Development of Safety Performance Function Based on Vehicle Automation Levels: A Case Study on Rearend Crashes

A Technical Report Submitted to the Rural Safe Efficient Advanced Transportation (R-SEAT) Center and United States Department of Transportation

FINAL REPORT

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DISCLAIMER

METRIC CONVERSION CHART

When You Know	Multiply by	To Find
Length		
inches (in)	25.4	millimeters (mm)
feet (ft)	0.305	meters (m)
yards (yd)	0.914	meters (m)
miles (mi)	1.61	kilometers (km)
Volume		
fluid ounces (fl oz)	29.57	milliliters (mL)
gallons (gal)	3.785	liters (L)
cubic feet (ft^3)	0.028	meters cubed (m^3)
cubic yards (yd^3)	0.765	meters cubed (m^3)
Area		
square inches (in^2)	645.1	millimeters squared (mm^2)
square feet (ft^2)	0.093	meters squared (m^2)
square yards (yd^2)	0.836	meters squared (m^2)
acres	0.405	hectares (ha)
square miles (mi^2)	2.59	kilometers squared (km^2)

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16. Abstract

Traditionally, transportation agencies rely on safety performance functions (SPFs) and safety effectiveness metrics to support network screening, identify high-risk roadway segments, and quantify the safety benefits of countermeasures. However, existing SPFs and safety effectiveness metrics were developed using crash data from conventional vehicles and do not explicitly account for the growing penetration of advanced driver assistance systems (ADAS)-equipped vehicles. As a result, combining crash data from conventional and automated vehicles may mask the distinct safety effects attributable to vehicle automation. Despite increasing ADAS adoption, no prior study has systematically developed SPFs and safety effectiveness metrics that explicitly capture the safety impacts of individual ADAS technologies on crash frequency and injury severity. While recent efforts have begun adapting traditional safety models to account for automated vehicles, comprehensive and transferable methodologies remain limited. Addressing this gap, the current study develops SPFs and safety effectiveness metrics tailored to ADAS-equipped vehicles, with a specific focus on rear-end crashes influenced by ADAS functionality. The results demonstrate the feasibility of isolating and quantifying the safety effects of ADAS technologies within established highway safety analysis frameworks. The proposed modeling approach provides a foundation for extending SPFs and safety effectiveness metrics to other crash types, enabling transportation agencies to more accurately evaluate and incorporate the safety benefits of vehicle automation into data-driven decision-making.

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EXECUTIVE SUMMARY

Traditional Safety Performance Functions (SPFs) and safety effectiveness metrics were built on the assumption that all vehicles operate like conventional, human-driven cars. With technologies such as automatic emergency braking, adaptive cruise control, and lane-keeping assistance now common on U.S. roadways, that assumption no longer holds. Without distinguishing between Advanced Driver Assistance Systems (ADAS)-equipped and non-ADAS vehicles, existing crash prediction tools risk obscuring the true safety benefits of automation and limiting agencies' ability to make informed investment decisions. The study's main goal was to update crash prediction methods by creating SPFs and safety effectiveness metrics calibrated specifically for ADAS-equipped vehicles, focusing on rear-end crashes along interstate highways. Rear-end collisions were chosen because they are both frequent and closely tied to reaction time and car-following behavior areas, where ADAS technologies are designed to intervene. By incorporating vehicle-level automation attributes into the modeling process, the study moves beyond infrastructure-only approaches toward a more realistic vehicle–infrastructure framework that reflects the evolving fleet.

Using six years of crash data (2017–2023) from Ohio interstates, the research separated rear-end crashes based on ADAS-related and non-ADAS-related categories. Two modeling strategies were tested and evaluated for their goodness of fit in calibrating the two crash data sets. The first model was based on a Correlated Bivariate Negative Binomial (C-BNR) model, jointly estimating crash frequencies for both vehicle groups while capturing shared unobserved roadway and traffic influences. The second model was an Uncorrelated Bivariate Negative Binomial (U-BNR) model, treating two crash types independently.

Across all goodness-of-fit measures, R^2, MAE, and MSE, the correlated model consistently outperformed the uncorrelated model, underscoring the importance of accounting for latent correlations and technological differences in mixed fleets. Findings also show that ADAS-equipped vehicles experience roughly a 54% reduction in rear-end crash frequency on interstate segments, despite representing a minority of the fleet during the study period. Several roadway and exposure variables, such as AADT per lane, median type, and posted speed limit, were significant predictors for both ADAS and non-ADAS crashes. These results confirm that while roadway characteristics remain important, automation introduces distinct safety effects that must be explicitly modeled. By producing scalable SPF and safety effectiveness metric frameworks tailored to ADAS-equipped vehicles, this project directly supports national priorities around emerging technologies, rural safety, and data-driven decision-making. The resulting tools can be applied to network screening, benefit–cost analysis, and Highway Safety Improvement Program (HSIP) evaluations, helping agencies proactively adapt to increasing automation rather than reacting after the fact.

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INTRODUCTION

1.1 Background

Roadway crashes remain one of the most prominent causes of the increase in the mortality rate in the world (*1*, *2*). More than 90% of crashes often result from human factors such as delayed reaction times, distracted driving, or misjudgment of stopping distances, which are preventable at most (*3*). In response, Advanced Driver Assistance Systems (ADAS) have emerged as a critical technological intervention to mitigate such incidents by augmenting driver awareness and decision-making capabilities (*4–6*). ADAS encompasses a suite of features, including forward collision warning (FCW), automatic emergency braking (AEB), and adaptive cruise control (ACC), which collectively aim to reduce collision risks through real-time monitoring and automated interventions (*7*, *8*). Development of ADAS stems from improvements in sensor technologies, artificial intelligence, and processing capabilities, which make possible instantaneous awareness and action in intricate driving scenarios (*9*, *10*). It should be noted that these technologies are aimed at preventing specific crash types, for instance, rear-end, sideswipe, and head-on crashes.

Rear-end crashes represent one of the most frequent and preventable crashes, accounting for more than 29% traffic-related injuries and fatalities, especially on highways (*6*). Studies show that ADAS technologies hold the promise of reducing these types of crashes. For instance, FCW systems exhibit significant safety benefits in passenger vehicles, with studies reporting up to 27% reduction in rear-end crash rates when combined with driver alerts (*11*). Effectiveness increases when FCW is integrated with AEB, where the system not only warns but also autonomously applies brakes if the driver fails to respond. Real-world crash data analyses indicate that AEB systems alone can prevent 40% of low-speed rear-end collisions in urban environments (*12*). For heavy vehicles, front crash prevention systems show varying effectiveness depending on the struck vehicle type, with 32% reduction when colliding with passenger cars, but only 12% for motorcycle impacts (*13*). These technological strides have positioned ADAS as a cornerstone of intelligent transportation systems, yet their widespread adoption remains contingent on evaluating contributions toward crash reduction, which has been under investigated in this knowledge space.

A key research deficiency stems from the absence of standardized approaches for evaluating and quantifying ADAS benefits in varied and uncertain real-world scenarios in terms of crash reduction. Since these crashes are strongly associated with traffic flow instability, sudden deceleration, and limited driver reaction time, conditions that ADAS technologies are explicitly designed to address. As a result, these crashes provide a critical and policy-relevant context for assessing the effectiveness of ADAS. However, despite growing evidence that ADAS can reduce crash risk, existing Safety Performance Functions (SPFs) and safety effectiveness metrics used in practice were largely developed under the assumption of a homogeneous vehicle fleet and do not explicitly account for vehicle automation (*14*, *15*). Consequently, traditional SPFs and safety effectiveness metrics may overestimate crash risk or fail to fully capture the safety benefits of

ADAS, particularly in mixed-fleet environments where exposure and crash processes differ between ADAS and non-ADAS vehicles (*16*, *17*).

1.2 Objective of the Project

The primary objective of this study is to develop SPFs and safety effectiveness metrics specifically calibrated for automated and ADAS-equipped vehicles for application in highway crash prediction. Unlike traditional SPFs and safety effectiveness metrics, which were developed using crash data from conventional vehicle fleets, the proposed research explicitly accounts for the presence of automation technologies in mixed traffic environments. The study isolates the safety effects of ADAS-equipped vehicles, particularly rear-end crash scenarios, by incorporating vehicle-level automation attributes into predictive frameworks. To accomplish this objective, the research

- Develop statistically robust SPF models that differentiate between ADAS-equipped and non-ADAS vehicles while accounting for roadway geometry, traffic exposure (e.g., AADT), and segment-level characteristics.
- Estimate corresponding safety effectiveness metrics that quantify the effectiveness attributed to ADAS technologies.
- Validate and compare the predictive performance of the developed models against traditional highway safety prediction methods.

Ultimately, this study updates crash prediction by creating vehicle–infrastructure models that let agencies account for automation-related safety impacts in core highway safety decisions.

1.3 Project Relevance to R-SEAT Research Thrust and USDOT Strategic Plan

This project directly supports the Rural Safety Efficient Advanced Transportation (R-SEAT) center's research thrusts and several goals outlined in the U.S. Department of Transportation (USDOT) Strategic Plan through the following themes:

Emerging Technology Integration in Rural Systems: The project evaluates the safety impacts of ADAS in rural environments by developing SPFs and safety effectiveness specifically calibrated for ADAS-equipped vehicles. As automation becomes increasingly integrated into the vehicle fleet, rural transportation systems must adapt their safety evaluation tools to capture its influence accurately. Traditional SPFs and safety effectiveness metrics were developed under conventional vehicle assumptions and do not reflect the changing vehicle–infrastructure dynamics introduced by automation.

Safety of High-Risk and Rural Road Users: Rural roadways consistently experience higher fatality rates than urban facilities, particularly for high-speed crash types such as rear-end collisions. This project advances safety in rural systems by isolating the protective effects of ADAS technologies and quantifying their effectiveness in reducing crashes. The results provide agencies with analytical tools to evaluate how increasing penetration of driver assistance technologies can reduce severe crash outcomes.

Data-Driven Decision Making and System Efficiency: The project contributes to transportation system efficiency and modernization by enhancing predictive crash modeling frameworks to incorporate vehicle-level automation attributes. By advancing SPF and safety effectiveness metrics methodologies beyond infrastructure-only predictors, the research supports a more integrated vehicle–infrastructure analytical framework. This approach enables transportation agencies to more accurately forecast crash risk under varying levels of ADAS market penetration, supporting more precise benefit–cost evaluations and Highway Safety Improvement Program (HSIP) investment decisions.

Resilience and Adaptation to Technological Change: As vehicle automation penetration increases, rural transportation networks must remain resilient and adaptable to technological transitions. This project enhances resilience by equipping agencies with predictive tools that anticipate how automation influences crash patterns. Rather than reacting to safety trends after widespread adoption, the proposed framework allows proactive adaptation of policies, infrastructure planning, and safety countermeasures. By quantifying automation-related safety performance, the research ensures that rural systems remain responsive, forward-looking, and capable of managing technological change without compromising safety outcomes.

1.4 Report Structure

The report is organized as follows: Section 1 introduced the study by presenting the background on ADAS, outlining the project objectives, and describing its relevance to the R-SEAT research thrusts and the USDOT Strategic Plan. Section 2 provides a comprehensive literature review of performance effectiveness and current approaches to safety performance assessment. Section 3 describes the data preparation process, including roadway characteristics, crash data, and integration of NHTSA VIN decoder information used to identify ADAS-equipped vehicles. Section 4 details the methodological framework, presenting the Correlated and Uncorrelated Bivariate Negative Binomial Regression models used to estimate crash frequencies and quantify ADAS effects. Section 5 presents and discusses the results, including model goodness-of-fit comparisons, parameter estimates, safety effectiveness metrics, and posterior probability analyses. Finally, Section 6 summarizes the key findings, contributions, and implications for integrating ADAS into modern highway safety evaluation practices.

LITERATURE REVIEW

ADAS, particularly FCW, has been widely developed and deployed to mitigate the high frequency and severity of rear-end crashes, which remain among the most common and economically costly collision types worldwide (*2*). Because human driving behavior contributes roughly 90% of crashes, FCW technologies can both enhance performance and, under certain conditions, introduce unintended consequences (*6*). Research by Izquierdo-Reyes et al., (2018), demonstrates that multimodal alert systems combining visual, auditory, and haptic cues significantly improve driver reaction times, underscoring the potential of these systems to prevent imminent collisions. However, the real-world effectiveness of FCW in reducing rear-end crashes depends on several interacting factors, including system accuracy, environmental conditions, and driver engagement (*19*). Adverse weather or low-light conditions can degrade sensor performance, while excessive trust in automation may foster driver complacency (*20*). Additionally, the diversity of real-world driving environments, from dense urban traffic to high-speed freeway segments, creates challenges for consistent system performance and universal applicability (*2*, *21*). These complexities highlight the need for continued evaluation of ADAS technologies under varied operational conditions to fully understand their safety benefits and limitations

Nevertheless, the successful deployment of ADAS hinges not only on technological capabilities but also on user acceptance and trust. A central challenge in this domain is the calibration of trust, as both over-trust and distrust can diminish system effectiveness (*22*, *23*). Real-world effectiveness studies, therefore, play a critical role in understanding how these systems perform under actual driving conditions. For example, the prospective and retrospective assessment framework developed by (*21*) shows that collision-mitigation systems can achieve up to 68% effectiveness in avoiding imminent rear-end crashes when sensor data are integrated with vehicle dynamics. Similarly, field data from (*6*) indicate notable generational improvements in ADAS reliability, with model year 2020 systems exhibiting 40% fewer false positives compared to 2015 implementations. These findings underscore the need for continued evaluation of ADAS performance and effectiveness, particularly as technologies evolve and penetrate the vehicle fleet (*24*). Such assessments rely on a range of metrics, extending from crash-reduction outcomes to measurable changes in driver behavior, providing a more comprehensive understanding of how ADAS contributes to roadway safety.

For instance, the proper application of ADAS in commercial vehicle operations leads to notable safety advancements. Wu et al., (2023) (*25*) examined the effect of ADAS on commercial truck drivers by analyzing naturalistic driving data, showing that technologies such as lane departure warnings and forward collision alerts decrease critical incidents by 23% when they are in active operation. Nevertheless, the research also noted differences in efficacy depending on the type of roads. According to the evaluation in Park et al., (2021) (*26*), bus-specific applications have a comparable trend, with ADAS decreasing side-swipe incidents by 28%. Performance evaluation methods differ greatly among studies, as naturalistic driving data (*25*), crash statistics (*27*), and controlled field tests by Benmimoun et al., (2011) (*28*) illustrate different yet complementary strategies. The research findings indicate that although ADAS shows quantifiable safety advantages, its performance varies, which calls for ongoing improvements in both hardware functionality and algorithmic decision-making systems. Addressing these limitations requires future studies to develop adaptive performance metrics that capture the evolving interplay among system functionalities, driver behaviors, and roadway or infrastructure characteristics (*29*).

Moreover, evaluating ADAS through established safety performance metrics reveals considerable variation in methodological approaches and reported effectiveness across system categories. Relatively little attention has been given to ADAS technologies' integration with traditional safety metrics such as SPFs (*30*). For example, Matsuo et al., (2022) (*31*) assessed the safety of vulnerable road users by leveraging probe vehicle data enriched with collision-warning information. Similarly, the empirical Bayes framework presented by Persaud & Lyon, (2007) (*32*) offers a statistically rigorous approach for the before-after safety evaluations, where the study combines observed crash data with model-based predictions from reference sites to estimate expected crashes without treatment. Hence, enabling an unbiased before–after evaluation that accounts for regression-to-the-mean and other confounding factors.

Conclusively, the existing literature reveals a research gap: limited work has established a structured framework for evaluating the safety benefits of ADAS using traditional roadway safety tools. There is no widely adopted methodology for developing SPFs that explicitly quantify the crash-reduction benefits of ADAS technologies, especially for crash types such as rear-end collisions, where these systems are expected to have an impact. Likewise, few studies provide a systematic approach for estimating how much crash reduction can be attributed to ADAS under real-world operating conditions. To address this gap, the present study aims to develop a focused safety performance metric derived directly from observed crash data and to establish a replicable framework for constructing SPFs that quantify the benefits of ADAS technologies in a crash-type-specific manner.

DATA PREPARATION AND PREPROCESSING

3.1 Study Area

This research mainly utilized all the major interstates in Ohio, which include I-70, I-71, I-74, I-75, I-76, I-77, I-80, and I-90, as shown in Figure 1. Three primary data sources were incorporated in this study: (i) Road characteristics; (ii) Vehicle automation extracted from the National Highway Traffic Safety Administration (NHTSA); and (iii) Crash data between 2017 and 2023.

3.2 Road Characteristics

Roadway characteristic information was extracted from the 2023 Ohio Department of Transportation's (ODOT) roadway inventory data from the ODOT Transportation Information Mapping System (TIMS) portal. Variables from road inventory data extracted for each roadway segment include those identified in the Highway Safety Manual (HSM) (*15*) as they potentially influence the SPF of rear-end ADAS and non-ADAS crashes. This includes the Annual average daily traffic (AADT), the number of lanes, median width, median type, shoulder width, shoulder type, speed limit, and access control that represented the geometric design of the selected road function were considered.

This study performed re-segmentation in accordance with HSM guidelines to ensure uniform segments for the analysis, that is, initiating a new segment whenever any of the relevant variables exhibited significant changes (*15*). The relevant HSM variables were used as constraints to guide the re-segmentation process. Because the study encompassed the entire state of Ohio, additional constraints, such as county name, route number, and route type, were incorporated to localize segmentation. Moreover, since the analysis focused on interstate facilities whose primary function is mobility, only a small number of partially access-controlled segments were identified, and the shoulder type was consistently bituminous concrete. Consequently, the access-control and shoulder-type variables were excluded from further analysis. Finally, to address the potential correlation between AADT and the number of lanes, AADT was normalized by dividing it by the number of lanes to obtain AADT per lane, representing the number of vehicles traveling through each lane per day, similar to a study by (*36*).

Figure 1: Selected Ohio Interstate Network as Study Area

Pearson correlation analysis between explanatory variables revealed that the variables had mild to low correlation, suggesting that they can be used as independent variables (*37*). Table 1 shows the distribution in proportion for the variables used in the study.

Table 1: Descriptive Statistics

Variable	**Category**	**Count (%)**
Median Type	Flexible Barrier	149 (15.38%)
	Unprotected	352 (36.33%)
	Unspecified Barrier	223 (23.01%)
	Rigid Barrier	245 (25.28%)
Number of Lanes	> 7 lanes	175 (18.06%)
	2 - 4 lanes	379 (39.11%)

Variable	Category	Count (%)
	5 - 6 lanes	415 (42.83%)
Shoulder Type	Bituminous Concrete	682 (70.38%)
	Non-Bituminous Concrete	287 (29.62%)
Speed Limit	< 55 mph	131 (13.52%)
	60-65 mph	502 (51.81%)
	> 70 mph	336 (34.67%)
Access Control	Full Access Control	931 (96.08%)
	No / Partial Access Control	38 (3.92%)
Left Shoulder Width (ft)	Mean	8.431
	Standard Deviation	4.478
	Maximum	30
	Minimum	2
Right Shoulder Width (ft)	Mean	11.114
	Standard Deviation	2.532
	Maximum	24
	Minimum	3
Lane Width (ft)	Mean	12.019
	Standard Deviation	0.181
	Maximum	16
	Minimum	11
Median Width (ft)	Mean	39.7
	Standard Deviation	48.911
	Maximum	550
	Minimum	2
Annual Average Daily Traffic (AADT) per lane (veh/day/lane)	Mean	12206
	Standard Deviation	5269
	Maximum	34169
	Minimum	1607
Segment Length (miles)	Mean	1.337
	Standard Deviation	1.853
	Maximum	14.681
	Minimum	0.04
ADAS Related Crash Count (crash/seg)	Mean	10.525
	Standard Deviation	15.449
	Maximum	130
	Minimum	0
	Count	10,199 (31.22%)
Non-ADAS Related Crash Count (crash/seg)	Mean	23.19
	Standard Deviation	33.465
	Maximum	264
	Minimum	0
	Count	22,471 (68.78%)

3.3 Crash Data

Crash data were obtained from the Ohio Department of Public Safety (ODPS) through the Electronic Crash Submission system. The dataset includes detailed crash-level and unit-level information such as crash document number, vehicle identification number (VIN), manner of collision, route number, route type, and location of the crash (longitude and latitude). Records were filtered to include only rear-end crashes that occurred on the specified interstate routes, as identified by route numbers in the ODPS database. The final dataset consisted of 32,670 rear-end crash records that met the inclusion criteria across the specified interstate corridors from 2017 to 2023.

3.4 Vehicle Automation Level

To identify the types of ADAS present in vehicles involved in rear-end crashes, the study utilized VINs extracted from crash data. Because VINs are unique to each vehicle, the National Highway Traffic Safety Administration's (NHTSA) VIN decoder portal was employed to retrieve comprehensive vehicle specifications (*38*). These details were subsequently merged with crash records using the document number as a linking variable. Vehicles equipped with ADAS technologies designed to mitigate rear-end collisions were then identified. The systems considered included Adaptive Cruise Control (ACC), Automatic Emergency Braking (AEB), Forward Collision Warning (FCW), Rear Automatic Braking, Driver Monitoring Systems, and Rear Cross Traffic Alert (RCTA). Analysis of six years of crash data revealed that 31.22% of rear-end crashes involved at least one vehicle equipped with ADAS, whereas 68.78% involved only conventional vehicles lacking such systems, as shown in Table 1.

METHODS AND MATERIALS

The proposed methodology for this study includes a correlated bivariate Negative Binomial (C-BNR) model, which was compared with the uncorrelated Negative Binomial (U-BNR) model to evaluate its performance. The subsection that follows provides details about the formulation of these models.

4.1 Correlated Bivariate Negative Binomial Regression (C-BNR)

The C-BNR model jointly estimates two crash types using a count-based framework that incorporates their correlation, assuming that the crash types share similar contributing factors. In this study, ADAS-related and non-ADAS-related rear-end crashes occurring on the same roadway segments are modeled together, supporting this assumption and helping to avoid biased estimates for each crash type (*37*, *39*). Furthermore, the C-BNR model accounted for the correlation between the two crash types through a random-effect term estimated via a bivariate normal distribution. The C-BNR model that predicts the total number of crashes on the segment can be written as shown in Equation 1.

$$\binom{Y_{Ai}}{Y_{NAi}} \sim BivNegBinomial\left(\binom{\lambda_{Ai}}{\lambda_{NAi}}, \binom{\alpha_A}{\alpha_{NA}}\right) \tag{1}$$

where,
$\ln(\lambda_{Ai}) = \beta_{A0} + \beta_{Ai}X_i + \varepsilon_{Ai}$,
$\ln(\lambda_{NAi}) = \beta_{NA0} + \beta_{NAi}X_i + \varepsilon_{NAi}$,

$BivNegBinomial$ represents the bivariate Negative Binomial distribution,
Y_{Ai} and Y_{NAi} are estimated ADAS and non-ADAS-related rear-end crashes, respectively.
λ_{Ai} and λ_{NAi} are the crash rates (crashes per mile) for ADAS and non-ADAS related rear-end crashes, respectively,
α_A and α_{NA} are the over-dispersion parameters for ADAS and non-ADAS related rear-end crashes, respectively.
β_{Ai} and β_{NAi} are vectors of regression coefficients for ADAS and non-ADAS related rear-end crashes, respectively.
β_{A0} and β_{NA0} are population-level intercept parameters for ADAS and non-ADAS related rear-end crashes, respectively, and
X_i is the vector of independent variables,

For ADAS-related and non-ADAS-related rear-end crashes that occurred on the segment (i), denoted by, respectively, a random effect term (ε_{Ai} and ε_{NAi}) were added to the regression to account for the segment-level unobserved heterogeneity. As shown in Equation 2, the random-effect terms for the two jointly estimated regressions are assumed to follow a multivariate normal distribution characterized by a zero-mean vector and a covariance matrix (Σ).

$$\begin{pmatrix} \varepsilon_{Ai} \\ \varepsilon_{NAi} \end{pmatrix} \sim MVNormal\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \Sigma\right) \quad (2)$$

where,

$$\Sigma = \begin{pmatrix} {\sigma_{Ai}}^2 & \rho\sigma_{Ai}\sigma_{NAi} \\ \rho\sigma_{Ai}\sigma_{NAi} & {\sigma_{NAi}}^2 \end{pmatrix}$$

σ_{Ai} and σ_{NAi} are the standard deviations of the random effect for ADAS and Non-ADAS related rear-end crashes, respectively.
MVNormal stands for multivariate Normal distribution and
ρ is the correlation coefficient of unobserved heterogeneity.

Parameter Estimation
The C-BNR model parameters shown in Equation 1 were estimated using a full Bayesian framework through the Markov Chain Monte Carlo (MCMC) simulation. This required specifying prior distributions for all model parameters. Non-informative priors were selected to ensure minimal influence on the posterior estimates. As shown in Figure 2, the regression coefficients (. β_{A0}, β_{NA0}, β_{Ai} and β_{NAi}) were assigned normal priors with a mean and standard deviation of 0 and

10, respectively. The overdispersion parameters (α_A and α_{NA}) were assigned to a half-normal distribution that was centered on 0 and had a standard deviation of 2. For the random effects components of the bivariate model, a multivariate normal distribution was specified with a zero-mean vector and a covariance matrix defined by the standard deviations (σ_{Ai} and σ_{NAi}) and the correlation parameter ρ. Where the standard deviation terms were modeled using Half-Cauchy (0,1) priors, while the correlation parameter followed the Lewandowski Kurowicka-Joe-correlation (LKJ-correlation) distribution with a shape parameter of 2. Finally, the model convergence was evaluated using the Gelman-Rubin Diagnostic, which compares within-chain and between-chain variance. The model convergence is indicated by the diagnostic values approaching 1 (*40*).

4.2 Uncorrelated Bivariate Negative Binomial Regression (U-BNR)

For the U-BNR model, the unobserved heterogeneity terms for ADAS-related and non-ADAS-related rear-end crashes were treated as independent, implying no correlation between the two crash types. The formulation of the U-BNR model is presented in Equation 3.

$$\binom{Y_{Ai}}{Y_{NAi}} \sim BivNegBinomial\left(\binom{\lambda_{Ai}}{\lambda_{NAi}}, \binom{\alpha_A}{\alpha_{NA}}\right) \tag{3}$$

where
$\ln(\lambda_{Ai}) = \beta_{A0} + \beta_{Ai}X_i + \varepsilon_{Ai}, \ln(\lambda_{NAi}) = \beta_{NA0} + \beta_{NAi}X_i + \varepsilon_{NAi},$

The random-effect terms for the ADAS and non-ADAS regression equations were modeled as normally distributed with a mean of zero and standard deviations (σ_{Ai} and σ_{NAi}) as shown in Equation 4.

$$\varepsilon_{Ai} \sim Normal\ (0, \sigma_{Ai}), \varepsilon_{NAi} \sim Normal\ (0, \sigma_{NAi}) \tag{4}$$

where
$\sigma_{Ai} \sim half - cauchy\ (1)$ and $\sigma_{NAi} \sim half - cauchy\ (1),$

The parameter estimation for the U-BNR model was also calibrated using the MCMC simulation approach. Where the prior distributions assigned to the model parameters mirrored those used in the C-BNR framework, with normal priors specified for the regression coefficients and half-normal priors for the overdispersion parameter. Variable significance was assessed using the 95% Bayesian Credible Interval (BCI), a commonly applied criterion for determining whether a predictor meaningfully influences the outcome (*41*). A predictor was deemed significant when its 2.5%–97.5% credible interval did not include zero, indicating that both bounds of the interval were either entirely positive or entirely negative.

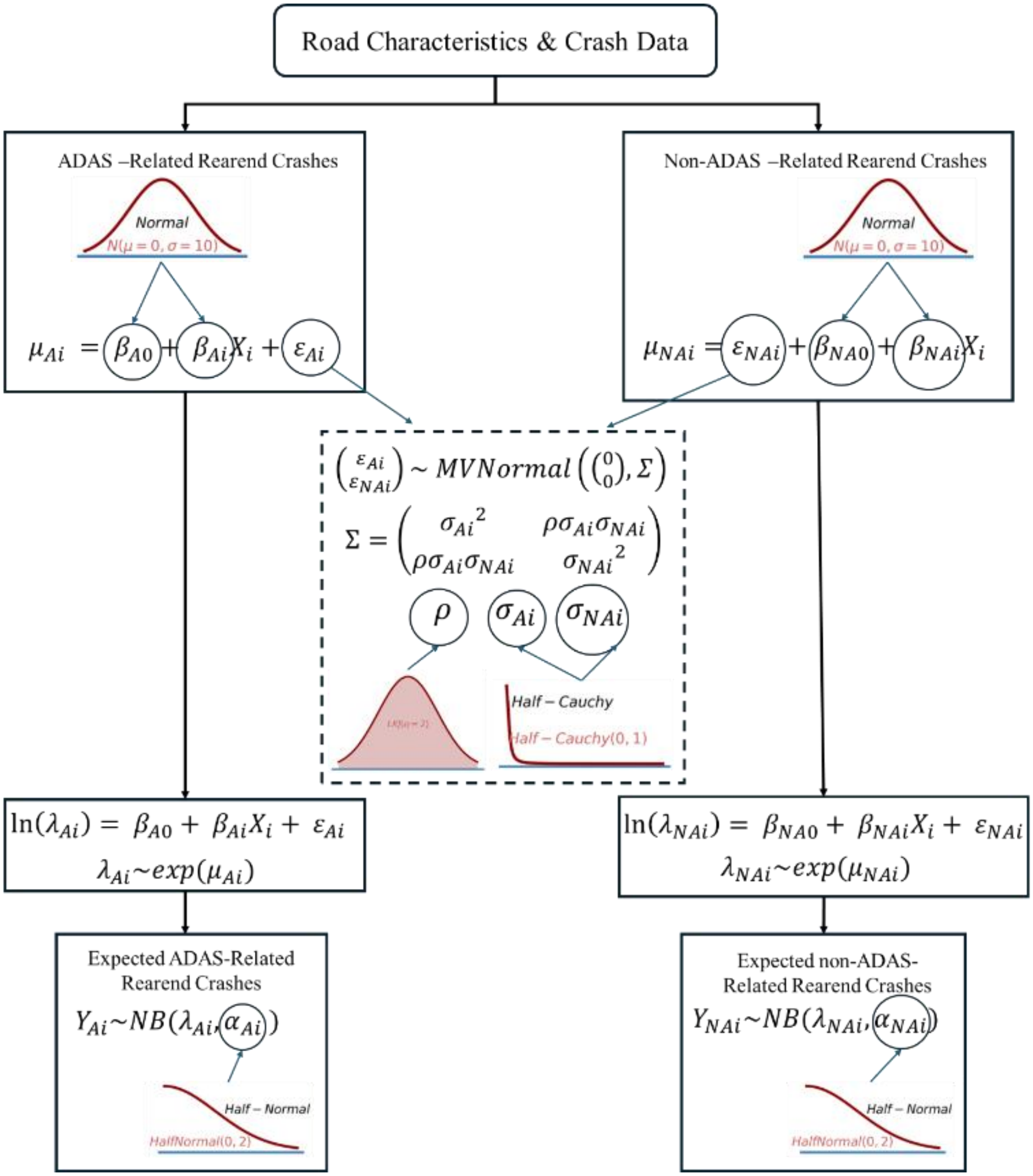


Figure 2: Graphical representation of the C-BNR with prior distributions

Model Comparison

To evaluate whether accounting for the potential correlation between ADAS-related and non-ADAS-related rear-end crashes improved model performance, several goodness-of-fit measures were examined: the correlation coefficient between observed and predicted crash counts (R^2), the mean absolute error (MAE; Equation 5), and the mean squared error (MSE; Equation 6). Higher R^2 values and lower MAE and MSE values indicate better model fit.

$$MAE = \frac{\sum_{i=1}^{n} |\hat{y}_i - y_i|}{n} \tag{5}$$

$$MSE = \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n} \quad (6)$$

where,

n is the total number of segments,

y_i is the observed number of target rear-end crashes in segment i, and

$\hat{y}_i$ is the predicted number of target rear-end crashes in segment i

RESULTS AND DISCUSSION

Posterior distributions for all parameters were obtained using 20,000 MCMC iterations, with the first 10,000 iterations discarded as burn-in and the remaining 10,000 retained for inference. The Gelman-Rubin diagnostic values were approximately 1, indicating satisfactory convergence across chains. The retained posterior samples were therefore used to generate summary statistics for both the ADAS and non-ADAS crash models, including the 95% Bayesian credible intervals (2.5th and 97.5th percentiles), posterior means, and standard deviations.

5.1 Model Goodness-of-Fit

Table 2 reports two goodness-of-fit statistics, MAE and MSE, both of which decrease as model performance improves. Comparison of these metrics across the C-BNR and U-BNR models shows that the C-BNR framework provides more accurate predictions of ADAS-related and non-ADAS-related rear-end crash frequencies. This finding indicates that modeling the correlation between the two crash types enhances predictive capability. By incorporating shared latent effects, the C-BNR model reduces estimation uncertainty, which theoretically and empirically supports its superior predictive performance relative to the U-BNR model (*37*).

Table 2: Performance Comparison of Bivariate Models

	Correlated Bivariate NB Model		**Uncorrelated Bivariate NB Model**	
	ADAS Crashes	**Non-ADAS Crashes**	**ADAS Crashes**	**Non-ADAS Crashes**
MAE	1.933	3.277	3.244	5.168
MSE	9.818	32.972	28.927	75.699

MAE – Mean Absolute Error, MSE – Mean Squared Error, NB – Negative Binomial

Furthermore, Figure 3 shows the value of incorporating the potential correlation between ADAS-related and non-ADAS-related rear-end crashes within the bivariate modeling framework. When this correlation was modeled, the predictive accuracy for ADAS-related crashes improved substantially, with the R^2 increasing from 0.94 to 0.98 (Figure 3a and 3c). A similar improvement was observed for non-ADAS crashes, where the R^2 rose from 0.97 to 0.99 (Figure 3b and 3d). Given that the C-BNR model consistently produced the strongest goodness-of-fit results, the subsequent discussion focuses exclusively on the C-BNR findings and the interpretation of the results derived from this model.

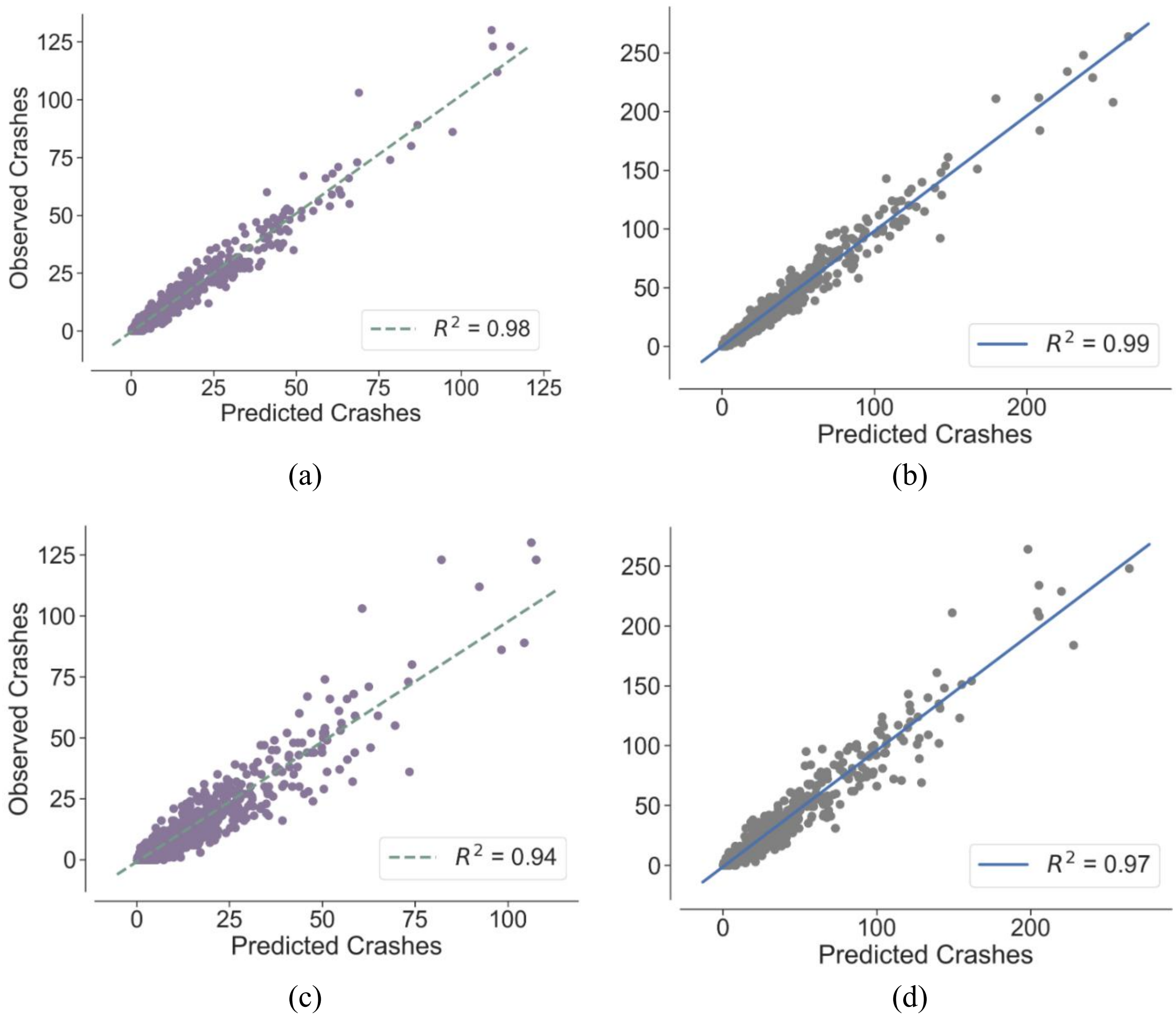


Figure 3: Correlation plots for ADAS and Non-ADAS rear-end crashes (a) ADAS C-BNR model, (b) Non-ADAS C-BNR model, (c) ADAS U-BNR model, (d) Non-ADAS U-BNR model

5.2 C-BNR Model Results

Table 3 summarizes the posterior estimates obtained from the C-BNR model. The results reveal a strong positive correlation between ADAS-related and non-ADAS-related rear-end crashes ($\rho = 0.997$), suggesting that both crash types are influenced by shared underlying factors. However, there were latent influences likely stemming from variables not included in the model, such as roadway design characteristics, driver behavior, or prevailing weather conditions. Of the fourteen categories examined from seven variables of each crash type, nine were statistically significant at the 95% BCI: four for ADAS-related crashes and five for non-ADAS crashes; three variables were significant for both crash types. These significant variables included the logarithm of AADT per lane, posted speed limit, and median type. The subsequent sections provide a detailed interpretation of these key variables. It is also important to note that segment length was incorporated as an offset term in the C-BNR specification, ensuring that crash frequency is modeled to scale proportionally with segment length (*42*).

Table 3 Parameter Estimates for C-BNR Model

Variable	**Category**	**ADAS Related Crashes**				**Non-ADAS Related Crashes**			
		Mean	**Std. dev**	**BCI 2.5%**	**BCI 97.5%**	**Mean**	**Std. dev**	**BCI 2.5%**	**BCI 97.5%**
Intercept	N/A	-13.26	2.39	-17.80	-8.50	-13.43	2.23	-17.85	-8.97
Median Type	*Flexible barrier*	*Base*							
	Unprotected	-0.141	0.113	-0.353	0.086	-0.119	0.105	-0.329	0.088
	Unspecified barrier	**0.515**	**0.122**	**0.286**	**0.750**	**0.688**	**0.115**	**0.465**	**0.917**
	Rigid barrier	0.202	0.125	-0.046	0.450	**0.298**	**0.116**	**0.063**	**0.525**
Median Width (ft)	continuous	0.000	0.001	-0.002	0.001	-0.001	0.001	-0.003	0.000
Speed Limit (mph)	*< 55mph*	*Base*							
	60-65 mph	**-0.675**	**0.111**	**-0.893**	**-0.460**	**-0.770**	**0.105**	**-0.991**	**-0.574**
	> 70 mph	**-2.009**	**0.138**	**-2.279**	**-1.744**	**-2.057**	**0.130**	**-2.315**	**-1.812**
Left Shoulder Width (ft)	continuous	0.002	0.009	-0.016	0.020	-0.002	0.009	-0.019	0.015
Right Shoulder Width (ft)	continuous	-0.029	0.015	-0.059	0.000	-0.025	0.014	-0.052	0.002
Lane Width (ft)	continuous	0.122	0.184	-0.243	0.476	0.198	0.174	-0.144	0.534
Log of AADT per lane (Veh/day/Lane)	**continuous**	**1.407**	**0.098**	**1.219**	**1.601**	**1.412**	**0.088**	**1.236**	**1.585**
Correlation	N/A	0.997	0.002	0.9913	0.9996				

Note: C-BNR = a bivariate model assuming there is a correlation between unobserved heterogeneity characteristics for ADAS and Non-ADAS related crashes; **BCI** = Bayesian credible interval; **AADT** = annual average daily traffic per day per lane. Segment length was used as an offset variable; the numbers in bold represent significant variables. **N/A** = Not Applicable.

Logarithm of AADT per Lane

Traffic volume is a fundamental exposure variable in crash frequency modeling, reflecting the level of interaction and conflict potential among vehicles. The results indicate that an increase in the logarithm of AADT per lane is associated with a statistically significant rise in the expected number of rear-end crashes for both crash types. Specifically, a one-unit increase in log (AADT per lane) increased the expected frequency of ADAS-related rear-end crashes by a posterior mean of 1.407 (95% BCI [1.219,1.601]) and non-ADAS-related rear-end crashes by 1.412 (95% BCI [1.236,1.585]). These findings reflect the heightened exposure and interaction density associated with higher traffic volumes, which increase the likelihood of vehicle-to-vehicle conflicts and sudden deceleration events (*15*, *43*). This relationship is well documented in the traffic safety literature, where higher traffic volumes are consistently linked to elevated rear-end crash risks due to increased platooning, reduced headways, and greater conflict opportunities among vehicles (*44*, *45*).

Speed Limit

The posted speed limit was one of the statistically significant variables at the 95% BCI that influenced the frequency of both ADAS and non-ADAS related crashes. Using posted speeds below 55 mph as the base category, the posterior means for segments with posted speeds of 60–65 mph and greater than 70 mph were negative. This indicates that higher posted speed limits were associated with fewer ADAS- and non-ADAS-related crashes. Specifically, at a posted speed of 60–65 mph, the expected number of crashes decreased by a mean of −0.675 (95% BCI [−0.893, −0.460]) for ADAS-related crashes and −0.770 (95% BCI [−0.991, −0.574]) for non-ADAS crashes. At posted speeds greater than 70 mph, the reductions were even larger, with mean decreases of −2.009 (95% BCI [−2.279, −1.744]) for ADAS-related crashes and −2.057 (95% BCI [−2.315, −1.812]) for non-ADAS crashes. The results indicate that higher posted speed limits on interstate highways are associated with lower crash frequencies for both ADAS- and non-ADAS-involved rear-end crashes, reflecting roadway context rather than the safety of higher speeds per segment.

Interstate segments with higher posted speeds are typically designed to support high-speed operations through uniform horizontal and vertical alignment, longer sight distances, wider lanes and shoulders, and full access control, all of which reduce conflict points and promote stable traffic flow (*15*, *46*). These facilities also tend to exhibit lower speed variability, a key factor in reducing rear-end crash types that are sensitive to sudden speed differentials (*44*, *45*, *47*). In contrast, lower posted speed segments (base category) on interstates often coincide with transitional or constrained areas such as urban approaches, work zones, or complex interchange spacing, which inherently elevate crash risk. The consistent reductions observed for both ADAS and non-ADAS crashes suggest that roadway design and traffic flow characteristics dominate crash occurrence at the segment level, with ADAS technologies operating within these broader infrastructural constraints (*48*). Consequently, while higher speeds increase injury severity when crashes occur, well-designed high-speed interstate segments can experience fewer crashes overall due to superior geometric design and operational stability (*47*).

Median Type

Medians primarily serve to separate opposing traffic streams, while also providing a recovery area for errant vehicles and space for emergency stopping. Key median characteristics commonly evaluated in crash frequency analyses include the presence of a median, its width, barrier type, and surface treatment (*37*). Accordingly, this study incorporated median width and median type as representative geometric variables to assess the safety effects of medians on both ADAS- and non-ADAS-related rear-end crashes. Because median width did not exhibit a statistically significant association with either crash type at the 95% Bayesian credible interval, the discussion that follows focuses exclusively on the effects of median type.

Using segments with flexible median barriers as the base category, roadway segments with unspecified median barriers exhibited a significantly higher expected frequency of rear-end crashes for both crash types. The posterior mean increases were 0.515 (95% BCI [0.286,0.750]) for ADAS-related crashes and 0.688 (95% BCI [0.465,0.917]) for non-ADAS-related crashes, indicating a consistent and statistically credible association. In addition, segments with rigid median barriers were associated with a higher expected frequency of non-ADAS-related rear-end crashes, with a posterior mean increase of 0.298 (95% BCI [0.063,0.525]). No statistically significant association was observed between rigid barriers and ADAS-related crashes, as the corresponding credible interval included zero.

The results imply that the increased rear-end crash risk on segments with unspecified and rigid median barriers likely reflects constrained roadway environments characterized by narrow shoulder widths and unforgiving median surfaces, which limit lateral clearance and reduce opportunities for evasive maneuvers or safe recovery during sudden deceleration events (*49*). These constraints appear to disproportionately affect non-ADAS-equipped vehicles, which rely solely on driver perception–reaction capabilities and lack automated braking or warning assistance (*50*). In contrast, segments with flexible median barriers are typically associated with wider shoulders and more forgiving roadside designs, offering greater recovery space and reduced traffic turbulence, thereby lowering rear-end crash risk. Collectively, the findings underscore the importance of median and shoulder design in rear-end crash prevention and suggest that geometric constraints may diminish the safety benefits of advanced vehicle technologies in constrained median environments.

5.3 Quantification of Effectiveness

Figure 4 illustrates the posterior distributions of the expected crash frequency for roadway segments under ADAS-equipped and non-ADAS conditions. These distributions are derived from the Bayesian model's posterior draws and reflect uncertainty in the estimated mean crash frequency after accounting for observed roadway, traffic, and exposure characteristics. The spread of each distribution represents posterior variability across draws, capturing both parameter uncertainty and latent heterogeneity in the modeled safety performance. Comparison of the two distributions provides insight into differences in expected crash outcomes associated with ADAS presence, while preserving the full probabilistic characterization of the estimates rather than relying on point summaries alone.

The safety effectiveness metric is derived directly from the posterior means estimates of expected rear-end crashes for ADAS-related and non-ADAS-related crash processes, obtained under identical roadway, traffic, and exposure conditions. By taking the ratio of these estimated mean crash frequencies, the approach provides a transparent and internally consistent measure of relative safety performance while fully preserving uncertainty. As shown in Figure 5, the posterior mean of the ADAS-to-non-ADAS crash ratio is approximately 46.14%, with a 95% Highest Density Interval (HDI) spanning 43.80% to 48.26%, indicating that ADAS-equipped vehicles experience about a 53.86% reduction in rear-end crash frequency compared with non-ADAS-equipped vehicles. The fact that the entire HDI lies well below 100%, hence provides strong Bayesian evidence of a statistically credible safety benefit.

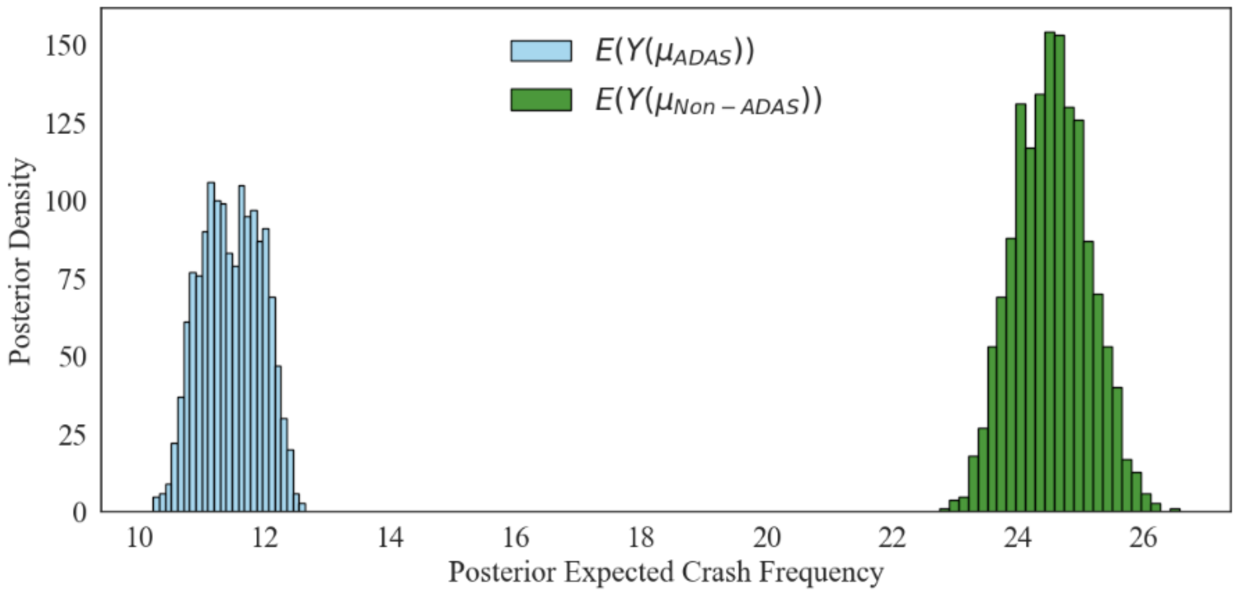


Figure 4: Posterior distributions of the expected crash frequency

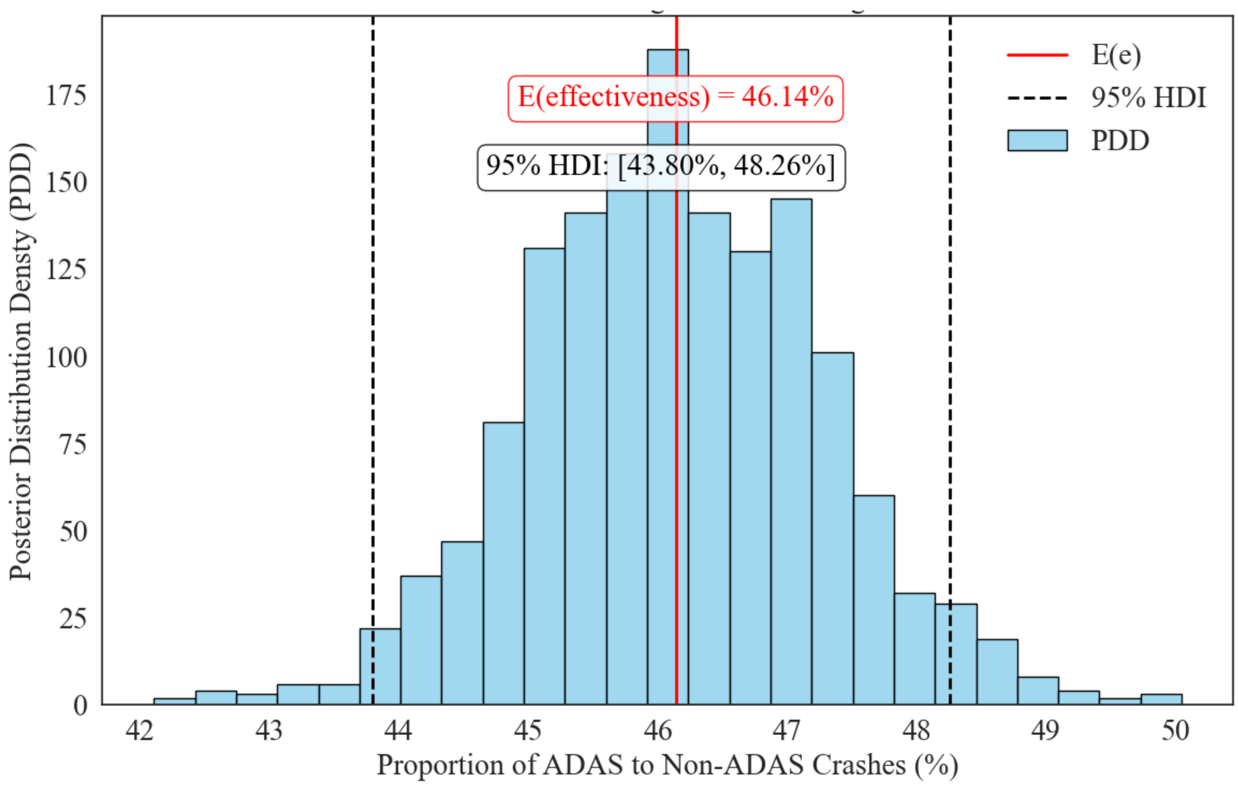


Figure 5: Impact of ADAS vehicles based on rear-end crashes

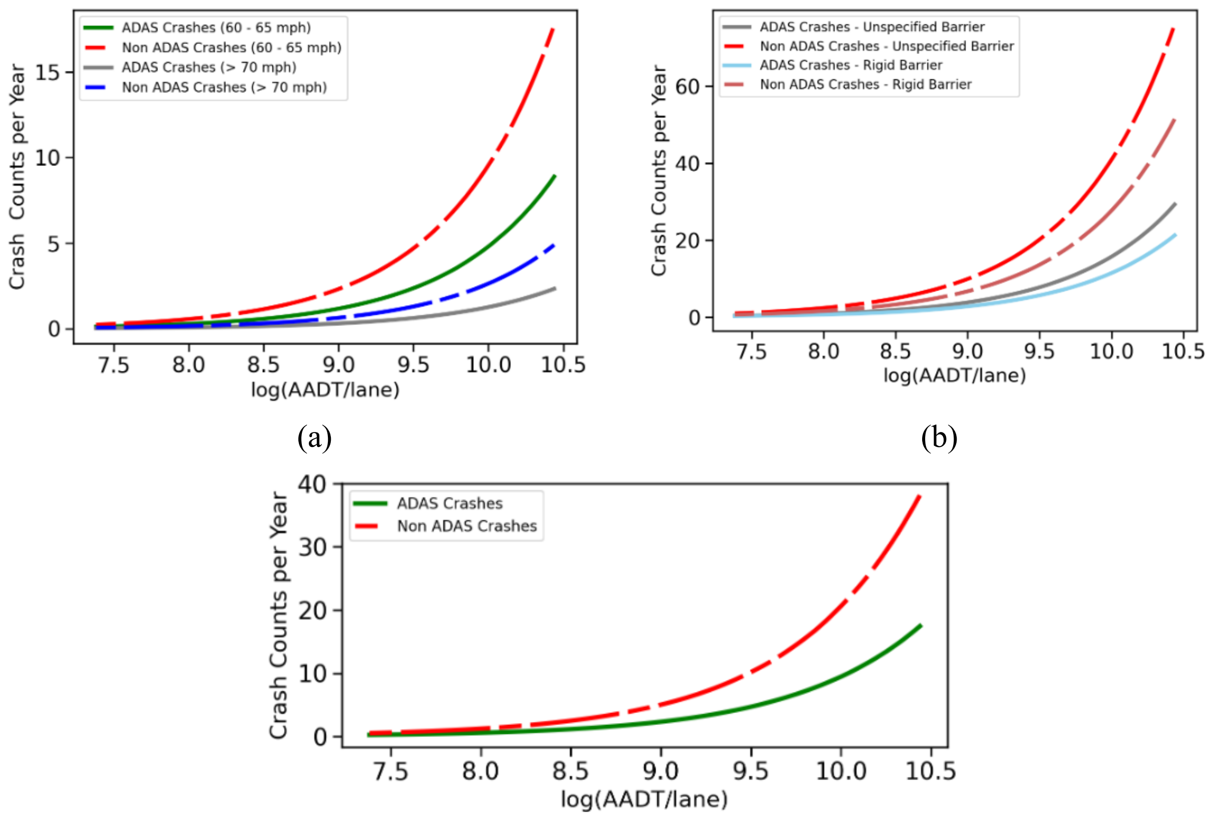
Notably, these benefits were observed even though ADAS-equipped vehicles represented only about 30% of the vehicle population used to define ADAS-related crashes in the analysis. Despite this relatively low penetration level, the ratio-based safety effectiveness metric indicates a substantial reduction in crash involvement for ADAS-equipped vehicles, underscoring the robustness of the observed effect. As ADAS adoption increases, the aggregate safety benefits are likely to grow, both through a higher proportion of vehicles directly benefiting from ADAS functionalities and through broader system-level effects, such as smoother traffic flow and fewer abrupt braking events. While future penetration scenarios are beyond the scope of this study, the findings suggest that the proposed ratio-based safety effectiveness metric provides a scalable and policy-relevant framework for evaluating the evolving safety impacts of ADAS as market penetration continues to expand.

5.4 Posterior Probability Plots

Marginal-effect plots were developed to examine how key explanatory variables influence the frequency of ADAS-related and non-ADAS-related rear-end crashes. Only those predictors that were significant at the 95% BCI for both crash types were included in these visualizations. Figure 6 displays the posterior predictive trends for crash frequency as a function of (a)log AADT per lane, (b) median type (unspecified and rigid barrier), and (c) posted speed limit (60-65 and >70 mph). To generate these predictions, the log-AADT and the focal categorical variables were systematically varied while all other categorical predictors were held at their respective reference categories. Because each panel in Figure 6 is based on a different set of variable manipulations, the predicted crash frequencies shown in panels (a) through (c) should not be interpreted as directly comparable.

Across all three figures, a clear and consistent pattern emerges in which rear-end crash frequency increases nonlinearly with log(AADT per lane), reflecting the dominant role of traffic exposure in rear-end crash occurrence. As shown in Figure 6(a), this increasing trend is evident across higher posted speed limit categories (60–65 mph and >70 mph), with non-ADAS-related crashes occurring at consistently higher frequencies than ADAS-related crashes, particularly at moderate to high traffic volumes. At lower AADT per lane levels, crash frequencies for ADAS and non-ADAS vehicles are relatively similar; however, as traffic volumes increase, the divergence between the two curves becomes more pronounced, suggesting that ADAS-equipped vehicles may offer some mitigation benefits under higher-demand conditions but do not eliminate rear-end crash risk as congestion intensifies.

A similar exposure-driven pattern is observed in Figure 6(b), where segments with unspecified and rigid median barriers exhibit substantially higher rear-end crash frequencies for both ADAS and non-ADAS vehicles as AADT per lane increases. Notably, non-ADAS vehicles experience the steepest growth in crash frequency, particularly on segments with unspecified barriers, reinforcing the compounding effect of high traffic volumes and constrained median environments. Figure 6(c) further confirms this relationship at an aggregate level, showing that increasing AADT per lane leads to higher rear-end crash frequencies regardless of vehicle technology, though non-ADAS crashes remain consistently more frequent. Collectively, these figures indicate that while posted speed limit influences crash occurrence, its effect is secondary to that of traffic volume and median design, with exposure-related factors driving the rate of increase in rear-end crash frequency for both ADAS- and non-ADAS-equipped vehicles.



(c)

Figure 6: Posterior probability plots (a) speed limit and crash count trend; (b) median type and crash count trend; (c) logAADT per lane and crash count trend

CONCLUSION

This study set out to address a critical gap in highway safety analysis: the absence of Safety Performance Functions (SPFs) and safety effectiveness metrics that explicitly account for Advanced Driver Assistance Systems (ADAS) in a mixed vehicle fleet environment. Traditional crash prediction models were developed under the assumption of a homogeneous fleet composed entirely of conventional vehicles. However, as ADAS technologies such as automatic emergency braking, adaptive cruise control, and lane-keeping assistance become increasingly prevalent, the underlying crash-generation process has evolved. Failing to distinguish between ADAS-equipped and non-ADAS vehicles risks masking the true safety effects of automation and may lead to biased crash predictions and misinformed infrastructure investment decisions. This research provides a systematic and data-driven response to that challenge.

Using six years (2017–2023) of crash data from Ohio interstate highways, this study disaggregated rear-end crashes into ADAS-related and non-ADAS-related categories and evaluated their crash-generation processes within a unified statistical framework. Rear-end crashes were selected because they are among the most frequent crash types on high-speed facilities and are directly influenced by driver reaction time, car-following dynamics, and deceleration behavior conditions that ADAS technologies are specifically designed to address. By isolating ADAS-equipped vehicles from conventional vehicles in the modeling process, the study avoided the aggregation bias inherent in traditional SPFs and enabled a more accurate quantification of automation-related safety effects.

Methodologically, the study advanced crash modeling practice by implementing a Correlated Bivariate Negative Binomial (C-BNR) model that jointly estimates ADAS and non-ADAS crash frequencies while accounting for shared latent roadway and traffic characteristics. This approach recognizes that both crash types occur on the same physical roadway segments and are influenced by common unobserved factors, such as driver population characteristics, enforcement intensity, geometric design nuances, and environmental variability. The C-BNR model was compared to an Uncorrelated Bivariate Negative Binomial (U-BNR) model that treats ADAS and non-ADAS crashes as independent processes. Across multiple goodness-of-fit measures, including R^2, Mean Absolute Error (MAE), and Mean Squared Error (MSE), the correlated model consistently demonstrated superior predictive performance. This finding underscores the importance of accounting for technological heterogeneity and shared unobserved influences when modeling crash frequencies in transitional fleet environments.

The results provide strong empirical evidence of the safety benefits associated with ADAS technologies. Even though ADAS-equipped vehicles represented a minority of the fleet during the study period, the analysis indicates an estimated 54% reduction in rear-end crash frequency attributable to ADAS presence on interstate segments. Key roadway and exposure variables—such as the logarithm of AADT per lane, median type, and posted speed limit remained statistically significant predictors for both ADAS and non-ADAS crashes, confirming that infrastructure characteristics continue to play a central role in crash occurrence. However, the magnitude of crash frequency differed meaningfully between the two vehicle categories, demonstrating that automation modifies, rather than replaces, traditional crash risk relationships.

From a practical standpoint, the study provides transportation agencies with a modernized and defensible analytical framework that integrates vehicle-level automation into established safety management processes. The development of ADAS-specific SPFs and safety effectiveness metrics enable agencies to refine network screening, project prioritization, benefit–cost analysis, and Highway Safety Improvement Program (HSIP) evaluations. Rather than relying solely on historical crash trends derived from conventional fleets, agencies can now begin to anticipate how increasing automation penetration will alter crash patterns over time. This proactive capability is particularly important for rural and high-speed facilities, where rear-end crashes contribute substantially to severe injury and fatal outcomes.

The broader contribution of this research lies in its transition from infrastructure-only safety models toward an integrated vehicle–infrastructure analytical paradigm. As vehicle technology continues to evolve, crash prediction models must evolve accordingly. The modeling framework developed in this study is transferable and scalable; it can be extended to other crash types, roadway classifications, and higher levels of automation. Future research may incorporate additional explanatory variables such as interchange influence areas, horizontal curvature, vertical grade, weather conditions, and land-use context to further refine predictive accuracy. Additionally, as data availability improves, exposure measures disaggregated by vehicle automation level could provide even more precise estimates of safety benefits.

In conclusion, this study demonstrates that explicitly accounting for ADAS technologies in crash prediction models leads to more accurate, informative, and policy-relevant safety analyses. The findings confirm that automation produces measurable reductions in rear-end crash frequency, even at relatively low market penetration levels. By adopting correlated modeling techniques and disaggregating crash data by automation status, the research establishes a methodological foundation for incorporating emerging vehicle technologies into mainstream highway safety evaluation. As the vehicle fleet continues its transition toward higher levels of automation, the tools and insights developed in this project will support data-driven, forward-looking transportation safety decision-making and help ensure that infrastructure planning remains aligned with technological advancement and evolving roadway safety dynamics.

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