Updates to Risk Factors for SHSP Emphasis Areas

Impaired Driving

PREPARED FOR

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PREPARED BY

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Purpose & Background

The Massachusetts Department of Transportation (MassDOT) is updating the risk-based network screening maps in the IMPACT tool to incorporate recent crash data and build on lessons learned from previous analyses. This document describes the updated systemic analysis performed by VHB for impaired driving-related crashes using crash data from 2017 through 2021. For this analysis, VHB used the default "Impaired Driving" query[1] in the MassDOT IMPACT tool. The definition reads as: any crash in which one or more of the drivers has the "Alcohol Suspected" flag reported as "Yes".[2]

Note that the purpose of this report is to identify the factors most correlated with the frequency and severity of impaired driving-related crashes; causality was not directly investigated. As such, agencies interested in developing targeted countermeasure programs are encouraged to perform some initial investigation into causality of the target crash in their jurisdiction. This will allow the agency to develop targeted countermeasures.

Data Analysis and Focus Crash Types

To establish context, VHB first used the MassDOT IMPACT "Test of Proportions" tool[3] to summarize fatal injury (K) and suspected serious injury (A) of impaired driving crashes. To identify overrepresented crash attributes, VHB compared KA impaired driving crashes to all KA crashes in the State. 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. Figure 1 and Figure 2 show how the lower and upper bounds, respectively, are calculated based on the proportion of crashes (*p*) and the number of crashes in the sample (*N*). If the lower bound of impaired driving KA crashes is larger than the upper bound of the comparison group, the attribute was considered "overrepresented" for the data.

$$95\%\ Confidence\ Interval, Lower\ Bound\ =\ p - 1.96 * \sqrt{\frac{p(1-p)}{N}}$$

Figure 1. Calculation of the lower bound of the 95 percent confidence interval for the proportion of crashes with an attribute.

$$95\%\ Confidence\ Interval, Upper\ Bound\ =\ p + 1.96 * \sqrt{\frac{p(1-p)}{N}}$$

Figure 2. Calculation of the upper bound of the 95 percent confidence interval for the proportion of crashes with an attribute.

Table 1 summarizes notable overrepresentations found in the analysis. VHB included the following data elements in their analysis:

- Access Control.

[1] https://www.mass.gov/info-details/impact-emphasis-area-definitions

[2] MassDOT. *Impact Emphasis Area Definitions.* Available at: https://www.mass.gov/info-details/impact-emphasis-area-definitions. Accessed March, 2023.

[3] https://apps.impact.dot.state.ma.us/sat/TestofProportions

- Age of Driver – Oldest known.
- Age of Driver – Youngest Known.
- Age of Non-Motorist – Oldest Known.
- Age of Non-Motorist – Youngest Known.
- County Name.
- Crash Day of Week.
- Crash Month.
- Curb.
- Driver Contributing Circumstances.
- Driver Distracted By.
- Facility Type.
- Federal Functional Class.
- First Harmful Event.
- First Harmful Event Location.
- FMCSA Reportable.
- Functional Class.
- Jurisdiction.
- Left Shoulder Type-linked.
- Left Shoulder Width-linked.
- Light Conditions.
- Manner of Collision.
- Max Injury Severity Reported.
- Median Type.
- Operation.
- Opposite Number of Travel Lanes.
- Right Shoulder Type-linked.
- Right Shoulder Width-linked.
- Road Contributing Circumstance.
- Road Surface Condition.
- Roadway Junction Type.
- Speed Limit.
- Terrain Type.

- Total Lanes.
- Traffic Control Device Type.
- Trafficway Description.
- Urban Type.
- Weather Conditions.

Table 1. Summary of Key Overrepresentation Findings.

Crash Field	Crash Attribute	Percent of Impaired Driving KA Crashes	Percent of All KA Crashes
Traffic Control Device Type	No controls	81.40%	71.77%
Age of Driver - Youngest Known	21-24	19.80%	13.86%
	25-34	34.80%	27.33%
Crash Day of Week	Sunday	23.60%	14.51%
	Saturday	22.30%	16.09%
Curb	None	51.20%	40.86%
First Harmful Event	Collision with guardrail	6.50%	4.03%
	Collision with other light pole or other post/support	2.70%	1.41%
	Collision with tree	14.50%	7.43%
	Collision with unknown fixed object	4.30%	2.02%
	Collision with utility pole	10.90%	5.13%
First Harmful Event Location	Outside roadway	18.30%	10.08%
	Roadside	15.40%	9.29%
	Shoulder - unpaved	3.60%	1.70%
Light Conditions	Dark - lighted roadway	48.60%	26.43%
	Dark - roadway not lighted	20.90%	9.60%
Manner of Collision	Head-on	13.70%	10.98%
	Single vehicle crash	55.20%	42.37%
Right Shoulder Type-linked	Stable - Unruttable compacted subgrade	15.60%	10.63%
Right Shoulder Width-linked	2	26.80%	19.76%
Driver Contributing Circumstances	Exceeded authorized speed limit	7.02%	4.04%
	Operating vehicle in erratic, reckless, careless, negligent or aggressive manner	29.71%	8.57%
	Other improper action	5.10%	3.01%
	Wrong side or wrong way	2.39%	1.31%
	Physical impairment	9.37%	1.61%
Driver Distracted By	Other activity (searching, eating, personal hygiene, etc.)	6.84%	2.86%
	Passenger	1.03%	0.39%

Crash Field	Crash Attribute	Percent of Impaired Driving KA Crashes	Percent of All KA Crashes
	Unknown	34.81%	29.79%
Road Contributing Circumstances	None	85.60%	77.40%
Roadway Junction Type	Not at junction	74.50%	59.26%
Urban Type	Rural	5.90%	3.78%
Weather Condition	Clear	71.89%	68.20%

From a safety management perspective, it is notable that impaired driving-related KA crashes were overrepresented in rural areas (although these crashes represent a relatively small percentage overall), particularly on roadways without traffic control devices and away from junctions. All these factors indicate a potential for a higher speed, which may lead into a higher severe crash frequency. These crashes were also more frequent in areas with narrower shoulder widths and where curbs were absent. Additionally, they occurred with higher frequency during weekends and among younger drivers aged 21 to 34 years. Unsurprisingly, various forms of erratic driver behavior were prominently observed in the driver contributing circumstances field. These included exceeding the authorized speed limit, operating the vehicle in an erratic, reckless, careless, negligent, or aggressive manner, engaging in other improper actions, driving on the wrong side or in the wrong direction, and being physically impaired. Furthermore, distractions caused by passengers or engaging in other activities such as searching, eating, and personal hygiene were also statistically disproportionately present in these crashes. Nighttime hours, both on illuminated and non-illuminated roadways, exhibited a higher occurrence of such crashes. Regarding the manner of collision, head-on and single-vehicle crashes were overrepresented in impaired driving-related KA crashes. The specific types of collisions overrepresented in these cases included collisions with guardrails, light poles or other posts/supports, trees, unknown fixed objects, and utility poles. Interestingly, these crashes were more common under clear weather conditions, and no particular roadway circumstances impacted these crashes more.

MassDOT should consider these findings when identifying potential impaired driver countermeasures. The National Highway Traffic Safety Administration's (NHTSA) *Countermeasures that Work*[4] includes several examples of effective campaigns targeting impaired driving including administrative license revocation or suspension (ALR/ALS), high-blood alcohol level (BAC) sanctions, publicized sobriety checkpoints, high-visibility saturation patrols, preliminary breath test devices, alcohol screening and brief intervention, and minimum drinking age 21 laws. While these are notable results, they should not restrict the analysis from focusing on all impaired driver crashes. These results should be considered when developing projects and countermeasures at impaired driver risk sites. Ultimately, the focus crash type for this analysis is all impaired driving crashes.

Crash Tree and Focus Facility Type

After concluding that the impaired driving focus crash type should include all impaired driving crashes, VHB developed a crash tree to identify the roadway characteristics and lighting conditions under which severe impaired driving crashes tend to occur most often. Figure 3 shows the crash tree. It is evident that the majority of KA crashes related to impaired driving took place in urban areas. Although most of these crashes occurred outside of junctions, a significant portion of these also happened within junctions. Among the crashes outside junctions, most of these occur during nighttime. These nighttime crashes occurred more at locations where the right shoulder was narrower.

[4] https://www.nhtsa.gov/book/countermeasures/countermeasures-work/alcohol-and-drug-impaired-driving

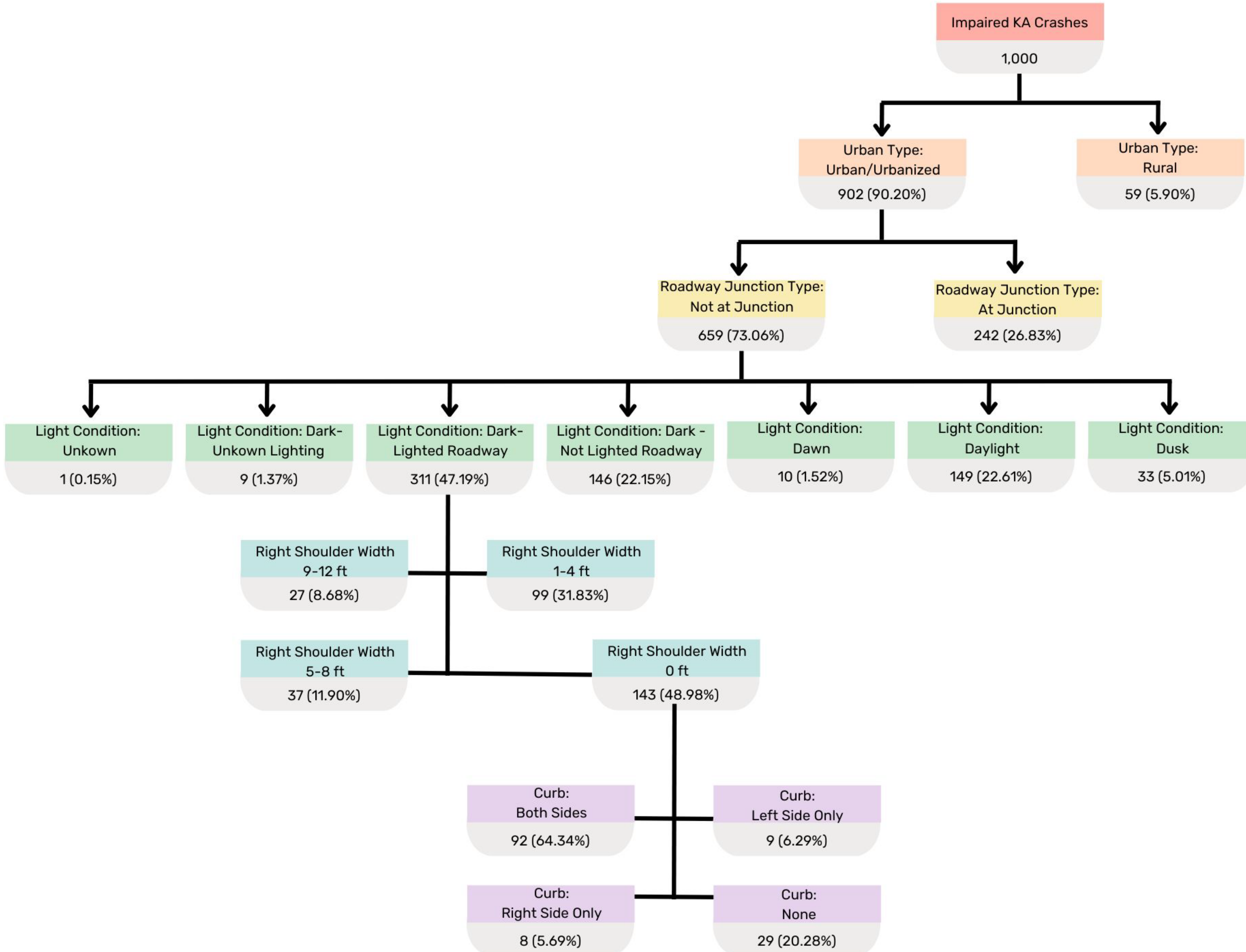

Figure 3. Crash tree summarizing KA impaired driving crashes in Massachusetts

While the analysis above points towards some potential focus for this emphasis area (e.g., urban areas, not at a junction, roadways with narrower shoulders, and during nighttime), impaired driving crashes are best addressed directly using educational campaigns. As a result, VHB recommends performing a town-based analysis of impaired driving crashes. This allows for the prioritization of towns for the reception of grants and encouragement for impaired driving safety campaigns.

Risk Factor Analysis

After identifying focus crash types and trends, VHB proceeded with the risk factor analysis. The following sections describe the methodology, data, and results of this analysis.

Methodology

Negative binomial regression is a standard approach to crash frequency modeling given that crash frequency data are typically overdispersed count data. As such, VHB used a negative binomial count regression modeling approach to identify community-level characteristics associated with higher frequencies of impaired driving-related KA crashes. Negative binomial regression is commonly used in transportation safety as it applies to over-dispersed count data (i.e., the variance exceeds the mean of the observed data). The dependent variable in the model is the number of impaired driving-related KA crashes, making a count model appropriate for the data. The functional form of the negative binomial regression model is shown in Figure 4.[5]

$$\lambda_i = e^{\beta X_i + \varepsilon_i}$$

Figure 4. Negative binomial regression functional form.

Where:

$e^{\varepsilon i}$ = gamma-distributed error term with a mean equal to one and variance equal to α.

λ_i = expected number of impaired driving-related KA crashes at location i.

β = vector of estimated parameters.

X_i = vector of independent variables that characterize location i and influence impaired driving-related KA crash frequency.

When modeling, VHB began with road exposure variables and added additional variables one at a time, monitoring the coefficients to ensure the inclusion of a variable did not result in large changes in magnitude. Additionally, VHB included variables with p-values upwards of 0.25 assuming the magnitude of the results made sense. VHB did not select a strict level of significance, as Hauer notes this could lead to misunderstanding or outright disregard for potentially noteworthy results.[6]

Data

VHB used ArcGIS to manage and integrate data for this analysis. VHB aggregated data at the city and town level. In Massachusetts, all roads and geographic areas are covered by town jurisdictions. Due to

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[5] Lord, D., Mannering, F., 2010. The Statistical Analysis of Crash-Frequency Data: A Review and Assessment of Methodological Alternatives. Transp. Res. Part A Policy Pract. 44 5 , 291–305. doi:10.1016/j.tra.2010.02.001
[6] Hauer, E. (2004). The harm done by tests of significance. *Accident Analysis & Prevention*, *36*(3), 495-500.

limitations with crash data acquisition, VHB excluded the City of Boston from the analysis. MassDOT provided VHB with various sources of data, as described in the following sections.

Crash Data

VHB obtained total impaired driver crashes by town using the MassDOT IMPACT Test of Proportions tool. VHB then joined these totals to the town-level data set.

Roadway Data

VHB downloaded the Massachusetts statewide Road Inventory 2021 file, available at https://geo-massdot.opendata.arcgis.com/datasets/342e8400ba3340c1bf5bf2b429ad8294/about. Based on discussions with MassDOT, VHB filtered the roadway data 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. VHB aggregated the 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. VHB used spatial analysis to assign driver license zip codes to the relevant town, joining the driver license totals by age. VHB then calculated the average number of licensed drivers by age group for each town and integrated with town-level data.

School Location Data

VHB obtained primary and secondary school location data from the Massachusetts Bureau of Geographic Information (MassGIS) open data portal (https://www.mass.gov/info-details/massgis-data-massachusetts-schools-pre-k-through-high-school). VHB then used spatial analysis to determine the total number of schools in each town.

College and University Data

VHB accessed college and university location data from the MassGIS open data portal (https://www.mass.gov/info-details/massgis-data-colleges-and-universities). Although these data contain several categories of trade schools and other atypical technical training institutions, VHB only included "Colleges, universities, and professional schools," "Fine arts schools," "Junior colleges," and "Other technical and trade schools" for the purposes of this analysis.

Citation Data

VHB obtained traffic citation count data by town for a five-year period between 2015 and 2019. These data included total citations, as well as subsets of counts for speeding-, seat belt-, impaired driving-, and distraction-related traffic citations.

Additional Data

VHB obtained several additional data sources for integration into the data set, including census and American Community Survey (ACS) data, public health data from the Massachusetts Department of Public Health (DPH), alcohol shop location data, healthy aging data from DPH, seatbelt use survey data at the county level, and environmental justice (EJ) data provided by Environmental Justice Community Block

Group Data Update. Note that, regarding EJ data, the reports may change if the final layers were used but they were not available at the time the analyses were performed. The version of Massachusetts 2020 Environmental Justice Block Group data available at the time of the analysis was a preliminary version that was later updated with a final.

Results

The following sections describe the results of the negative binomial regression modeling effort.

Variables of Interest

To account for unobserved influences due to road facilities and traffic exposure, VHB established a base model that included the natural log of the mile years (i.e., the product of five years of data and total centerline mileage in the town). Before including additional variables in the negative binomial, VHB developed a correlation matrix of input variables. Highly correlated variables are indicators of potential complications in the model development process. Although VHB considered all potential variables in this matrix, Table 2 shows the correlation matrix for the following 10 variables (listed here) included in the final impaired driver model. Note the maximum correlation between any two variables is -0.44, below the standard value of 0.7, above which there are concerns of serial correlation.

1. Population density between 300 and 2,000 residents per square mile in the city or town.
2. Population density greater than 2,000 residents per square mile in the city or town.
3. Indicator that Alcoholic Beverages Control Commission (ABCC) licenses per 1,000 residents in the city or town is 0.5 or greater.
4. Indicator that proportions of Centerline Mileage in the City/Town that is Rural or Urban Principal Arterial[7] is Greater than 0.05.
5. Indicator that annual impaired driving citations per centerline mile is greater than 0.5.
6. Indicator that annual distracted driving citations per centerline mile is greater than 0.25.
7. Indicator that proportions of driver seat belt use less than 0.8.
8. Indicator that proportions of younger population (age 15-24) is greater than 0.10.
9. Indicator that proportions of older population (65+) is greater than 0.2.
10. Indicator that GINI index higher than the state average. Note that, GINI index is a measure of statistical dispersion intended to represent the income inequality, the wealth inequality or the consumption inequality in the defined area.

[7] Federal functional class 2.

Table 2. Correlation Matrix of Input Variables.

Variables	Pop Density: 300-2000	Pop Density: >2000	ABCC proportion	Functional Class 2	Impaired Citations	Distracted Citations	Unbelted survey	Younger Population	Older Population	GINI Index
Pop Density: 300-2000	1.000									
Pop Density: >2000	-0.418	1.000								
ABCC proportion	0.100	0.129	1.000							
Functional Class 2	-0.099	-0.124	0.076	1.000						
Impaired Citations	0.408	0.162	0.233	-0.002	1.000					
Distracted Citations	0.060	0.437	0.140	-0.065	0.395	1.000				
Unbelted survey	0.065	-0.078	0.041	0.176	0.021	-0.034	1.000			
Younger Population	0.243	-0.016	0.122	-0.037	0.283	0.140	-0.072	1.000		
Older Population	-0.220	-0.176	-0.175	0.001	-0.256	-0.295	0.116	-0.409	1.000	
GINI Index	-0.052	0.007	-0.042	-0.023	-0.074	0.005	0.045	-0.185	0.065	1.000

Model Results

Table 3 documents the negative binomial regression results and presents coefficients, standard error, z-value, p-value, and 95 percent confidence intervals for each variable included in the final model. The model predicts the number of KA impaired driving crashes expected in a town. The natural log of the product of centerline mileage and 5 years of crash data were included in the model to offset exposure for each town. The independent variables include a mix of population, roadway, citation, and income inequality (GINI index) related variables.

Town population density provides some overall level of exposure for the town – towns with high relative population densities experienced a higher frequency of severe impaired driving-related crashes. Not surprisingly, a higher proportion of ABCC licenses per 1,000 residents was positively correlated with impaired KA crashes. The high proportion of rural or urban principal arterial may be associated with a lower level of design (compared to freeways and interstates), increased stops, and increased conflicts.

The impaired driving citation metric provides some direct measure of the level of impaired driving in the town, while the distracted citation metrics provide an additional surrogate level of exposure for risky driving behaviors. Not surprisingly, towns with a lower level of seat belt use also demonstrated a higher likelihood of severe impaired driving-related crashes – as a low-level of seat belt use is a surrogate for elevated risk-taking behavior by drivers. Towns with a higher proportion of younger population also experienced more of these crashes supporting a higher likelihood of impaired driving behavior among the younger population. On the contrary, towns with a higher proportion of older population indicated a lower likelihood of impaired driving-related KA crashes. Interestingly, towns having a GINI Index higher than the state average experienced significantly lower impaired driving-related crashes. While available studies focusing on impaired driving-related crashes are limited, findings largely align with the few prior available studies on this topic.[8,9]

[8] Identification of factors associated with various types of impaired driving. https://www.nature.com/articles/s41599-022-01041-7

[9] Analyzing the Effect of Distractions and Impairments on Young Driver Safety Using Naturalistic Driving Study Data. https://ascelibrary.org/doi/10.1061/JTEPBS.TEENG-7265

Table 3. Negative Binomial Count Regression Model Results.

Variable (Number)	Coefficient	Standard Error	z-value	P>|z|	95% Confidence Interval	
Intercept	-6.696	0.334	-20.070	<0.001	-7.351	-6.041
Between 300 and 2,000 residents per square mile in the city or town	0.360	0.127	2.844	0.004	0.111	0.609
More than 2,000 residents per square mile in the city or town	0.457	0.150	3.054	0.002	0.163	0.751
ABCC licenses per 1,000 residents in the city or town is 0.5 or greater	0.614	0.307	1.998	0.046	0.012	1.216
Proportion of centerline mileage in the city/town that is rural or urban principal arterial is greater than 0.05	0.325	0.110	2.965	0.003	0.109	0.541
Annual impaired driving citations per centerline mile is greater than 0.5	0.315	0.125	2.516	0.012	0.070	0.560
Annual distracted driving citations per centerline mile is greater than 0.25	0.331	0.094	3.506	<0.001	0.147	0.515
Proportion of driver seat belt use less than 0.8	0.189	0.084	2.236	0.025	0.024	0.354
Proportion of younger population (age 15-24) is greater than 0.10	0.176	0.110	1.594	0.111	-0.040	0.392
Proportion of older population (65+) is greater than 0.2	-0.242	0.105	-2.300	0.021	-0.448	-0.036
GINI index higher than the state average	-0.320	0.114	-2.805	0.005	-0.543	-0.097
Natural Log of the product of centerline mileage and years – Offset	1.000	NA	NA	NA	NA	NA
alpha	0.10					

Note: Number of observations = 349; AIC=1242.6, Log likelihood = -609.3115

Conclusions and Recommendations

The purpose of this analysis is to identify town-level risk factors for fatal and serious injury impaired driving crashes. Instead of using the coefficients in the negative binomial regressions results from Table 3, VHB recommends that MassDOT assign risk scores between 0 and 1 based on the character of the risk factor. VHB and MassDOT made this decision to avoid overly weighting any one risk factor, especially considering potential data issues with the risk factor data which may cause biases. Table 4 summarizes the suggested risk scoring schema. Where a binary predictive variable was used, binary risk scores are applied. From a modeling perspective, the cutoffs for the binary variables were determined by using visual representations of the data and smaller bins to find the cutoffs which make the most sense.

Table 4. Town-level risk factors for Impaired Driver KA Crashes.

Risk Factor for Impaired Driver KA Crashes	Suggested Scoring
Between 300 and 2,000 residents per square mile in the city or town	0.75 if true; else
More than 2,000 residents per square mile in the city or town	1 if true; 0 otherwise
ABCC licenses per 1,000 residents in the city or town is 0.5 or greater	1 if true; 0 otherwise
Proportion of centerline mileage in the city/town that is rural or urban principal arterial is greater than 0.05	1 if true; 0 otherwise
Annual impaired driving citations per centerline mile is greater than 0.5	1 if true; 0 otherwise
Annual distracted driving citations per centerline mile is greater than 0.25	1 if true; 0 otherwise
Proportion of driver seat belt use less than 0.8	1 if true; 0 otherwise
Proportion of younger population (age 15-24) is greater than 0.10	1 if true; 0 otherwise
Proportion of older population (65+) is greater than 0.2	1 if less than 0.2; 0 otherwise
GINI index higher than the state average (state average is 0.4826)	0 if true; 1 otherwise
Maximum potential score for a town:	**9.0**

Table 5 provides an example application of the risk factors of a hypothetical town. To provide context for these risk factor scores in relation to other emphasis areas, MassDOT can normalize the cumulative score by dividing by the total potential score for a town. This would generate a risk score out of 100 percent for each town. Under this approach, the normalized risk score for the example town is 63.9 percent (5.75 divided by 9.0).

Table 5. Example Risk Score Calculation for Impaired Driving Crashes.

Variable	Town Characteristic	Risk Factor	Risk Score
Between 300 and 2,000 residents per square mile in the city or town	Population density of 750	0.75 if true; else	0.75
More than 2,000 residents per square mile in the city or town	Population density of 750	1 if true; 0 otherwise	0
ABCC licenses per 1,000 residents in the city or town is 0.5 or greater	Proportion is 0.63	1 if true; 0 otherwise	1
Proportion of centerline mileage in the city/town that is rural or urban principal arterial is greater than 0.05	Proportion is 0.08	1 if true; 0 otherwise	1
Annual impaired driving citations per centerline mile is greater than 0.5	Proportion is 0.45	1 if true; 0 otherwise	0

Variable	Town Characteristic	Risk Factor	Risk Score
Annual distracted driving citations per centerline mile is greater than 0.25	Proportion is 0.28	1 if true; 0 otherwise	1
Proportion of driver seat belt use less than 0.8	Proportion is 0.91	1 if true; 0 otherwise	0
Proportion of younger population (age 15-24) is greater than 0.10	Proportion is 0.15	1 if true; 0 otherwise	1
Proportion of older population (65+) is greater than 0.2	Proportion is 0.30	1 if less than 0.2; 0 otherwise	0
GINI index higher than the state average (state average is 0.4826)	Index is 0.52	0 if true; 1 otherwise	1
Total Risk Score:			5.75
Risk Percent Score (Out of 9.0):			63.9%

Generally, the model and risk factors produce results that were expected by the VHB and MassDOT team. Several factors point toward increased impaired driver exposure (e.g., higher population density, and younger person population), which is expected to be correlated with higher impaired driving 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 impaired driver population (e.g., impaired driving citations, lower seat belt use rate, and distracted driving citations)[10,]. The presence of low-speed facilities (e.g., arterials) point toward the correlation of infrastructure and impaired driving crash frequency. Having a higher ABCC license per 1,000 residents is also directly correlated with impaired driving crash frequency.

MassDOT ranked the towns at both the statewide and MPO levels 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. For impaired driving-related crashes, normalized risk scores range from 0.11 to 0.97. The maximum value (0.97) received a percentile rank of 100 and other values received a percentile rank accordingly. For example, a town with a normalized risk score of 0.75, the calculated percentile rank was 98.86, and fell in the primary risk category. MassDOT then assigned risk categories 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 top 5 percent or next 10 percent may not be equal to 5 percent or 10 percent. This is a byproduct of the weak ranking approach.

Table 6 and Table 7 show the distribution of towns and crashes with the normalized risk score (presented as percentages) across these categories for statewide and MPO rankings, respectively. Note the goal was to see a higher proportion of target crashes for primary and secondary risk sites than proportion of towns. Similarly, Figure 5 is a map of the risk towns ranked statewide, while Figure 6 is a map of the risk towns ranked by MPO. These figures indicate the towns in the State that may deserve a higher-level of attention to reduce statewide impaired driving-related crashes. Note that it may be more appropriate to utilize

[10] Identification of factors associated with various types of impaired driving. https://www.nature.com/articles/s41599-022-01041-7

statewide ranking for towns, particularly for the ones that are in the MPOs/RPAs with few towns, as the results for these towns may be skewed. There is a total of 29 towns in the primary risk category (top 5 percent), that captured 16.80 percent of the severe impaired driving-related crashes. Similarly, there are 39 towns in the secondary risk category (next top 10 percent), which captured additional 15.50 percent of the severe impaired driving-related crashes. The towns that are in the primary risk category for severe impaired driving-related crashes are Fall River, Lenox, Chelsea, Freetown, Woburn, Leominster, Dalton, Methuen, Revere, West Bridgewater, Brockton, Burlington, Wareham, Bourne, Whitman, Somerset, Great Barrington, Raynham, Marion, Quincy, Natick, Sutton, Worcester, Randolph, Salem, Stoneham, North Andover, Newburyport, and Westport. Nine of these towns were under Boston Region MPO, and six of these were under Pioneer Valley Planning Commission. A higher number of secondary risk category towns for impaired driving-related crashes were also under these two MPOs.

Table 6. Statewide Risk Categories.

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	66.67%	97.22%	29	8.26%	16.80%
	Secondary Risk Site	63.89%	63.89%	39	11.11%	15.50%

Table 7. Distribution of Risk Towns my MPO.

MPO	Risk Category	Minimum Normalized Risk Score Percentage	Maximum Normalized Risk Score Percentage	Number of Towns	Percent of Scored MPO Towns	Percent of Target Crashes in MPO
Berkshire Regional Planning Commission	Primary	66.67%	66.67%	3	9.38%	31.25%
	Secondary	55.56%	63.89%	5	15.63%	15.63%
Boston Region MPO	Primary	66.67%	66.67%	9	9.28%	16.82%
	Secondary	63.89%	63.89%	9	9.28%	6.23%
Cape Cod Commission	Primary	97.22%	97.22%	1	6.67%	7.14%
	Secondary	63.89%	63.89%	2	13.33%	8.93%
Central Massachusetts Regional Planning Commission	Primary	66.67%	77.78%	2	5.00%	15.31%
	Secondary	63.89%	63.89%	6	15.00%	13.27%
Franklin Regional Council of Governments	Primary	52.78%	55.56%	2	7.69%	26.32%
	Secondary	44.44%	44.44%	2	7.69%	15.79%
Martha’s Vineyard Commission	Primary	52.78%	52.78%	1	14.29%	25.00%
	Secondary	44.44%	44.44%	1	14.29%	25.00%
Merrimack Valley Planning Commission	Primary	75.00%	75.00%	1	6.67%	4.84%
	Secondary	66.67%	66.67%	2	13.33%	20.97%
Montachusett Regional Planning Commission	Primary	63.89%	75.00%	2	9.09%	22.50%
	Secondary	52.78%	55.56%	3	13.64%	22.50%
Nantucket Planning and Economic Development Commission	Primary	44.44%	44.44%	1	100.00%	
	Secondary	N/A	N/A	0	0%	0%
Northern Middlesex Council of Governments	Primary	63.89%	63.89%	1	11.11%	8.89%
	Secondary	55.56%	55.56%	1	11.11%	15.56%
Pioneer Valley Planning Commission	Primary	55.56%	63.89%	6	13.95%	28.28%
	Secondary	52.78%	52.78%	5	11.63%	11.11%
Old Colony Planning Council	Primary	75.00%	75.00%	1	5.88%	12.22%
	Secondary	66.67%	66.67%	2	11.76%	12.22%
Southeastern Regional Planning and Economic Development District	Primary	77.78%	86.11%	2	7.41%	2.24%
	Secondary	75.00%	75.00%	3	11.11%	16.42%

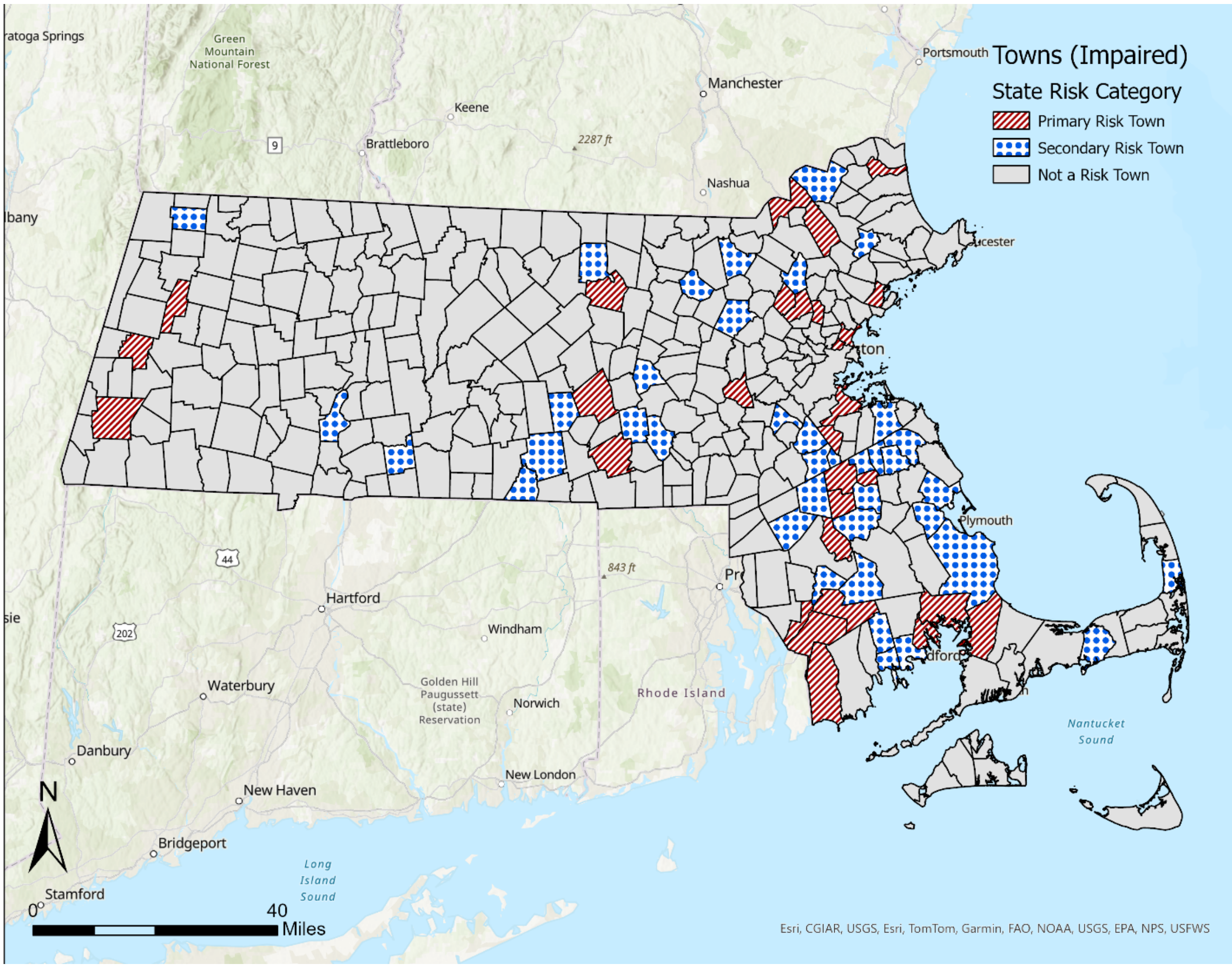

Figure 5. Map depicting the primary and secondary risk towns for severe impaired driving crashes, ranked statewide.

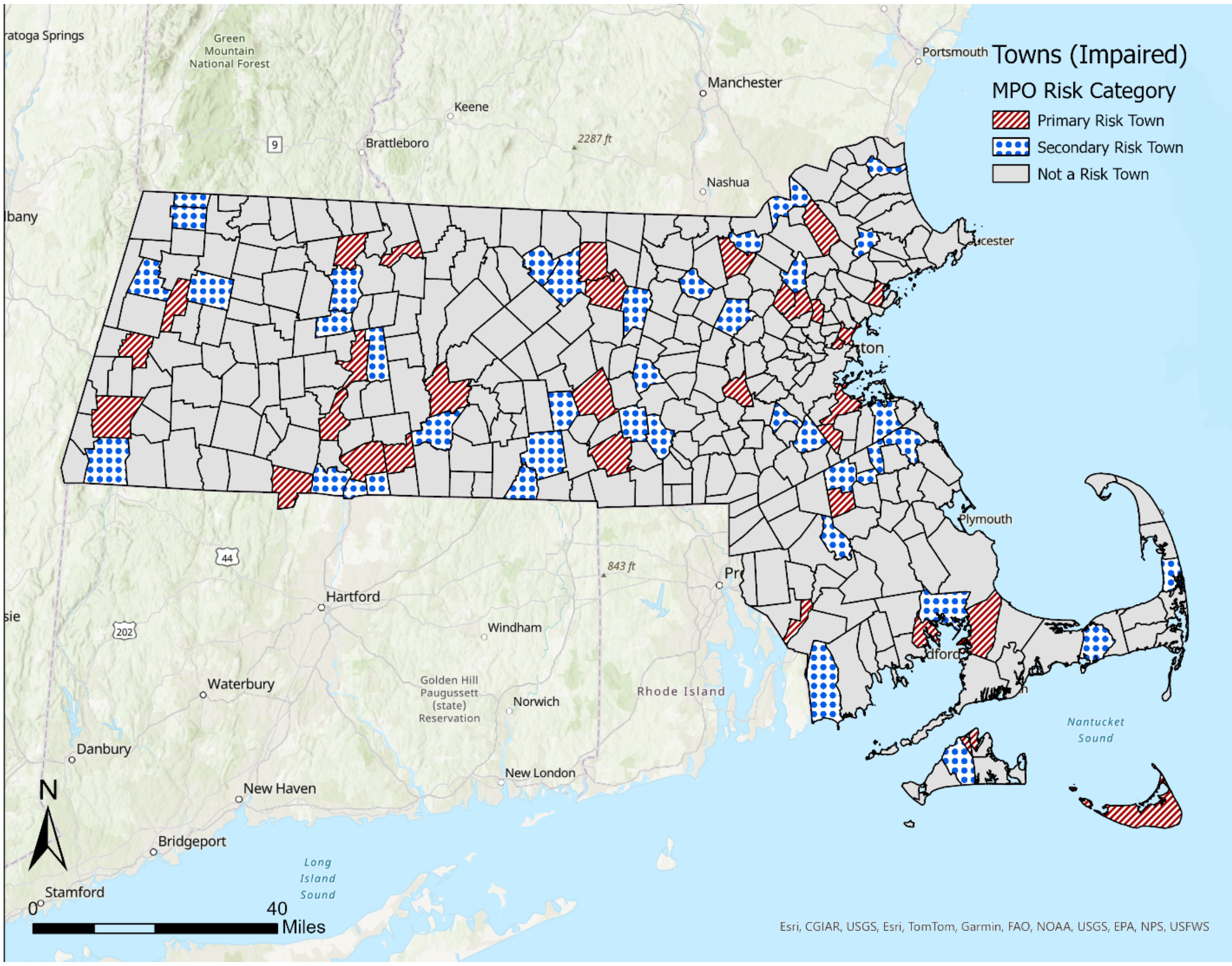

Figure 6. Map depicting the primary and secondary risk towns for severe impaired driving crashes, ranked by MPO.