0.060	0.036
Proportion of licensed drivers aged 65 or older	0.015	0.530	0.231	0.062
MPO is Southeastern Regional Planning & Economic Development District (SRPEDD) or Old Colony Planning Council (OCPC)	0	1	0.157	0.364
MPO is Martha's Vineyard Commission (MVC)	0	1	0.020	0.140
MPO is Cape Cod Commission (CCC) or Boston Region MPO (BRMPO)	0	1	0.343	0.475

Factors Impacting Younger Driver Crashes

Table 4 presents the results of the younger driver crash model. The natural log of the product of centerline mileage and number of years (5 years) were included in the model to offset exposure for each town. MPO was added as a random parameter to capture spatial variance across various locations within the state.

The results showed that as the population age 15-24 increased, there was a higher frequency of severe young driver crashes. This outcome is expected since this variable indicates the presence of young drivers in the town. The relationship between crash frequency with high proportion of interstate, freeway, and expressway centerline mileage suggests the more high-speed mileage in the town, the higher severe expected crash frequency. Additionally, the coefficients for unbelted citations, impaired driving citations, and observed unbelted occupants suggest a correlation between elevated risk-taking behavior and severe young driver crash frequency. Interestingly, while the status as an EJ-E community is positively correlated with young driver crash frequency, the status as an EJ-I community is negatively correlated (shown as the status as not an EJ-I community being positively correlated with crash frequency). It is possible that higher income households have more vehicles for young drivers to use, thus leading to more young driver exposure – reinforced by the positive correlation between the average number of vehicles per household and young driver crash frequency. Finally, the coefficient is negative for the proportion of licensed drivers that are aged 16 to 21, suggesting that young driver crash frequency decreases as the proportion of licensed drivers aged 16 to 21 increases. Results largely align with findings from the prior studies on younger driver crashes (*11*, *22*).

Table 4 Mixed-Effect Negative Binomial Regression Model Results for Younger Driver Crashes

Variables	Coefficient	Std. Error	z-value	p-value
Intercept	-8.503	0.633	-13.439	<0.001
Natural log of population aged 15-24 in the town	0.311	0.048	6.547	<0.001
Indicator the town is an EJ-E community.	0.428	0.150	2.852	0.004
Indicator the town is not an EJ-I community.	0.209	0.100	2.087	0.037
Average number of vehicles per household in the town.	0.324	0.225	1.437	0.151
Indicator the proportion of centerline mileage that is interstate, freeway, or expressway is greater than 0.025.	0.223	0.086	2.596	0.009
Indicator the annual unbelted citations per centerline mile in the town is greater than 1.0.	0.356	0.092	3.863	<0.001
Indicator the annual impaired driving citations per centerline mile in the town is greater than 1.5	0.179	0.131	1.364	0.173
Percent of drivers belted in the survey is 85 percent or less.	0.416	0.159	2.620	0.009
Proportion of licensed drivers aged 16 to 21 in the town.	-2.725	1.505	-1.810	0.070
Natural log of the product of centerline mile length and 5 years of crash data in the town. (Offset)	1	N/A	N/A	N/A
Overdispersion parameter	0.183			

Factors Impacting Older Driver Crashes

Table 5 presents the results of the older driver crash model. Similarly, the natural log of the product of centerline mileage and number of years (5 years) were included in the model to offset exposure for each town. MPOs were added as independent variables in this model unlike the younger driver model due to higher occurrence of older driver crashes in few MPOs.

Results showed two risk factors correlating with exposure to older drivers – natural log of population aged 65 or older and the proportion of licensed drivers aged 65 and older to be significant. Healthy aging-related indicators were found to be correlated with increased older driver crash risk. The significant variables include the percentage of persons aged 65 or older with reported cognitive issues, if the town has two or fewer assisted living facilities, and the presence of at least 1 senior care provider in the town – which all point toward potential challenges for older drivers in the town. Additional risk factors appear to be correlated with general risk-taking behaviors on roadways within the town, including more than 0.5 impaired driving citations per centerline mile and more than three speeding citations per centerline mile. These findings align with prior work on severe older driver crashes (*6*–*8*). The higher proportion of interstates, freeways, and expressways points towards a higher proportion of high-speed driving, and thus elevated crash energy in the town. In addition to these, few MPOs were found to experience higher frequency of severe older driver crashes.

Table 5 Negative Binomial Regression Model Results for Older Driver Crashes

Variable	Coefficient	Std. Error	z-value	p-value
Constant	-8.506	0.418	-20.32	<0.001
Proportion of mileage that is interstate, freeway, or expressway	3.139	1.113	2.82	0.005
The number of senior care providers in the town is more than 0.	0.288	0.095	3.02	0.003
Annual impaired driving citations per centerline mile in the town is greater than 0.5.	0.230	0.102	2.25	0.025
Annual speeding citations per mile in the town is greater than 3.	0.193	0.081	2.38	0.017
Natural log of persons aged 65 or older in the town.	0.348	0.049	7.03	<0.001
2 or fewer assisted living facilities in the town	0.170	0.113	1.51	0.131
The percentage of persons aged 65 or older with self-reported cognitive issues	2.430	1.128	2.16	0.031
Proportion of licensed drivers aged 65 or older	0.569	0.552	1.03	0.303
MPO is SRPEDD or OCPC	0.508	0.101	5.02	<0.001
MPO is MVC	0.734	0.422	1.76	0.078
MPO is CCC or BRMPO	0.295	0.086	3.43	0.001
Natural log of the product of centerline mile length and 5 years of crash data in the town. (Offset)	1	N/A	N/A	N/A
alpha	0.176	0.156		

RISK SCORE DEVELOPMENT

As previously mentioned, the purpose of this analysis is to identify town-level risk factors for younger and older driver crashes with fatal and serious injuries. Instead of using the coefficients in the negative binomial regressions results from Tables 3 and 4, MassDOT assigned risk scores between 0 and 1 based on the character of the risk factor. This avoids overly weighting any one risk factor, especially considering potential data issues with the risk factor data which may cause biases. Where the statistical significance of the variable was not strong (i.e., p-value > 0.05), MassDOT assigned a maximum risk score of 0.5 instead of 1 for the risk factor. Where a binary predictive variable was used, MassDOT applied binary risk scores. From a modeling perspective, the cutoffs for binary variables were determined using visual representations of the data and smaller bins to find the cutoffs which make the most sense.

To provide context for these risk factor scores in relation to other emphasis areas, the cumulative scores can be normalized by dividing by the total potential score for a town. This would generate a risk score out of 100 percent for each town. The towns can then be ranked using the normalized risk score and the percentile score of ranking (rank kind equal to weak) function in ArcGIS. For each normalized risk score, a percentile rank for the given score was computed relative to all the normalized risk scores. If there are repeated occurrences of the same normalized risk score, then the percentile rank corresponds to values that are less than or equal to the given score. The advantage of the weak ranking approach is that it guarantees that the highest normalized score will receive a percentile rank of 100 percent. Following that, risk categories can be assigned using the computed ranks. For example, towns ranked in the top 5 percentile (95 through 100) were categorized as "Primary Risk Town" and towns ranked in the next 10 percentile (85 through 95) were categorized as "Secondary Risk Town"; the remaining towns were not categorized. In instances where there are large, repeated occurrences of the same normalized risk score, the percentage of segments computed for the top 5 percent or next 10 percent may not be equal to 5 or 10 percent. This is a byproduct of the weak ranking approach.

Risk Scores for Younger Driver Crashes

Table 6 summarizes the suggested risk-scoring for younger driver crashes based on the model results presented in Table 4. The table also provides an example application of the risk factors to a hypothetical town. The normalized risk score for the example town is 46.3 percent (3.47 divided by 7.5). Assigning risk factors allowed to consider all the variables identified in the crash data analysis. Several factors point toward increased young driver exposure (e.g., younger person population, income, vehicles per household), which is expected to be correlated with severe young driver crash frequency. Additionally, several factors measure the surrogate level of risk in the town, indicating an increased likelihood of risk-taking behavior that is likely to be present in the young driver population (e.g., seat belt use, impaired driving citations, unbelted citations). Finally, two risk factors point toward the correlation of infrastructure and young driver crash frequency: the presence of high-speed facilities (interstate, freeway, and expressway mileage) and historically underinvested infrastructure (correlated with EJ-E community status).

The risk scores suggested in this study were applied to 350 towns in Massachusetts. Table 7 provides the distribution of towns and crashes at each risk category with the normalized risk score (presented as percentages) across these categories for statewide rankings. Note the goal was to see a higher proportion of target crashes for primary and secondary risk sites than the proportion of towns. It can be seen that the top 5 percent of towns in the primary risk category are capturing approximately 14.0 percent of the severe younger driver crashes, and the next top 10 percent are capturing an additional 22.4 percent of target crashes. Finally, the study suggested 18 towns in the primary risk category and 35 towns in the secondary risk category, as visualized in Figure 1. The figure displays the towns in the State that require a higher level of attention to reduce younger driver severe crashes.

Table 6 Example Risk Score Calculation for Younger Driver Crashes

Variable	**Risk Factor**	**Town Characteristics**	**Risk Score**
Natural log of population aged 15-24 in the town.	Continuous from 0 to 1 for range of values. A population of 2,234 was higher than 23 percent of towns.	Population of 2,234	0.23
Indicator the town is an EJ-E community.	1 if true; 0 otherwise.	Town is not an EJ-E community.	0
Indicator the town is not an EJ-I community.	0.5 if true; 0 otherwise.	Town is not an EJ-I community.	0.50
Average number of vehicles per household in the town.	Continuous from 0 to 1 for range of values. An average of 1.45 was higher than 40 percent of towns.	1.45.	0.40
Indicator the proportion of centerline mileage that is interstate, freeway, or expressway is greater than 0.025.	0.5 if true; 0 otherwise.	Proportion is 0.01.	0
Indicator the annual unbelted citations per centerline mile in the town is greater than 1.0.	1 if true; 0 otherwise.	Metric is 1.25.	1.0
Indicator the annual impaired driving citations per centerline mile in the town is greater than 1.5.	1 if true; 0 otherwise.	Metric is 1.7.	1.0
Percent of drivers belted in the survey is 85 percent or less.	1 if true; 0 otherwise.	86 percent of drivers were belted.	0
Proportion of licensed drivers aged 16 to 21 in the town.	Continuous from 0.5 at the lowest proportion to 0 at the highest proportion.	Proportion is 0.20.	0.34
		Total Risk Score:	**3.47**
		Risk Percent Score (Out of 7.5):	**46.3%**

Table 7 Statewide Risk Categories for Younger Driver Crashes.

State	Risk Category	Minimum Normalized Risk Score Percentage	Maximum Normalized Risk Score Percentage	Number of Towns	Percent of Scored State Towns	Percent of Target Crashes
MA	Primary Risk Site	95.16	100	18	5.1%	13.9%
	Secondary Risk Site	85.19	94.87	35	10.0%	22.4%

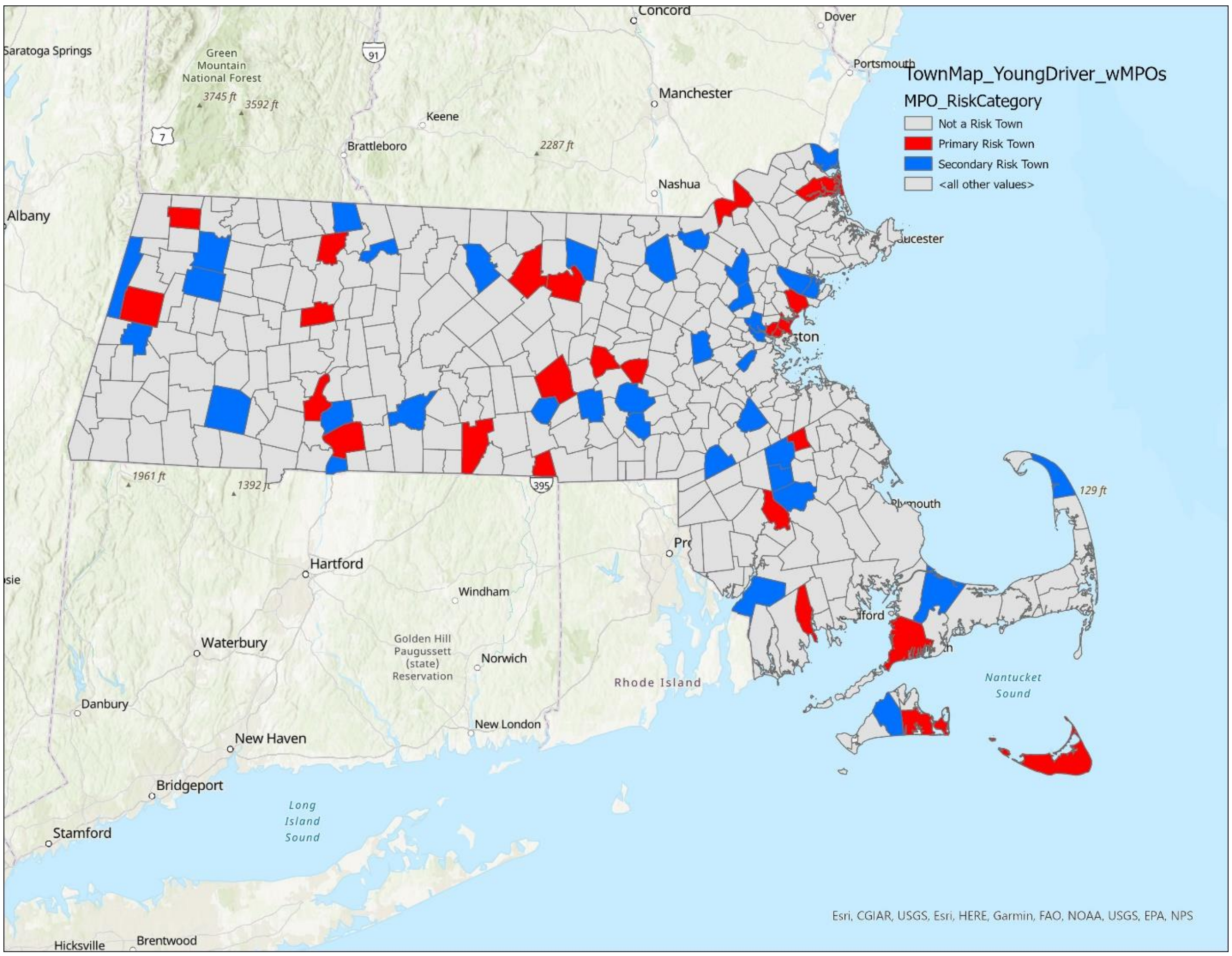

Figure 1. Map Depicting the Primary and Secondary Risk Towns for Severe Younger Driver Crashes, Ranked by MPO.

Risk Scores for Older Driver Crashes

Table 8 summarizes the suggested risk-scoring for older driver crashes based on the model results presented in Table 5. The table also provides an example application of the risk factors to a hypothetical town. The normalized risk score for the example town is 52.3 percent (4.71 divided by 9.0).

Similar to younger driver crashes, the risk scores suggested in this study were applied to 350 towns in Massachusetts. Table 9 provides the distribution of towns and older driver crashes at each risk category with the normalized risk score (presented as percentages) across these categories for statewide rankings. It can be seen that the top 5 percent of towns in the primary risk category are capturing approximately 15.0 percent of the severe older driver crashes, and the next top 10 percent are capturing an additional 20.0 percent of target crashes. Finally, the study suggested 18 towns in the primary risk category and 35 towns in the secondary risk category, as presented in Figure 2.

Table 8 Example Risk Score Calculation for Older Driver Crashes.

Variable	Risk Factor	Town Characteristic	Risk Score
Proportion of mileage that is interstate, freeway, or expressway	Continuous from 0 to 1 for the range of values.	0.009	0.25
The number of senior care providers in the town is more than 0.	1 if true; 0 otherwise	3	1
Annual impaired driving citations per centerline mile in the town is greater than 0.5.	1 if true; 0 otherwise	0.2	0
Annual speeding citations per mile in the town is greater than 3.	1 if true; 0 otherwise	4.1	1
Natural log of persons aged 65 or older in the town.	Continuous from 0 to 2 for the range of values.	5.011	1.1
2 or fewer assisted living facilities in the town	1 if true; 0 otherwise	3	0
The percentage of persons aged 65 or older with self-reported cognitive issues	Continuous from 0 to 0.5 for the range of values.	2.1%	0.14
Proportion of licensed drivers aged 65 or older	Continuous from 0 to 0.5 for the range of values.	3.4%	0.47
MPO is SRPEDD or OCPC	0.75 if true; else	MPO is SRPEDD	0.75
MPO is MVC	1 if true; else	MPO is SRPEDD	0
MPO is CCC or BRMPO	0.25 if true; 0 otherwise	MPO is SRPEDD	0
		Total Risk Score:	**4.71**
		Risk Percent Score (Out of 9):	**52.3%**

Table 9 Statewide Risk Categories for Older Driver Crashes

State	Risk Category	Minimum Normalized Risk Score Percentage	Maximum Normalized Risk Score Percentage	Number of Towns	Percent of Scored State Towns	Percent of Target Crashes
MA	Primary Risk Site	95.16	100	18	5.1%	14.8%
	Secondary Risk Site	85.18	94.87	35	10.0%	19.9%

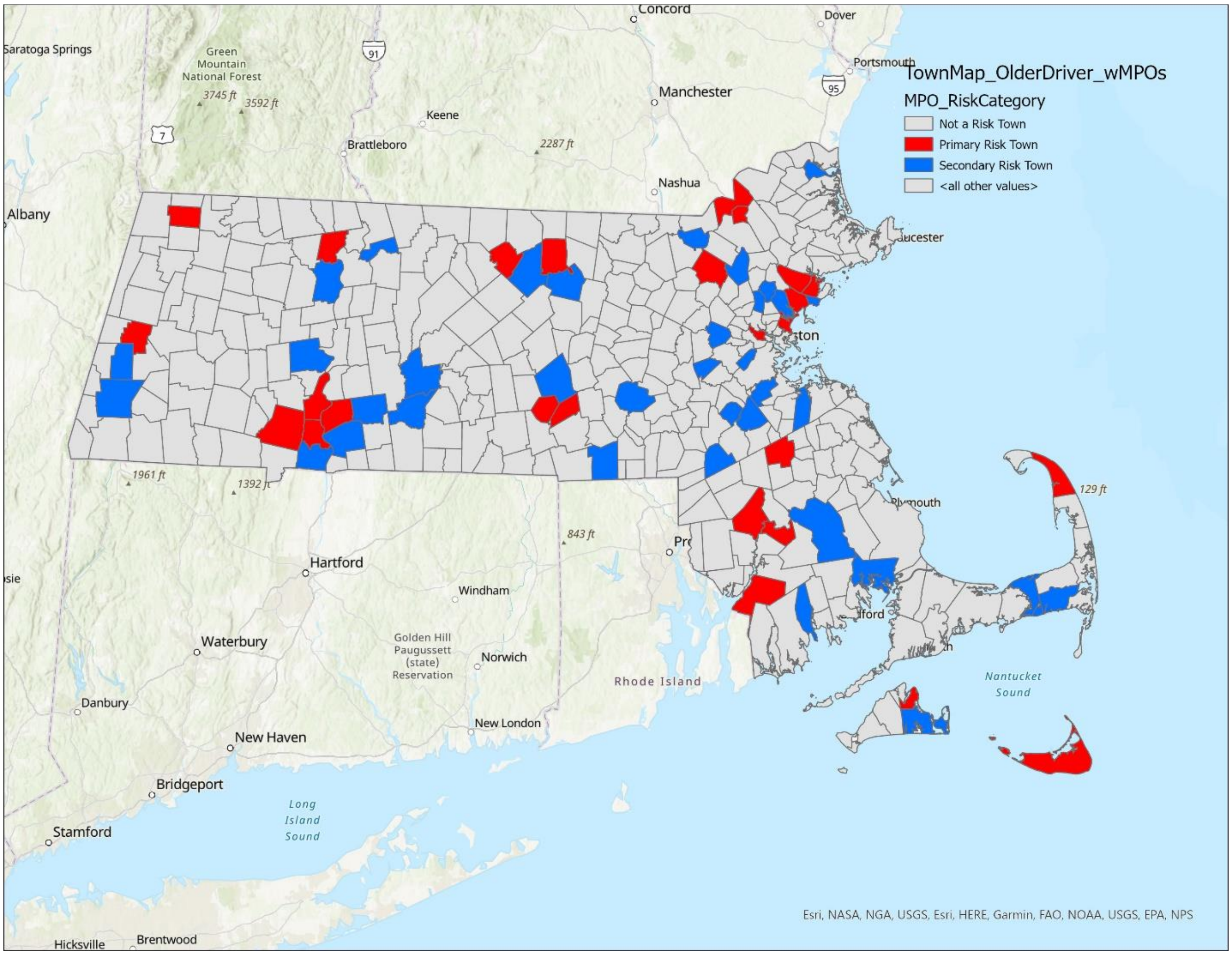

Figure 2. Map Depicting the Primary and Secondary Risk Towns for Severe Older Driver Crashes, Ranked by MPO.

CONCLUSIONS

Systemic safety analysis is a data-driven approach to identify and treat high-risk sites to prevent severe crashes before they happen. This study aimed to identify risk factors and critical communities associated with severe crashes involving younger and older drivers in Massachusetts. The analysis utilized a systemic approach to safety and focused on municipal-level crash analysis, aiming to identify towns and cities for prioritizing targeted safety improvement programs. The study first analysed crash data to identify overrepresented crash attributes in the databases for both focus crash types. Following that, SPFs were developed for severe younger and older driver crashes using NBR models. Separate comprehensive databases were prepared for these analyses that include crash, roadway, driver license, educational institution location, citation, healthy aging, seat belt use, and environmental justice data.

The results of the analysis revealed several key findings. For younger driver crashes, the presence of young drivers in the town, as indicated by the population aged 15-24, was positively correlated with severe crash frequency. Surrogate measures of risk-taking behaviors, such as unbelted citations, impaired driving citations, and observed unbelted occupants, were also significant factors contributing to crash frequency. Additionally, the presence of high-speed facilities and historically underinvested infrastructure, associated with the EJ community status, were positively correlated with young driver crash frequency. For older driver crashes, the presence of older drivers in the town, as indicated by the population aged 65 or older, was positively correlated with crash frequency. Several healthy aging indicators, such as reported cognitive issues and the presence of assisted living and senior care providers, were associated with increased older driver crash risk. General risk-taking behaviors on roadways, including impaired and speeding driving, were also significant risk factors. Furthermore, the presence of high-speed facilities, such as interstates, freeways, and expressways, indicated a higher proportion of high-speed driving and elevated crash energy in the town.

To implement the models as maps, the study assigned risk scores between 0 and 1 based on the character of each variable included in the SPF, instead of directly using regression coefficients. For variables with weak statistical significance (p-value > 0.05), a maximum risk score of 0.5 is assigned. Binary risk scores are used for binary predictive variables. The risk scores were then normalized to provide a risk score out of 100 percent. The risk scores were then applied to 350 towns in Massachusetts, which were then ranked using a “weak” ranking approach. Towns are then categorized as primary risk towns if they rank in the top 5 percentile and secondary risk towns if they rank in the next 10 percentile. The remaining towns are not categorized. This resulted in 18 towns in the primary risk category and additional 35 towns in the secondary risk category. In the case of younger drivers, the top 5 percent of towns categorized as primary risk are associated with approximately 14.0 percent of severe younger driver crashes, while the next top 10 percent captured an additional 22.4 percent of target crashes. For older drivers, the top 5 percent of primary risk towns captured approximately 15.0 percent of severe older driver crashes, and the next top 10 percent captured an additional 20.0 percent of target crashes.

The identified towns in the primary and secondary risk categories require higher-level attention to reduce both younger and older driver severe crashes. By focusing on these towns, transportation agencies, and stakeholders can prioritize resources and implement targeted countermeasure programs to enhance road safety for both age groups. MassDOT and their safety partners should consider these findings when identifying potential younger driver and older driver countermeasures. The National Highway Traffic Safety Administration’s (NHTSA) Countermeasures that Work includes several examples of effective campaigns targeting younger and older drivers. Countermeasures targeting the younger drivers include Graduated Driver Licensing (GDL), learner's permit length and supervised hours, intermediate restrictions on nighttime driving and passengers, and cell phone restrictions (*23*). Example strategies for older drivers include formal courses, general education, license screening and testing, and license restrictions (*24*).

In summary, this study demonstrates the importance of adopting a systemic safety approach to address the challenges posed by younger and older driver crashes. The findings highlight the significance of exposure, risk-taking behaviors, and infrastructure characteristics in influencing crash frequency. By proactively addressing these risk factors, agencies can work towards achieving the goal of reducing fatal and serious injury crashes, ensuring safer roads for all road users, regardless of age. This analysis should not restrict further in-depth investigations into specific sites and factors impacting these focus crash types.

DISCLAIMER

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AUTHOR CONTRIBUTION

The authors confirm their contribution to the paper as follows: study conception and design: J. Gooch, M.S. Mahmud, F. Gross, B. Polin; data collection: J. Gooch, M.S. Mahmud, B. Polin; analysis and interpretation of results: J. Gooch, M.S. Mahmud; draft manuscript preparation: J. Gooch, M.S. Mahmud, F. Gross. All authors reviewed the results and approved the final version of the manuscript.

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