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Safety Performance of Centerline Raised Pavement Markers

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16. Abstract

Centerline raised pavement markers (RPM) have emerged as a justifiable rural road safety countermeasure for preventing run-off-road (ROR) and opposite-direction crashes. These devices supplement lane markings, enhance positional guidance, alert drivers to changes in roadway geometry, and reduce encroachment. This research evaluated the safety effect of centerline raised pavement markers (RPM) installed on rural roads in Indiana and proposed a practical and systemic approach for identifying road segments that require more attention. To support the Indiana Department of Transportation (INDOT) in this task, the study develops a set of Crash Modification Factors (CMFs) that reflect the safety effects of installing raised pavement markers on the target crashes.

The analysis is based on crash data collected from Indiana rural two-lane roads during the 2015-2023 period, which comprised more than 20,000 crashes across over 8,000 roadway segments. In addition to the effect of RPMs, the study also investigated the joint safety effects of RPMs and other countermeasures, including rumble strips (RS) and shoulders and lane widths. The results help determine the joint effect of any combination of these road cross-section features on reducing the crash occurrence and severity.

A panel analysis (cross-sectional combined with before-and-after analyses) through a negative binomial model with random effects was implemented to safety-related data from two-lane rural roads during the studied nine-year period. The safety effects across sites with and without raised pavement markers were estimated while controlling local factors such as traffic volume and road geometry.

This study confirmed a statistically significant reduction in ROR crashes associated with the implementation of raised pavement markers (RPMs) equal to 15% at daytime and 11% at nighttime on average across the treated Indiana roads. The opposite-direction collisions, including head-on and opposite-direction sideswipe crashes, were significantly reduced at nighttime by nearly 22%. The daytime opposite-direction crashes showed no significant change after RPMs implementation.

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EXECUTIVE SUMMARY

Introduction

This research evaluated the safety effect of centerline raised pavement markers (RPMs) installed on rural roads in Indiana. The studied effects included changes in crash frequencies at three levels of crash severity outcome. The study results were meant to support a practical and systemic approach to selecting road segments that may require safety-targeted improvements. To support the Indiana Department of Transportation (INDOT) in this task, the reported study has developed a set of Crash Modification Factors (CMFs) that reflect the effects of RPMs on both run-off-road (ROR) crashes and opposite-direction crashes (head-on collisions and opposite-direction sideswipes).

The analysis is based on the crash data reported on Indiana rural two-lane roads in the 2015–2023 period. The crash data used comprised more than 20,000 crashes on more than 8,000 roadway segments. In addition to estimating the effect of RPMs, the study also covered the joint safety effect of installing RPMs combined with installing rumble strips, widening shoulders, and widening traffic lanes.

A panel analysis (cross-sectional combined with before-and-after analyses) was applied to safety-related data from two-lane rural roads during the studied 9-year period. The safety effects across sites with and without RPMs were estimated while controlling local factors such as traffic volume and road geometry.

The obtained CMFs include both the sole effect of RPMs and the combined effects from the joint use of RPMs with other safety features. These results deliver evidence-based recommendations for prioritizing roadway safety improvements. To illustrate the potential safety improvement with RPM installations and to help implement the results, the implementation section included in the report provides an example benefit–cost analysis for a selected roadway segment. This analysis uses the Empirical Bayes (EB) methodology to produce estimates of adjusted annual crash frequencies by combining observed crash data with crash frequencies predicted with the safety performance model.

Findings

This study confirmed a statistically significant reduction in run-off-road crashes associated with the implementation of RPMs equal to 15% at daytime and 11% at nighttime on average across the treated Indiana roads. The opposite-direction collisions, including head-on and opposite-direction sideswipe crashes, were significantly reduced at nighttime by nearly 22%. The daytime opposite-direction crashes showed no significant change with RPM implementation.

Implementation

To support INDOT and other transportation agencies in applying the study findings, a methodology for project-level implementation has been developed. It includes:

1. **Crash frequency estimation using a negative binomial model:** A cross-sectional before-and-after analysis through a negative binomial model is used to estimate the crash frequencies on segments with and without pavement markers installed.
2. **Crash severity estimation using safety performance functions (SPFs):** Given the limited availability of clear zone and roadside hazard data, severity proportions were estimated using exposure-based SPFs for property damage only (PDO) and non-PDO crashes.
3. **Crash frequency estimation using an implementation model and the EB method:** The expected number of ROR crashes on a road segment is estimated using the developed equation. The EB method is used to combine recorded crashes with model-based estimates to produce the best crash frequency estimate. This estimate then split into the frequencies of PDO and non-PDO crashes using the SPF proportions obtained in the previous step.
4. **CMFs applications:** Once crash frequencies are calculated, the expected effect of road improvements (e.g. RPMs) is quantified using the provided CMFs. These values reflect the Indiana specific road conditions to provide Indiana specific guidance.
5. **Integration into benefit–cost analysis:** The obtained crash reduction estimates and the Indiana unit crash costs are converted into monetary benefits. These computational steps are consistent with the INDOT framework for prioritization of roadway improvement projects.

The proposed methodology is meant to help INDOT assess the safety impacts of road cross-section improvements when roadside data is not available. An Excel-based tool was developed to facilitate the use of SPFs, CMFs, and EB estimates.

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1. INTRODUCTION

1.1 Research Problem

This research aims to evaluate the safety effect of centerline raised pavement markers (RPM) on rural roads in Indiana and to propose a practical and systemic approach for identifying road segments that require more attention. To support the Indiana Department of Transportation (INDOT) in this task, the study develops a set of Crash Modification Factors (CMFs) that reflect the safety effects of installing RPMs on reducing run-off-road (ROR) and opposite-direction (head-on and opposite-direction sideswipe) crashes.

The analysis is based on crash data collected from Indiana rural two-lane roads during the 2015–2023 period which comprised more than 20,000 crashes across over 8,000 roadway segments. In addition to the effect of RPMs, the study also investigated the joint safety effects of RPMs and other countermeasures, including rumble strips and widening shoulder and lane widths. The results help determine the joint effect of any combination of these road cross-section features on reducing the crash occurrence and severity.

The findings comprise multiple CMFs applicable to a sole use of RPMs and to combined use with the other improvements to allow INDOT the evidence-based comparison of the studied alternative roadway improvements.

1.2 Research Scope

A cross-sectional before-and-after analysis includes estimating the safety performance of two-lane rural roads across sites with and without RPMs installed, while controlling local factors including traffic volume and road geometry. Rural state-administered highways are included in the analysis. Road segments affected by nearby intersections, as well as crashes with driver impairment listed as potential causes, are outside of the project scope and are not included in the presented analysis. Furthermore, segments shorter than 0.03 mi are not considered in the study. It is assumed that the presented report helps INDOT make informed decisions about RPM installation on state-administered rural segments in Indiana. CMFs, a well-established decision-making tool, are developed using negative binomial modeling results. Additionally, this study deploys the Empirical Bayes (EB) methodology to generate adjusted estimates of annual crash frequencies by combining recorded crash data with predicted crash frequencies. Moreover, benefit–cost ratios estimated for various service lives of RPMs are hoped to be found useful in economic evaluations of both new roadways and existing roads considered for improvements.

1.3 Report Outlines

This report is organized into seven chapters that present the specific research elements on RPMs and their effects on crash frequency and severity. The organization of the document is as follows.

The first chapter provides the background, the motivation of the study, the research objectives, and the scope.

The second chapter delivers a comprehensive literature review of previous research on RPMs. It summarizes the key findings, results, challenges, and gaps identified in the research literature. Additionally, this chapter offers an insight into the current Indiana practices and policies regarding RPM use.

The third chapter describes the data sources used in the study and characterizes the dataset. It presents an initial exploration of the data, including descriptive statistics and data visualization to summarize the available information.

The fourth chapter describes the development of the statistical models needed to estimate the crash frequency and evaluate the safety impact of RPMs combined with other roadway characteristics. It introduces the negative binomial (NB) model with random effects and explains its formulation, assumptions, and justifies its suitability for the research task at hand. The estimation process is detailed by explaining the variable selection, model fitting criteria, and statistical significance of the variables. The chapter presents the modeling results by discussing the influence of key variables on roadway safety.

The fifth chapter presents the simplification of the models for agency implementation through CMFs that quantify the expected safety impacts of RPMs under given roadway configurations. In addition, CMFs that capture the joint effects of RPMs and rumble strips are presented.

The sixth chapter illustrates use of the research results and obtained CMFs to estimate the economic safety benefits of the researched countermeasures. Further, a detailed example that illustrates the step-by-step procedure of calculating the safety benefits is provided based on EB methodology and benefit–cost analysis.

Finally, the seventh chapter summarizes the report and its limitations. It also proposes areas for potential future research that might further improve the accuracy of the crash prediction models.

2. CURRENT STATE OF PRACTICE AND KNOWLEDGE

2.1 Literature Review

In 2016, there were nearly 3 million mi of rural roads in the United States; however, only 19% of the population lived in rural areas (Labi et al., 2017). In Indiana, rural roads constitute almost 75% of the state-administered road network. The 2023 Indiana Crash Facts (Palmer et al., 2023), reported 928 fatal crashes statewide. Although 29% of crashes occurred on nonurban roads, they accounted for approximately 54% of all fatalities. The fatality rate on rural roads was 6.5 fatalities per 100,000 population, four times higher than the 1.6 fatality rate on urban roadways.

Both environmental and behavioral factors contributed to the elevated fatality rate on rural roads. Many rural roads lack basic safety features such as paved shoulders or medians. Rural roads are typically low-volumes facilities without frequent busy intersections. Drivers feel encouraged to move at speeds higher than speed limits and to reduce their attention. The Federal Highway Administration (FHWA) identified alcohol-related crashes, poor seat belt usage, and slow emergency medical response times as significant contributors to rural crash severity (Chandler & Anderson, 2010) A past study on driver risk perception under different environments reported that drivers often perceive rural conditions as safer compared to urban conditions, which can lead to risk-taking behaviors and aggressive driving (Cox et al., 2017).

Therefore, transportation agencies often focus their efforts on reducing crashes and fatalities on rural two-lane roads. This effort is mainly to address the two following collision types:

1. Head-on crashes when two vehicles traveling in opposite directions collide, and
2. ROR crashes when a vehicle crosses an edgeline, centerline, or otherwise leaves the traveled lane (FHWA, 2023)

Among the 198,247 crashes reported in 2023, run-off-road crashes represented 23,063 (11.63%) and head-on crashes accounted for 4,453 (2.25%). Although these types of crashes are not the most frequent, they exhibit the highest fatality rates: 12.7 fatalities per 1,000 ROR crashes, and 21.1 fatalities per 1000 head-on collisions (Palmer et al., 2023). Additionally, these crashes were found to be more likely to occur on segments away from major intersections and under poor lighting conditions. For instance, while daytime crashes had a fatality rate of 3.4 per 1,000 incidents, nighttime crashes had a significantly higher fatality rate of 8.5 per 1,000 incidents (Palmer et al., 2023).

For the above reasons, RPMs emerged as a justifiable rural road safety countermeasure. These devices supplement lane markings, enhance positional guidance, alert drivers of changes in roadway geometry, and reduce encroachment into the opposite-direction traffic lane during inclement weather and low-light conditions (Jiang, 2006). However, their effectiveness has not been fully evaluated nationwide and not at all in Indiana.

Early RPM implementations faced two challenges: (1) reduced retroreflectivity due to water or snow accumulation; and (2) increased maintenance requirements due to troublesome snowplowing operations, marker detachment, casting failure, pavement failure, and adhesive failure (Zamenian & Abraham, 2020). In response, several RPM types have been tested and implemented nationwide, such as snowplowable RPMs with metal castings, recessed RPMs, and nonsnowplowable RPMs. The last type is used in regions where snowfall is not expected. Among these options, the snowplowable RPMs outperform other types in regions with significant snowfall under dry and wet weather conditions (Bahar et al., 2004).

Although no nationwide standards exists for RPM implementation, Grant and Bloomfield (1998) provided guidance and recommended practices that remain applicable nowadays. National Cooperative Highway Research Program (NCHRP) Report 1015, "Performance Criteria for Retroreflective Markers" (Pike et al., 2022), further confirms these recommendations. For example, an 80-ft spacing interval is recommended on tangent segments, a practice commonly followed across several districts in Indiana. For roadway segments with a degree of curvature between 8 and 9 degrees, the maximum allowable spacing is reduced to 40 ft. The guidance also recommends ensuring adequate visibility to provide a preview distance of approximately 2–5 s. Furthermore, RPMs should be installed along both the centerline and the left edgeline; however, placement along the right edgeline is discouraged, as it may confuse drivers and increase the risk of roadway departure crashes. Maintenance practices vary across states, but most agencies recommend inspecting or refurbishing the markers every 2–4 years.

In spite of the standards mentioned above, a nationwide survey conducted by Liu et al. (2018) found that RPM-related practices, such as installation, placement, maintenance, and replacement, vary significantly between states. For instance, 59% of the states surveyed reported selective RPM installation, while 32% reported nonselective installation.

Despite the inconsistent application of RPMs, they are expected to bring notable safety benefits, particularly on rural roads under adverse conditions such as nighttime or wet weather. Therefore, several studies have addressed the effectiveness of RPM implementation.

Wright et al. (1982) conducted a before-and-after study to assess the impact of centerline RPMs on nighttime crashes across 662 horizontal curves in Georgia between 1975 and 1980. Daytime crashes at the same locations served as a control group. Results showed a nighttime crash reduction of 22% and no correlation between RPM effect and changes in ADT or degree of curvature. Although other safety countermeasures were implemented alongside RPMs, their individual effects were not isolated. The study only accounted for average daily traffic (ADT) and degree of curvature.

Later, Kugle et al. (1984) conducted a before-and-after study to assess the impact of RPMs on crash reduction using crash data from 469 locations in Texas. The study focused on two-lane and four-lane roadways where RPMs were installed between 1977 and 1979. The analysis compared crashes by lighting conditions (daytime vs. nighttime), as well as by weather conditions (wet vs. dry) across crash types and severities. The results showed a statistically significant increase in nighttime crashes and no significant decrease in wet weather crashes. Specifically, nighttime ROR crashes increased by 11.9%, while nighttime head-on crashes rose by 16.5%. Moreover, nighttime crashes increased significantly across all the severity levels.

Mak et al. (1987) applied a before-and-after analysis that excluded locations affected by other roadway interventions. The resulting dataset consisted of 101 locations from which only 4.6% presented a statistically significant reduction in nighttime crashes, while 10.3% showed a significant increase. Crash severity was analyzed at just nine sites with at least 30 reported crashes, and these roads indicated an increase in severity after RPMs were installed. Furthermore, the evaluation indicated an increase in multiple-vehicle accidents, a decrease in fixed-object accidents, and no considerable change in single-vehicle crashes.

Similarly, Pendleton (1996) further investigated the effect of RPMs at 17 locations in Michigan where markers were installed along the centerline, using a before-and-after study. In addition, 42 nontreated locations served as the control group. Daytime and nighttime crashes were recorded over a 2-year period before and after installation. Several approaches were applied, mostly varying the comparison group; however, the study found that RPMs had no statistically significant effect on crash frequency.

The New York State Department of Transportation (NYSDOT, 1997) evaluated the safety impacts of raised reflectorized snowplowable pavement markers at 20 sites selected for installation. The study considered ROR, head-on, encroachments, and sideswipe crashes. The results indicated a 23% overall crash reduction across all conditions, with a significant 39% decrease during nighttime.

Likewise, Orth-Rodgers and Associates Inc. (1998) examined the effects of RPMs at 91 locations in Pennsylvania using crash data from 1991 to 1996. Crashes that occurred under unknown light or weather conditions, as well as observations with zero crashes, were excluded from the final dataset. The study showed nonsignificant effects on crash frequency at locations with raised markers, but a significant 20.1% crash increase at locations with recessed pavement markers.

The NCHRP (Bahar et al., 2004) evaluated the safety effects of permanent RPMs on two-lane roads across four states. Results varied depending on state and site selection criteria. In New York State, where locations were selected based on crash history, the total number of crashes dropped by 9.5%, and nighttime crashes decreased by 20%. In contrast, in New Jersey and Pennsylvania, where sites were selected randomly, the effects were not statistically significant. In Illinois, crashes even showed significant increases after RPM implementation. For two-lane roads under nighttime conditions, the study found that safety benefits tended to increase with higher traffic volumes but reduce with narrower lane and shoulder widths or with higher curvature degrees.

Agent and Green (2009) studied the effectiveness of snowplowable RPMs on rural two-lane roads in Kentucky. This study reported marginal reductions in crashes during nighttime wet conditions on segments with RPMs compared to those without RPMs. Similarly, Elvik et al., (2009) reported that RPMs installed as a standalone countermeasure did not provide significant safety benefits, as they found a crash modification factor of 0.99 for head-on collisions and noted that RPMs tend to be more effective in conjunction with other types of road markings.

Das et al. (2013) further evaluated the safety effects of RPMs on rural and urban freeways in Louisiana. Their findings showed that RPMs significantly reduced all crash types across all traffic volume levels on rural roads, yielding CMFs of 0.87 for both nighttime and all-day conditions. In contrast, the study found that RPMs are no longer effective on urban roads. Because this work is included on the CMF Clearinghouse webpage, it served as a useful start point for our expected results; however, several limitations identified by the authors warrant consideration. The study's CMFs were developed specifically for Louisiana, limiting their application to other locations. Also, the authors used a subjective score to account for the quality of RPMs over time that may not reflect true performance. Finally, the study did not consider any other countermeasures such as rumble strips that are commonly deployed along with RPMs in their analysis. These limitations present an opportunity for the current project. By examining the interactions between RPMs and other treatments, such as rumble strips or shoulder and lane widening, we aim to better understand their combined safety effects and produce more broadly applicable findings.

NCHRP Report 1015, "Performance Criteria for Retroreflective Markers," from Pike et al. (2022) presents a comprehensive study intended to provide practitioners updated strategies related to the use of RPMs. The research examined RPM effectiveness through three approaches: an operational assessment, a driver behavior study, and a safety analysis; however, only the latter two are relevant to the current project. The driver behavior component relied on large-scale data from multiple states and examined lateral positioning and speed as surrogate safety measures; however, RPM characteristics such as type, spacing, and condition were not recorded, limiting the detail of the analysis. The study concluded that RPMs on tangent segments were associated with increased vehicle speeds and identifiable shifts in driver lateral positioning, particularly when combined with other treatments such as rumble strips and paved shoulders, while no meaningful effects were observed on curves. The report also attempted to assess safety impacts through a cross-sectional and before-and-after approach, but comparable roadway segments were difficult to identify because RPMs are typically installed systemwide based on roadway class, and reliable information on installation and maintenance practices was unavailable. Consequently, a crash-based safety evaluation could not be completed.

Indeed, the reviewed literature on the safety effects of RPMs indicated the inconsistency in both the methodology (sample selection) and the results across studies. Some research studies reported significant reductions in total crashes, nighttime crashes, and crashes under wet conditions attributable to RPMs (Bahar et al., 2004; NYSDOT, 1997; Wright et al., 1982). In contrast, other research studies found increases in ROR and head-on crash rates following RPMs implementation (Kugle et al., 1984; Mak et al., 1987; Orth-Rodgers and Associates, Inc, 1998). Still, a few other studies observed no significant effects on crash frequency (Pendleton, 1996). A study on painted rumble strips as an alternative to RPMs was conducted in Indiana by (Brennan et al., 2014). While the study provided useful details regarding the technical aspects of the treatment, the reported considerable reduction in number of crashes was undermined by the small sample due to the experimental nature of the treatment.

Some of the past research methods that may raise concerns about uncontrolled factors and unchecked selection bias. These and other potential issues such as small samples may explain considerable variations of results across these studies. According to Bahar et al. (2004), one of the principal problems with previous research is regression-to-the-mean or selectivity bias, which can lead to overestimation of the safety benefits in crash reduction associated with RPMs. As site selection for RPM implementation is often based on locations with high crash records, crash frequency is likely to decrease over time even without any safety intervention. Additionally, poor selection of the comparison groups, for example, using daytime crashes as a baseline for nighttime crashes, can magnify the selectivity bias problem.

Other methodological issues involve the definition of exposure variables. For example, when evaluating safety benefits for nighttime crashes, the exposure should be adjusted to account for nighttime traffic volume. However, in some of the reviewed studies, this adjustment was only approximate, while in other cases, traffic volume changes were not considered at all. Another frequently observed limitation is that most studies evaluated for short "after installation" periods. This situation overlooks potential issues, such as an initial increase in risky situations while drivers adapt their behavior to the new system which could influence the measured safety impact. Moreover, it is often unclear how studies accounted for construction periods and the user's adaptation period to a new intervention. In addition, many studies fail to isolate the safety effect of RPMs on roads where other safety countermeasures are already in place. Similarly, the combined impacts of RPMs with other safety countermeasures or road features on crash frequency and severity remain unstudied.

2.2 Indiana Practice

It seems that there are no consistent general guidelines for RPM use across the United States. This void can be defended with various weather and climate conditions within the US borders that may considerably affect the performance of RPMs. Thus, individual states adopted their own approaches depending on roadway conditions and policy priorities. In Indiana, both the selective and nonselective implementation practices are followed. Site selection seems to be driven by crash records, elevated traffic volumes, or adverse weather conditions (Bahar et al., 2004) and probably other considerations such as maintenance issues. According to the INDOT (2021) design guidelines, RPMs are required on rural two-lane roads with ADT volumes greater than 3,000 vehicles per day, as well as on multilane roads with a functional classification of interstate, freeway or expressway, or other principal arterial. The adopted installation standards specify 80-ft spacing on tangent sections and 40-ft spacing in no-passing zones, while maintenance cycles are defined as a function of ADT. Jiang (2006) reported that Indiana had completed RPM installation on all interstate and multilane divided highways; however, their application on rural two-lane roads had remained limited.

2.3 Summary of Findings and Implications

Overall, the previous studies had not reached a consensus regarding the safety benefits that RPMs may provide on rural roads. While some research studies affirmed that the markers' implementation helped reduce crash frequency, other studies concluded that their effect were nonsignificant or even that they increased crash likelihood. Furthermore, past studies had methodological limitations, including the lack of consideration of the selectivity bias potential, the short postinstallation periods, and the inconsistent definitions of exposure. These drawbacks of the past studies raise questions about the accuracy of the reported effects. In addition, controlling the effect of other conditions such as roadway features, the presence other safety countermeasures remained to be addressed. These research gaps highlight the need for a more comprehensive and advanced analysis that considers roadway geometry, traffic exposure, and other safety countermeasures.

TABLE 3.1
Raised Pavement Markers Distribution by Number of Segments and Number of Miles.

Location	Type	Segments	Miles
Centerline	Snowplowable	1,192	754.97
	Reflective Tape	13	5.66
No RPM		7,078	4,519.48
Total		8,283	5,280.11

3. DATA DESCRIPTION

Data from various sources were acquired, verified, and combined to evaluate the safety performance of two-lane rural roads in Indiana. The assembled database includes a comprehensive set of variables: geometric features, crash data, traffic volume, RPMs, and rumble strips information. The primary data were provided by INDOT's Geographic Information Office. This dataset establishes the foundation for estimating and analyzing the relationship between road design elements and crash occurrences.

3.1 Raised Pavement Markers

INDOT included data on construction and refurbishment contracts for centerline RPMs implemented across the state during the 2015–2023 period. The contract records included the start and end dates of interventions, and RPM type (snowplowable or reflective tape). The distribution of RPMs based on type is presented in Table 3.1.

The installed reflective tapes account for only 5.66 mi, representing only 0.16% of the total sample in the dataset. This small proportion prevented their separate analysis. In particular, the insufficient sample size made it impossible to estimate the safety benefits attributable to the reflective tapes.

Moreover, data showed that the INDOT contracts that specified RPM installations along the edgeline represented less than 1% of all observations. Further, all these contracts were scheduled to end after the project analysis period. Therefore, the research scope was limited to centerline RPMs.

3.2 Geometric Features

INDOT's road inventory was the primary source of information about the geometric features of the analyzed roads. Information pertaining to functional classification, lane width (feet), shoulder width (feet) and length of each segment (miles), and other road features were included in INDOT's road inventory. The data were reorganized around the RPMs—the focus of the study. In a related Joint Transportation Research Program project from Barahona et al. (2025), the effect of shoulder width on ROR crashes was investigated. The shoulder width groups reported in that project were used in this research to maintain continuity and ease of comparing results.

Widths of lanes and shoulders affect vehicles' lateral position on the road. Narrower lanes typically lead to more centered driving and lower speeds, whereas wider shoulders can prompt

TABLE 3.2
Shoulder Width (SW) and Lane Width (LW) Distribution.

		LW [ft]						
		7	8	9	10	11	12	Total
SW [ft]	0	0	214	524	1,682	731	2,289	5,429
	1	0	0	0	39	15	106	160
	2	3	50	168	742	282	684	1,929
	3	0	3	10	81	27	150	271
	4	0	0	1	41	17	59	118
	5	0	3	2	8	16	21	50
	6	0	0	8	30	14	19	71
	7	0	0	3	7	5	8	23
	8	0	1	5	16	12	38	72
	9	0	0	3	11	4	11	29
	10	0	2	3	18	30	63	116
	11	0	0	0	0	1	0	1
	12	0	0	0	1	7	4	12
	13	0	0	0	0	0	0	0
	14	0	0	0	1	0	0	1
	15	0	0	0	0	1	0	1
	Total	3	273	727	2,677	1,162	3,441	8,283

drivers to edge closer to the roadway's limit, potentially increasing collision risks (Ben-Bassat & Shinar, 2011; Mecheri et al., 2017). Optimizing roadway design requires a good balance with a recommended 11 or 12 ft for lane width. However, many rural two-lane roads in Indiana were constructed based on earlier design specifications and have narrower lanes.

The shoulder and lane widths were provided by INDOT as integer values. It was found during the analysis that a combination of lane and shoulder widths (Table 3.2) is a better predictor of driver's behavior than the two separate values. Consequently, the combined values were used to estimate the risk of ROR and opposite-direction crash occurrences.

Horizontal alignment characteristics such as total deflection angle, degree of curvature per mile, maximum degree of curvature, and frequency of curves are calculated along each segment with the assistance of a software tool developed at the Purdue Center for Road Safety (CRS). This software was applied to determine the curvature characteristics of the road segment as described below.

Calculating the curvature of a segment represented with a polyline involved finding the curvature at discrete points along the polyline. A segment curvature estimated based on a series of connected polyline segments was used to measure the horizontal curve sharpness. This calculation needed angles between consecutive polyline segments. The operations presented below include calculating these angles, segment curvature, and the number of curves.

For each consecutive triplet of points $\left(P_{i-1}, P_i, P_{i+1}\right)$, two vectors are calculated:

$$\overrightarrow{v_\iota} = P_i - P_{i-1}, \overrightarrow{w_\iota} = P_{i+1} - P_i \qquad \text{(Eq. 3.1)}$$

Then, the angle θ_i between these two vectors is obtained:

$$\theta_i = \arccos\left(\frac{\overrightarrow{v_\iota} \cdot \overrightarrow{w_\iota}}{\left|\overrightarrow{v_\iota}\right|\left|\overrightarrow{w_\iota}\right|}\right) \qquad \text{(Eq. 3.2)}$$

The total segment deflection angle, δ, along the segment (small individual errors tend to cancel out when summed along the segment):

$$\delta = \sum_{i=1}^{n-1} \left|\theta_i\right| \qquad \text{(Eq. 3.3)}$$

The total segment deflection angle to left, δ_L, and to right, δ_R, (turn direction determined with the sign of the vectors cross product) is:

$$\delta_L = \sum_{i=1}^{n-1} \begin{cases} \left|\theta_i\right| \text{if cross product is positive} \\ 0 \text{ if cross product is negative} \end{cases} \qquad \text{(Eq. 3.4)}$$

$$\delta_R = \sum_{i=1}^{n-1} \begin{cases} \left|\theta_i\right| \text{if cross product is negative} \\ 0 \text{ if cross product is positive} \end{cases}$$

The deflection rates are calculated as the total deflection rate divided by the segment length. The sequences of deflection angles of the same sign and of sufficient length indicate the presence of horizontal curves. Other road segment horizontal alignment characteristics derived from their polylines are not found to affect road safety significantly and are not presented.

3.3 Clear Zones

The data provided by INDOT did not include any shapefile related to the clear zones. Thus, it was not possible to identify roadside features such as trees, utility poles, or ditches. Manually obtaining this information, even with the available video-log equipment in Indiana, is highly labor intensive. Conducting such analysis for all two-lane rural roads in Indiana was not feasible with the resources available for the project.

3.4 Crash Data

The police crash reports were obtained from the Automated Reporting Information Exchange System (ARIES). The ARIES database included information regarding crash location, type, number of vehicles involved and manner of collision. Each crash was assigned to a segment based on the location proximity and linked to roadway features and the presence of RPMs. The target crashes for this study were classified into two categories: ROR crashes and opposite-direction crashes, which include head-on and opposite-direction sideswipe. Crashes such as angle collisions, rear-end or same-direction sideswipe were not considered in the analysis.

- ROR: This type of crash involves vehicles leaving the roadway to the right or left, typically due to loss of control or driver error.
- Opposite-direction crashes:
  - Head-on crash occurs when a vehicle crosses the road centerline and collides with another vehicle traveling in the opposite direction.
  - Opposite-sideswipe crash occurs when two vehicles traveling in opposing directions collide with their sides.
- Other types of crashes not considered included: rear-end collisions, same-direction sideswipe collisions, and angle collisions.

TABLE 3.3
Total Crashes and Percentages Per Raised Pavement Marker Type.

Location	Type	Run-off-Road (ROR)	Head-On + Opposite-Direction Sideswipe	Total Target Crashes
Centerline	Snowplowable	1,068	165	1,233
	Reflective tape	3	3	6
Before RPM installation		2,204	373	2,577
Control segments		17,951	2,970	20,921
Total		21,226 (85.81%)	3,511 (14.19%)	24,737

TABLE 3.4
Run-Off-Road Crashes Per Severity.

Time	Daytime			Nighttime			
Type	**KA**	**BC**	**PDO**	**KA**	**BC**	**PDO**	**Total**
RPM Installed	52	133	381	41	111	353	1,071
Before RPM Installation	62	300	841	56	223	722	2,204
Control Segments	650	2,477	6,772	536	1,766	5,750	17,951
Total	764	2,910	7,994	633	2,100	6,825	21,226
%	**3.60%**	**13.71%**	**37.66%**	**2.98%**	**9.89%**	**32.15%**	**100%**

TABLE 3.5
Opposite Direction Crashes Per Severity.

Time	Daytime			Nighttime			
Type	**KA**	**BC**	**PDO**	**KA**	**BC**	**PDO**	**Total**
RPM Installed	27	25	54	15	16	31	168
Before RPM Installation	44	63	130	22	32	82	373
Control Segments	335	475	974	202	256	728	2,970
Total	406	563	1,158	239	304	841	3,511
%	**31.56%**	**16.04%**	**32.98%**	**6.81%**	**8.66%**	**23.95%**	**100%**

All crashes were categorized by their severity outcome according to the KABCO scale, where K represents fatal injury, A represents incapacitating injury, B represents minor injury, C represents possible injury, and O represents a property-damage-only (PDO) crash. Due to the relatively low number of crashes in each of the individual injury severity levels, the crashes were grouped into three categories: KA (fatal or incapacitating injury), BC (minor or possible injury), and PDO (property-damage-only) in the estimated crash severity model.

Additionally, reflective tapes account only for 0.02% of the total crashes recorded during the study period. This extremely low representation, combined with the limited number of roadway segments where reflective tape was installed, prevented obtaining meaningful results for both the types of markers. As a result, it was decided to treat RPMs regardless of type. This approach ensured a sample size sufficient for obtaining significant statistical results. The final count of ROR and opposite-direction crashes per severity is shown in Table 3.4 and Table 3.5, respectively.

3.5 Traffic Data

The volumes of traffic on rural roads in Indiana were obtained from the shapefiles provided online by INDOT. The historical traffic zone shapefiles are published yearly, and they are free to access. They contain information about the annual average daily traffic (AADT) in a specific year from 2015 to 2023. Seasonal factors for monthly adjustment of the traffic are also found on INDOT's repository. The distribution of traffic volumes across the studied segments, expressed in lane-miles and specified by the presence of RPMs, is shown in Figure 3.1.

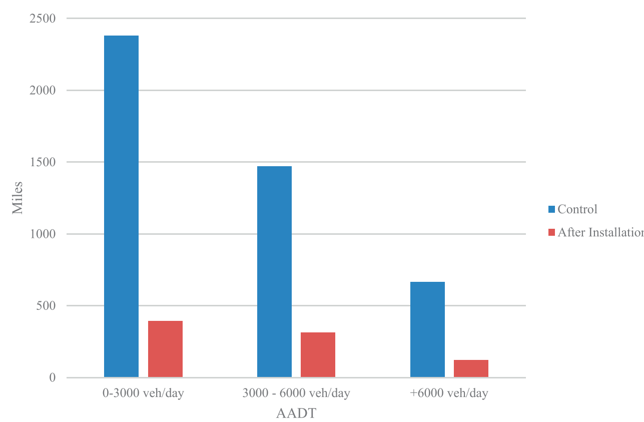

Figure 3.1 Histogram Relating Raised Pavement Marker and AADT.

3.6 Intersections

To focus the analysis on road segments, crashes that occurred within 250 ft from a major intersection were removed. A major intersection is defined as an intersection of a state-administered arterial or collector road. Unlike major intersections, minor intersections were retained for the analysis together with other geometric characteristics of the studied segments. The presence of intersections along a roadway segment introduces additional conflict points, which can increase the likelihood of crash occurrence. To account for this effect, the statistical models included the density of minor intersections (measured as minor intersections per mile) as a predictor variable. This approach helps ensure that the influence of minor intersections is properly captured and not taken by other variables in the model.

TABLE 3.6
Scenarios of Rumble Strips and Raised Pavement Markers on Indiana Rural Roads.

Raised Pavement Markers	Rumble Strips	Miles	Segments
Not installed	**Not installed**	3,266	5,078
Not installed	**Only road center**	1,076	1,704
Not installed	**Only road edge**	16	26
Not installed	**Road center and edge**	160	270
Installed	**Not installed**	558	863
Installed	**Only road center**	167	281
Installed	**Only road edge**	4	7
Installed	**Road center and edge**	30	54

3.7 Rumble Strips

Rumble strips are among countermeasures commonly used on road segments to avoid ROR and opposite-direction crashes. Rumble strips are installed on the side of the road (edge or shoulder), in the centerline of the road, or in combination. Rumble strips are meant to be a preventive measure against driver error and not to mitigate deficiencies of roadway design. They provide audible and vibratory warnings to drivers to trigger a corrective and timely action preventing ROR crashes (FHWA, 2018). The rumble strip installation data includes rumble strip placement: road center, edge, shoulder, or combination. As both RPMs and rumble strips are commonly used to reduce ROR and head-on crashes, their interaction is important to analyze (Table 3.6).

TABLE 3.7
Statistical Summary of Variables.

Continuous Variables					
Variable	**Explanation**	**Min**	**Max**	**Mean**	**Standard deviation**
AADT	Annual Average Daily Traffic in veh/day	25	30,767	3,675	2,705
L	Length of the roadway segment in miles	0.01	2.87	0.63	0.46
SW	Shoulder width in feet	0	15	1.06	1.85
LW	Lane width in feet	7	12	10.81	1.16
SL	Speed limit in mph	10	60	48.91	9.42
DA	Total deflection angle (in degrees) per mile	0	3,256.1	47.63	104.96
Crv	Total number of curves per mile	0	73.7795	2.76	4.67
Int	Number of minor intersections per mile	0	1,379.32	15.23	46.19

Categorical Variables				
Variable	**Explanation**	**Levels**	**Count**	**Percent**
FC_{PA}	Functional class	Principal Arterial	1,655	19.98%
FC_{MA}		Minor Arterial	2,354	28.42%
FC_{Coll}		Collectors	4,260	51.43%
FC_{Local}		Local Roads	14	0.17%
$SW_{0,1,2}$	Shoulder width	0–1–2 ft	7518	90.76%
$SW_{3,4}$		3–4 ft	389	4.70%
$SW_{5,6}$		5–6 ft	121	1.46%
SW_{7+}		7+ ft	255	3.08%
$LW_{\leq 10}$	Lane width	7–8–9–10 ft	3,673	44.34%
$LW_{11,12}$		11–12 ft	4,610	55.66%
Y2020	Indicator of year 2020 (COVID)	1	8,024	10.99%
		0	64,992	89.01%
RS	Rumble strip: 1 if RS installed, 0 otherwise	1	10,823	85.17%
		0	62,193	14.82%
RPM	Control Segments	Control	60,715	83.15%
	Segments before RPM installation	Before	7,446	10.19%
	Segments with RPM installed	After	4,855	6.65%

3.8 Data Descriptive Summary

The descriptive summary of the variables used in the analysis is presented in Table 3.7. In total, there were 8,283 road segments included in the dataset. They represent approximately 5,280 mi of roads. Rows in the table provides summary statistics for model variables applied to segment annual observations. Nine years of crash data (2015–2023) were assigned to the respective observations along with traffic, geometry, and rumble strip settings. In total, there were 73,016 observations.

4. STATISTICAL MODEL DEVELOPMENT

The focus of the presented research was to evaluate how RPMs, along with geometric features and rumble strips, influence the ROR and opposite-direction crashes to help the end user (INDOT) decide where the considered improvements should be implemented. This research objective was supported by the developed crash frequency models, which predict how the studied RPMs along with other cross-section elements affect the crash occurrence and its severity. The safety improvements estimated for the studied countermeasures are expressed with CMFs, which reflect the expected relative change in crash frequency at different severity levels in response to the selected improvement alternative.

4.1 Crash Frequency Model

4.1.1 Model Type Selection

Crash frequency data are inherently over-dispersed, meaning that the variance of observed crashes often exceeds the expected value. Therefore, the Poisson model, which assumes that variance and mean are equivalent, is unsuitable for crash frequency analysis (Lee et al., 2023; Lord & Mannering, 2010). The NB model addresses this limitation by introducing a dispersion parameter that allows the variance to exceed the mean, making it one of the most widely used models in transportation safety research (Islam et al., 2014). In its essence, the NB model extends the Poisson model by assuming that its mean follows a gamma distribution, thereby accounting for the unobserved heterogeneity in roadway segments (Lord & Mannering, 2010).

The NB model has been questioned by several authors regarding its applicability under conditions of low sample means and limited crash data, where many roadway segments present zero crashes over the study period. Previous studies suggested that low mean crash counts, often skewed toward zero, may lead to improperly estimated parameters and incorrect inferences (Llopis-Castelló et al., 2021; Lord & Mannering, 2010;

Rahman Shaon & Qin, 2016). Concerns have also been raised about potential estimation issues arising from incomplete or poor roadway data, which may further affect model reliability. To the contrary, (Hall & Tarko, 2019) demonstrated the validity of the NB-based modeling for low-volume and low-crash rural roads. By applying proper tests, they confirmed an unbiased model estimate for the entire range of observed values including locations with low counts. Small samples and underreporting issues apply to data and not to modeling methodology. Researchers continue applying NB modeling to a variety of conditions including low-mean data samples.

One of possible enhancements of the NB model is including random effects in the model structure if observations may be grouped in some meaningful way and these cluster-specific effects are not captured by observed variables. One natural grouping is annual observations having their own year effects not captured otherwise. In transportation safety studies, roadway segments within the same geographic region or functional classification often share similar unmeasured characteristics that influence crash frequency. These effects can be represented as random effects attributed to these groupings (clusters). Thus, the random-effects structure improves model accuracy by capturing this group-level unobserved heterogeneity and ensuring that parameter estimates reflect true variations across segments and are not biased by omitting group-level components (Lord & Mannering, 2010). This is particularly important for studies analyzing extensive networks where roadways are influenced by local geometric, environmental, and operational factors that are difficult to measure directly.

The NB model with random effects offers several advantages over other modeling approaches. Explicitly accounting for overdispersion, it provides more reliable parameter estimates than the Poisson model (Islam et al., 2014). The ability to model roadway-specific variations through random effects enhances its predictive accuracy, making it particularly useful for large-scale studies where crash frequency distributions differ across locations (Lord & Mannering, 2010). Furthermore, NB-based models allow for flexible variance structures, enabling transportation researchers to develop more realistic safety performance functions that can inform roadway design and policy decisions.

To evaluate the safety effectiveness of RPMs, the NB-based modeling methodology was applied to associate crash frequency with the presence of centerline RPMs. The study included 5,280 mi of rural two-lane highways across Indiana in the analysis, with crash data from 2015 to 2023 assigned to more than 8,000 segments. For each segment, traffic volumes (AADT); geometry features, such as length, number of curves, deflection angle rate, lane width, and shoulder width; and rumble strip settings, along with the presence of centerline RPMs, were included for analysis.

As discussed earlier in this section, a random-effects NB model was applied to account for potential heterogeneity among groups of segments coming from the same roadway. To capture this heterogeneity, a grouping variable was added to the model to address unobserved commonalities between segments belonging to the same road within the same township. This approach acknowledges local variations and unobserved factors that may differ across townships and roads, thereby potentially enhancing the robustness of the safety analysis.

The model structure is shown in Equation 4.1. The log of mean value μ is expected to have a linear relationship with explanatory variables ($X_1, X_2, \cdots X_j$). Because the proposed model includes random effects attributed to segments (grouped within roads and townships), the model intercept includes additional term α_{ID}, which represents the unobserved heterogeneity attributed to random effects. Variance, δ, is the summation of two terms, mean, a_i, is the expected number of crashes and product of the square of mean and dispersion parameter, ρ. When dispersion parameter, ρ, is close to zero, the NB model descends to its Poisson version.

$$
\begin{gathered}
CrashNum_i \sim NegativeBinomial\left(a_i, \delta\right) \\
a_i = \exp\left(\alpha_0 + \alpha_{ID} + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_j X_{ij}\right) \\
\alpha_{ID} \sim Normal\left(0,\ \sigma_{ID}\right) \qquad \text{(Eq. 4.1)} \\
\delta = a_i + \rho\ a_i^2
\end{gathered}
$$

In summary, the NB model in Equation 4.1 with random effects α_{ID} is a suitable tool for crash frequency analysis, effectively addressing overdispersion and unobserved heterogeneity. By incorporating segment-level variations, this approach enhances the reliability of crash frequency predictions and provides a practical foundation for roadway safety assessment and intervention planning.

The proposed model is meant to enable transportation safety officials to make data-driven decisions on rural highways in Indiana. Including key safety features, such as pavement marking, rumble strip installation, shoulder width, traffic exposure, and geometric design, will ensure that the safety evaluation reflects real-world conditions for safety-oriented infrastructure planning and adequate countermeasure selection.

4.1.2 Full Model Estimation and Results

The final models are the result of an iterative modeling process. Target crash types for this project included ROR and opposite-direction collisions (head-on + opposite-direction sideswipe) crashes. Because RPMs are expected to have a different impact on each type of crash, separate models were fitted for ROR and opposite-approach crashes. Also, animal-related crashes were analyzed independently to evaluate the impact of RPM on such types of crashes. Further, for each crash type, daytime crashes and nighttime crashes were modeled separately as RPMs have retroreflective elements that are intended to guide road users during nighttime.

Several methodologies were attempted for modeling, beginning with a model in which each observation represented a month-segment combination. This approach was dropped because it resulted in many zero-crash observations, which can lead to biased estimates. While one advantage of the monthly model is the ability to include weather as a predictor, this was not prioritized since RPMs are a long-term countermeasure that does not vary across the year with environmental conditions. Instead, an annual-observations approach was adopted, providing more aggregated data, reducing the zero counts, and resulting in more stable coefficient estimates.

Starting with a simple model, additional variables were incorporated one at a time to assess their significance and impact on the results. Similarly, nonsignificant variables were dropped from the analysis. Various approaches were tested for each variable, but the final set of predictors and the chosen level of aggregation were determined based on optimal values of AIC, BIC, and log-likelihood criteria. Interaction effects were also explored, but only the interaction between shoulder width and lane width was significant in the final model.

For example, speed limit was not a significant variable in the modeling process, as nearly all rural roads in the dataset have a speed limit of 55 mph. This lack of variation limits the ability of the model to detect any meaningful statistical differences related to speed. Since the speed limit remains constant across most observations, it does not contribute to explaining differences in crash occurrence or severity. As a result, including it in the model did not provide additional insights.

To determine the optimal grouping for the shoulder width (*SW*) variable, multiple configurations were tested during the modeling process. The initial grouping followed the same classification used in the data exploration phase: 0–1, 2–3, 4–5, 6, and 7+ ft. However, due to the statistical insignificance of one or more shoulder width levels and the distribution of the dataset, alternative groupings were explored. In the final grouping, widths of 0, 1, and 2 ft were combined, as there is no significant difference in a driver's ability to recover from a lane departure across these widths; widths of 3–4 and 5–6 ft were each treated as separate categories, while 7+ feet remained its own category. This grouping strategy was informed by current industry standards to ensure practical relevance. The final selection was based on achieving the best statistical significance for all variables in the model while maintaining alignment with roadway design practices. Similarly, for lane width (*LW*), multiple grouping strategies were evaluated; however, the most effective approach was to classify it into only two categories: 7–8–9–10 ft and 11–12 ft.

As mentioned earlier, separate models were fitted for ROR and opposite-direction (head-on plus opposite direction sideswipe) crashes. Additionally, each crash type was divided into daytime and nighttime crashes to capture differences in variable effects under different lighting conditions. The final models were selected based on the statistical significance of the estimated effects of the included variables.

The variables used in the final crash frequency models are the following:

- *Log (Length):* log of the length of the roadway segment measured in miles.
- *Log (AADT):* log of the annual average daily traffic volume.
- *RPM Status:* Categorical variable indicating the status of raised pavement markers on the segment.
  - Control: Segments that were not selected for RPM installation (baseline for comparison).
  - Before: Segments that were selected for RPM installation, but with the system not installed yet.
  - After: Segments with RPM installed.
- *RS:* Binary variable indicating the presence of rumble strips on the segment.
  - Run-off-road: The rumble strip presence was considered regardless of the location.
  - Head-on: Only centerline rumble strip presence was considered.
- *Deflection angle per mile [DA]:* Total deflection angle in degrees per mile.
- *Density of minor intersections [Int]:* Number of intersections with local roads per miles.
- *Curvature per mile [Crv]:* Total number of curves per mile.
- *SW:* Categorical variable indicating the shoulder width measured in feet.
  - 0–1–2 ft: Groups shoulder widths of 0, 1, and 2 ft (baseline for comparison).
  - 3–4 ft: Groups shoulder widths of 3 and 4 ft
  - 5–6 ft: Groups shoulder widths of 5 and 6 ft.
  - 7+ ft: Groups shoulder widths of 7 ft and above.
- *LW:* Categorical variable indicating the lane width measured in feet.
  - 11–12 ft: Group lane width of 11 and 12 ft (baseline for comparison).
  - ≤ 10 ft: Group lane width of 10 ft or less.
- $\sqrt{SW \cdot LW}$: Square root of the interaction between shoulder width and lane width.
- *Covid:* Binary variable for observations during year 2020.
- *Months in observations*: Variable indicating the number of months included in the yearly observations, excluding construction periods of RPMs and rumble strips.

4.1.2.1 Animal Related Crashes. One concern regarding the implementation of RPMs is the potential risk of increasing animal-related crashes, as their reflectivity might attract animals. Although these crashes did not fall within the original project scope, crash data were compiled, and preliminary models were developed. The modeling results are presented in Appendix A.

The results indicated that roadway features such as lane and shoulder width, as well as density of minor intersections, were not significant predictors of animal-related crash frequency. In contrast, roadway curvature, deflection angle, and the presence of rumble strips were found to be statistically significant. The coefficient estimates for the variable "RPM *status: Before*" suggests that there was no evidence of selection bias in the choice of segments where RPMs were installed. Moreover, the presence of RPMs was associated with a reduction in animal-related crashes, both during the day and at night, ranging between 39% and 52%.

Even though these results are promising, the analysis is limited. Key information, such as the nearness of habitats where animals are most likely to be present, was not available. In addition, there is no evidence of policies or practices specifically guiding RPM installation at sites with high rates of animal-related crashes. Therefore, further research is needed to better understand the relationship between RPMs and animal-related crash frequency. Full modeling results are provided in Section 10.1.

4.1.2.2 Opposite-Direction Crashes: Head-On+Opposite-Direction Sideswipe. The results for the opposite-direction crash count model are presented after excluding variables that were not statistically significant. For example, shoulder width and lane width were not included in the final model, as they did not have a significant effect on reducing this type of crash. Additionally, only the presence of centerline rumble strips was considered in this model, since the strips located on the side of the road are not expected to provide major safety benefits for opposite direction crashes.

The final modeling results for daytime and nighttime opposite direction crash frequency are presented in Table 4.1. The tables show the estimated effect of each variable included in the model, along with their corresponding statistical significance.

The variable *"RPM Status: Before"* showed no statistical significance, for both daytime and nighttime conditions. This suggests that the selection process did not have a selection bias issue. Based on this finding, a reduced model considering only the overall presence of RPMs and the other significant variables is presented in Table 4.2.

For opposite-direction crashes, both segment length and traffic volume were significant predictors of crash frequency. Longer and more congested segments were associated with higher crash risk under both daytime and nighttime conditions.

Raised pavement markers did not have a statistically significant impact on daytime crashes. However, at nighttime or under poor lighting conditions, RPMs were associated with a significant 24% reduction in crash frequency. This is consistent with previous research that suggests a stronger effect of RPMs in reducing nighttime crashes when they are supposed to supplement lane markings, enhance positional guidance, and reduce encroachment into the opposite-direction traffic lane.

For this model, only centerline rumble strips were considered, as edge or shoulder rumble strips do not directly influence the risk of opposite direction crashes. Centerline rumble strips were found to significantly reduce crashes during both daytime and nighttime, with their effect being nearly twice as strong at night. This result aligns with findings from prior studies, which highlight the effectiveness of rumble strips in alerting drivers leaving the road through vibration and noise.

Deflection angle and minor intersection density were also significant predictors. However, number of curves per mile was found to be not significant. Moreover, exposure adjustment variables such as *Covid* and *Months in observation* were found to be significant in both daytime and nighttime crash frequency models.

On the other hand, shoulder and lane width were not included in this model, as their p-values showed no statistical significance. This finding is logical because cross-sectional elements, such as shoulder and lane width, are expected to mainly influence ROR crashes by providing drivers with additional clearance to correct their travel direction in case of departure.

TABLE 4.1
Full Model: Opposite Direction Crashes.

	Daytime Crashes			Nighttime Crashes		
Dispersion Parameter	**1.5204**			**0.6826**		
Term	**Estimate**	**StdErr**	**Pr > |t|**	**Estimate**	**StdErr**	**Pr > |t|**
Intercept	-9.8420	0.3577	< 0.01	-10.246	0.4326	< 0.01
Log (Length)	0.6577	0.0384	< 0.01	0.8099	0.0522	< 0.01
Log (AADT)	0.6057	0.0361	< 0.01	0.7096	0.0478	< 0.01
RPM status: Before	0.1230	0.0743	0.0976	-0.0625	0.0988	0.5269
RPM status: After	-0.0601	0.1045	0.5651	-0.2556	0.1392	0.0663
RPM status: Control	0.0000			0.0000		
Rumble strips presence [RS]	-0.2092	0.0731	< 0.01	-0.3705	0.0951	< 0.01
Deflection angle [DA]	0.0019	0.0003	< 0.01	0.0011	0.0005	< 0.05
Density of minor intersections [Int]	0.0038	0.0013	< 0.01	0.0038	0.0018	< 0.05
Curves per mile [Crv]	0.0105	0.0080	0.1900	-0.0075	0.0128	0.5577
Covid	-0.3752	0.0859	< 0.01	-0.1615	0.1004	0.1077
Months in observation	0.1503	0.0185	< 0.01	0.1378	0.0232	< 0.01

TABLE 4.2
Reduced Model: Opposite Direction Crashes.

	Daytime Crashes			Nighttime Crashes		
Dispersion Parameter	**1.5227**			**0.6818**		
Term	**Estimate**	**StdErr**	**Pr > |t|**	**Estimate**	**StdErr**	**Pr > |t|**
Intercept	-9.7614	0.3555	< 0.01	-10.2791	0.431	< 0.01
Log (Length)	0.6517	0.0381	< 0.01	0.8132	0.0518	< 0.01
Log (AADT)	0.6036	0.036	< 0.01	0.7093	0.0478	< 0.01
RPM presence	-0.0826	0.1038	0.4257	-0.2436	0.138	0.0773
Rumble strips presence [RS]	-0.2201	0.0729	< 0.01	-0.3641	0.0947	< 0.01
Deflection angle [DA]	.00217	0.0002	< 0.01	.00094	0.0004	< 0.05
Density of minor intersections [Int]	0.0038	0.0013	< 0.01	0.0038	0.0018	< 0.05
Covid	-0.3783	0.0859	< 0.01	-0.1603	0.1004	0.1102
Months in observation	0.1472	0.0184	< 0.01	0.1395	0.023	< 0.01

In contrast, shoulder and lane width do not represent a significant factor in avoiding encroachment into the opposing lane nor crashes involving vehicles traveling opposite directions.

To account for changes in traffic pattern caused by the COVID-19 pandemic during the year 2020, the variable *Covid* was included. It was found to be statistically significant in the daytime crash model. In contrast, the variable was not significant in the nighttime model, likely because nighttime traffic volumes were less affected.

Finally, the variable *Months in observation* was included in the model to account for exposure across observations. This variable represents the number of months considered in each observation after excluding periods with RPM or rumble strip construction. As expected, it was significant with a positive coefficient, indicating that longer exposure periods lead to a higher number of crashes.

4.1.2.3 Run-Off-Road Crashes. The ROR crash frequency modeling results are presented in Table 4.3. The observations for these models are all the possible year-segment combinations, and the dependent variables represent the ROR crashes count during the study period. The tables show the magnitudes of the effects of each variable on the model, as well as the statistical significance of each variable.

The variable *RPM Status: Before* presented weak statistical significance, with a p-value greater than 0.1 for both daytime and nighttime conditions. Because this estimate is compared against segments not selected for RPM implementation, it suggests that the selection of segments was not based solely by elevated crash frequencies. As a result, it can be concluded that the selection process did not introduce a selectivity bias issue, and any potential bias that may exist was accounted for by the model. Based on this finding, a reduced model considering only the overall presence of RPMs is presented in Table 4.4.

Overall, ROR crash frequency model showed that AADT had a statistically significant positive effect on crash frequency in both day and night conditions. This aligns with the expectation that increasing traffic volumes increase the exposure to crashes. Similarly, longer roadway segments experience more crashes due to the increased exposure.

On the other hand, the variable *RPM presence* was found to be statistically significant, indicating a reduction in ROR crash frequency of approximately 14% during daytime conditions and 9% during nighttime conditions. Although RPMs are generally expected to be more effective at night by providing extra guidance to the drivers in poor lightning conditions, the results in this case indicated stronger effect on daytime conditions. A possible explanation is that, while RPMs improve roadway delineation at night, many nighttime ROR crashes may be attributed to factors such as driver distraction or drowsiness, in which case the additional visual cues may not be sufficient to prevent the crash once the conflict starts. Nonetheless, the findings support the conclusion that RPMs are an effective countermeasure for reducing ROR crash frequency under all lighting conditions.

The model confirmed that wider shoulders are associated with a lower risk of ROR crashes. Specifically, no significant safety difference was found between having no shoulder (0 ft) and a narrow shoulder of 1–2 ft, since both provide minimal opportunity for corrective maneuvers in case of lane departure. In contrast, wider shoulders significantly contribute to reducing daytime and nighttime ROR crashes by providing extra clearance zone for vehicles to recover and go back to the road.

However, the relationship is not linear. For example, segments with shoulders of 3–4 ft showed marginal benefits

TABLE 4.3
Full Model: ROR Crashes.

	Daytime Crashes			Nighttime Crashes		
Dispersion Parameter	2.5124			2.2945		
Term	**Estimate**	**StdErr**	**Pr > |t|**	**Estimate**	**StdErr**	**Pr > |t|**
(Intercept)	-5.7199	0.1707	< 0.01	-5.6137	0.1620	< 0.01
Log (Length)	0.6584	0.0176	< 0.01	0.6199	0.0190	< 0.01
Log (AADT)	0.2831	0.0177	< 0.01	0.3463	0.0189	< 0.01
RPM: Before Installation	0.0543	0.0349	0.1203	0.0576	0.0376	0.1256
RPM: After Installation	-0.1337	0.0480	< 0.01	-0.0821	0.0505	0.1037
Control Segments	0.0000			0.0000		
Rumble strips presence [RS]	-0.0922	0.0356	< 0.01	-0.1617	0.0381	< 0.01
Deflection angle [DA]	0.0015	0.0001	< 0.01	0.0015	0.0002	< 0.01
Density of minor intersections [Int]	0.0023	0.0007	< 0.01	0.0017	0.0007	< 0.05
Curves per mile [Crv]	0.0204	0.0037	< 0.01	0.0166	0.0040	< 0.01
Shoulder Width: 3–4 ft	-0.1658	0.0668	< 0.05	-0.2159	0.0712	< 0.01
Shoulder Width: 5–6 ft	-0.3707	0.1147	< 0.01	-0.2595	0.1184	< 0.05
Shoulder Width: 7+ ft	-0.3845	0.0898	< 0.01	-0.1600	0.0931	0.0859
Shoulder Width: 0–1–2 ft	0.0000			0.0000		
Lane Width: 7–8–9–10 ft	0.0309	0.0308	0.3146	0.0630	0.0315	< 0.05
Lane Width: 11–12 ft	0.0000			0.0000		
$\sqrt{SW*LW}$	0.0246	0.0069	< 0.01	0.0121	0.0071	0.0880
Covid	-0.2189	0.0348	< 0.01	0.0067	0.0351	0.8498
Months in observation	0.1583	0.0081	< 0.01	0.1193	0.0077	< 0.01

TABLE 4.4
Reduced Model: ROR Crashes.

	Daytime Crashes			Nighttime Crashes		
Dispersion Parameter	2.5154			2.2945		
Term	**Estimate**	**StdErr**	**Pr > |t|**	**Estimate**	**StdErr**	**Pr > |t|**
(Intercept)	-5.7039	0.1704	< 0.01	-5.5950	0.1615	< 0.01
Log (Length)	0.6585	0.0176	< 0.01	0.6199	0.0190	< 0.01
Log (AADT)	0.2836	0.0177	< 0.01	0.3467	0.0189	< 0.01
RPM presence	-0.1454	0.0474	< 0.01	-0.0940	0.0499	0.0594
Rumble strips presence [RS]	-0.0956	0.0355	< 0.01	-0.1653	0.0380	< 0.01
Deflection angle [DA]	0.0015	0.0001	< 0.01	0.0015	0.0002	< 0.01
Density of minor intersections [Int]	0.0023	0.0007	< 0.01	0.0017	0.0007	< 0.05
Curves per mile [Crv]	0.0205	0.0037	< 0.01	0.0166	0.0040	< 0.01
Shoulder Width: 3–4 ft	-0.1654	0.0669	< 0.05	-0.2160	0.0712	< 0.01
Shoulder Width: 5–6 ft	-0.3694	0.1147	< 0.01	-0.2583	0.1184	< 0.05
Shoulder Width: 7+ ft	-0.3841	0.0898	< 0.01	-0.1600	0.0932	0.0860
Shoulder Width: 0–1–2 ft	0.0000			0.0000		
Lane Width: 7–8–9–10 ft	0.0301	0.0308	0.3275	0.0621	0.0315	< 0.05
Lane Width: 11–12 ft	0.0000			0.0000		
$\sqrt{SW*LW}$	0.0246	0.0069	< 0.01	0.0121	0.0071	0.0876
Covid	-0.2203	0.0348	< 0.01	0.0052	0.0351	0.8818
Months in observation	0.1571	0.0080	< 0.01	0.1181	0.0076	< 0.01

compared to segments with shoulders with 0–1–2 ft, while shoulders of 5–6 ft had nearly double the effect during daytime and a significant increase at night. On the other hand, segments with shoulder width equal to 7 ft or more present essentially had the same safety benefits as 5–6 ft shoulders during daytime but significantly decreased benefits during nighttime conditions.

This outcome is consistent with previous research suggesting that driver behavior is not only influenced by roadway dimensions but also by perceived risk. When drivers feel more secure, in a forgiving roadway environment, they may adopt more aggressive driving behaviors, such as speeding, which results in increased crash risk. According to FHWA guidelines, the recommended shoulder width for two-lane rural roads are 4 ft and 6 ft, respectively (Amjadi, 2009).

The results suggest that lane width has no statistically significant effect on ROR crashes during daytime. However, during nighttime, the model exhibited that narrower lanes are associated with higher ROR crash risk. Lane widths of 10 ft or less have positive coefficients, suggesting that reducing lane width from the standard 11–12 ft increases crash risk, especially during poor lighting conditions.

Overall, the findings indicate that both wider shoulder and lanes contribute to a decreased crash frequency. However, the effect of shoulder width varies depending on the existing lane width. The relation between lane width and shoulder width suggests that simply increasing shoulder width without considering lane dimensions may not yield optimal safety benefits. Instead, an integral approach to cross-section design should be adopted, considering how different width combinations influence driver behavior and crash risk.

Another key finding is the effectiveness of rumble strips in reducing ROR crashes. The presence of rumble strips, regardless of the type or location, is associated with a statistically significant reduction in ROR crash frequency. Particularly, during nighttime, the rumble strip effects are almost double compared to daytime, consistent with the expectation that the vibration and noise generated by rumble strips are helpful to alert the drivers when they are about to leave the road. However, the analysis did not find a significant interaction between RPMs and rumble strips, likely due to the limited number of segments that include both countermeasures (edgeline RPMs and edge or shoulder rumble strips).

In addition, the model also shows the influence of roadway curvature and intersection density on ROR crashes. An increase in the total deflection angle and a greater number of curves lead to more ROR crashes, confirming that curved road segments pose a higher risk for vehicles. An increased number of intersections per mile also contributes to increased crash risk, likely due to the additional conflict points they introduce.

The variable *Covid,* which accounts for changes in traffic patterns during the year 2020, was found to be statistically significant in the daytime crash model. In contrast, the variable was not significant in the nighttime model, likely because nighttime traffic volumes were less affected.

Finally, the variable *Months in observation,* as expected, was significant with a positive coefficient, indicating that longer exposure periods lead to a higher number of crashes.

Overall, the results of the NB models with random effects provide insights into the factors influencing the frequency of ROR and opposite-direction crashes. Since the dependent variable represents crash counts, the estimated coefficients indicate how each predictor affects the expected crash frequency. Specifically, a positive coefficient corresponds to an increase in the expected number of crashes, while a negative coefficient corresponds to a decrease. Estimates with a p-value less than 0.05 are considered statistically significant, meaning their effect is unlikely to be due to random variation. Furthermore, all models exhibited low dispersion parameters, supporting the use of a negative binomial distribution rather than a Poisson distribution.

4.2 Crash Severity Model

To investigate the factors influencing crash severity, this study employed a random-effects binary logit model.

4.2.1 Model Type Selection

Crash severity is often analyzed using a multilevel ordered framework (e.g., fatal/incapacitating, minor/nonincapacitating, and property damage only). A data-specific consideration necessitated a different approach. In 2020, INDOT implemented a change in the definition of *incapacitating injury*. To ensure temporal consistency of crash severity data and to mitigate the potential estimation bias, all the severity outcomes above the PDO category were consolidated into a binary variable: injury (coded as 1). Consequently, the crashes reported as fatal, incapacitating injury, nonincapacitating injury, and possible injury were coded as 1, while noninjury PDO crashes were coded as 0.

Given this dichotomous dependent variable, the binary logit model was selected as the appropriate analytical tool. The inclusion of random effects further enhances the model by capturing unobserved heterogeneity that may exist among crash observations obtained from the same location over time (Washington et al., 2020). The variable used for random ID is the same as the one defined in Section 4.1.1. The model was formulated to predict the likelihood of an injury outcome as a function of various explanatory variables, with each crash treated as a single observation.

The probability of an injury crash $\left(Y_{ij}=1\right)$ for j-th observation within the i-th cluster, conditioned on the random effect α_i is given by the logistic function:

$$P\left(Y_{ij}=1 \middle| \alpha_i\right)=\frac{e^{\beta x_{ij}+\alpha_i}}{1+e^{\beta x_{ij}+\alpha_i}} \qquad \text{(Eq 4.2)}$$

$$\alpha_i \sim Normal\left(0, \sigma_\alpha^2\right)$$

Where:

Y_{ij} represents the injury severity outcome for the j-th observation within the i-th cluster.

β is a vector of fixed-effects regression coefficients, representing the effects of the predictor variables that are constant across all clusters.

x_{ij} is a vector of predictor variables for the j-th observation in the i-th cluster.

α_i is the random effect for the i-th cluster. It represents the unobserved, cluster-specific deviation from the overall average.

σ_α^2 is the variance of the random effects. It measures the amount of variation in the log-odds of the outcome between clusters.

TABLE 4.5
Variables Used in the Severity Model.

Variable Name	Variable Type	Description
RPM presence	Binary	1 indicates presence of RPM, 0 indicates its absence
LowSpeed	Binary	1 if posted speed limit (or advisory speed limit) of the road is less than 45 mph, 0 otherwise
Angle_per_mile	Numerical	Total deflection angle per mile
Alcohol	Binary	1 if the driver was under the influence of alcohol, 0 otherwise
Animal	Binary	1 if the crash involved an animal, 0 otherwise
Weather	Categorical	Weather condition at the time of crash: Blowing Sand/Soil/Snow Cloudy Fog/Smoke/Smog Rain Severe Cross Wind Sleet/Hail/Freezing Rain Snow
Horizontal_ Alignment	Categorical	Straight: No horizontal curves present Curve: If horizontal curve is present

4.2.2 Full Model Estimation and Results

Among several models considered, the best one was chosen using a combination of variable significance and goodness of fit measures such as log-likelihood. The variables used in the models are explained in Table 4.5.

4.2.2.1 Opposite-Direction Crash (head-on and sideswipe). The final severity models obtained for opposite direction crashes (head-on and opposite-direction sideswipe) are shown in Table 4.6. Similarly, to crash frequency models, a daytime and nighttime model were developed.

The binary logit models treat crash severity as a dichotomous outcome where a value of 1 indicates a crash resulting in an injury whereas a value of 0 indicates a PDO crash. A positive coefficient estimate for a given variable suggests an increased probability of an injury crash, whereas a negative estimate implies a decreased probability.

The analysis reveals that the presence of RPMs is not a statistically significant determinant of crash severity for either daytime (p = 0.703) or nighttime (p = 0.820) collisions. This result is in line with expectations as RPMs are intended to reduce crash frequency by improving lane delineation, not to alter the physical dynamics like vehicle speed that govern the severity of a crash once it occurs.

Conversely, *LowSpeed* variable was highly significant in the daytime model (p = 0.000) with a negative estimate (-0.5401), indicating that crashes on low-speed roadways are significantly less likely to result in injury. For the nighttime model, this variable was not statistically significant (p = 0.111).

Roadway geometry variables also demonstrated an influence on crash severity. The *Angle_per_mile* variable, representing road curvature, was significant for daytime crashes (p = 0.002) with a negative estimate (-0.0020), suggesting that crashes on

TABLE 4.6
Crash Severity Model: Opposite Direction Crashes.

	Daytime Crashes			Nighttime Crashes		
Term	**Estimate**	**StdErr**	**Pr > |t|**	**Estimate**	**StdErr**	**Pr > |t|**
(Intercept)	-0.0088	0.0678	0.897	-0.0002	0.0958	0.998
RPM presence	0.0770	0.2018	0.703	0.0634	0.2785	0.820
LowSpeed	-0.5401	0.1303	0.000	-0.3327	0.2085	0.111
Angle_per_mile	-0.0020	0.0006	0.002	-0.0014	0.0011	0.195
Alcohol	0.9741	0.2622	0.000	0.4421	0.1930	0.022
Animal	-2.4586	0.4682	0.000	-2.8036	0.2551	0.000
Weather: Blowing Sand/Soil/Snow	-0.3117	0.2655	0.240	-0.3112	0.3068	0.310
Weather: Cloudy	-0.0804	0.1171	0.492	-0.0564	0.1772	0.750
Weather: Fog/Smoke/Smog	0.0915	0.5056	0.856	0.4740	0.4662	0.309
Weather: Rain	-0.0805	0.1544	0.602	0.0164	0.2142	0.939
Weather: Severe Cross Wind	-0.0331	0.8203	0.968	-13.9618	447.85	0.975
Weather: Sleet/Hail/Freezing Rain	-1.0889	0.5891	0.065	-0.2590	0.4002	0.518
Weather: Snow	-0.8362	0.2434	0.001	-0.3913	0.2482	0.115
Weather: Clear	0.0000			0.0000		
Horizontal Alignment: Curve	0.4019	0.1148	0.000	0.2767	0.1674	0.098
Horizontal Alignment: Straight	0.0000			0.0000		

more curvaceous roads are associated with a lower probability of injury, perhaps due to drivers exercising greater caution and reducing speed. This effect was not statistically significant in the nighttime model (p = 0.195).

The Horizontal Alignment: Curve variable showed a positive association with crash severity. It was highly significant for daytime crashes (p = 0.000) and marginally significant for nighttime crashes (p = 0.098), with positive estimates of 0.4019 and 0.2767, respectively. This indicates that crashes occurring specifically on a curve are more likely to result in injury during both day and night.

Regarding contributing circumstances, alcohol involvement was a highly significant factor in increasing the likelihood of an injury crash. The variable was significant in both the daytime (p = 0.000) and nighttime (p = 0.022) models, with positive estimates of 0.9741 and 0.4421, respectively. Crashes involving an animal were found to be significantly less likely to result in injury. This variable was highly significant (p = 0.000) in both models and possessed large negative estimates (-2.4586 for daytime, -2.8036 for nighttime), which is consistent with the generally lower impact severity of a vehicle-animal collision compared to a vehicle-vehicle collision.

Finally, an analysis of weather conditions revealed limited statistical influence on crash severity. For daytime crashes, the presence of snow was significant (p = 0.001) with a negative estimate (-0.8362), indicating a reduced probability of injury. Sleet/hail/freezing rain was marginally significant (p = 0.065) with a similar negative association. These findings may be explained by drivers reducing speeds in such conditions. Other weather conditions were found to be statistically no different than clear weather, which was the reference condition.

4.2.2.2 Run-Off-Road Crashes. The severity of ROR crashes is highly dependent on roadside hazards. Since detailed information about these hazards is unavailable, it would be incorrect to model crash severity with conventional methods that rely on such data. An alternative methodology is proposed in Chapter 6.

5. MODEL APPLICATION

5.1 Model Simplification

The previous section presented the models with all the significant predictors. This section presents reduced models that include only the most relevant predictors to make their implementation easier for the end user. For example, geometric feature predictors such as deflection angle and curvature degree, although significant, the values they take are not straightforward to obtain. Further, modifying the deflection angle or curvature degree of the road is very expensive.

Another example is the variable *Months in observation.* This variable was incorporated during model estimation to properly account for variations in time exposure. However, when predicting annual crash frequencies for implementation, this variable assumes a constant value. Therefore, variables that become constant in the final application can be removed from the model with their effects accounted for by adjusting the model's intercept.

These simplifications ensure that the simplified models only contain variables that are easily measurable or reflect key interventions, thereby making them convenient for agency implementation. CMFs will be recalculated based on simplified models.

5.1.1 Run-Off-Road Crashes

For ROR crash frequency model, most predictors were statistically significant, except for lane width during daytime conditions. However, lane width cannot be evaluated as an isolated feature; rather, it should be considered in combination with shoulder width, as both jointly influence maneuver space. For this reason, lane width was kept in the model despite its initial significance. The ROR crash frequency equations intended for implementation are presented below in Equations (Eq. 5.1) and (Eq. 5.2), while Table 5.1 provides the details of the re-estimated results.

Daytime Crashes

$$a = 0.0051 \cdot Length^{0.6180} \cdot AADT^{0.2292} \cdot \exp[-0.1578 * RPM - 0.0620 * RS + 0.0026 * Int - 0.1887 * SW_{3-4\,ft} - 0.3865 * SW_{5-6\,ft} - 0.3940 * SW_{7+\,ft} + 0.0467 * LW_{\leq 10} + 0.0251 * \sqrt{(LW * SW)} \quad \text{(Eq. 5.1)}$$

Nighttime Crashes

$$a = 0.0066 \cdot Length^{0.5801} \cdot AADT^{0.2966} \cdot \exp[-0.1102 * RPM - 0.1358 * RS + 0.0019 * Int - 0.2390 * SW_{3-4\,ft} - 0.2742 * SW_{5-6\,ft} - 0.1611 * SW_{7+\,ft} + 0.0737 * LW_{\leq 10} + 0.0124 * \sqrt{(LW * SW)} \quad \text{(Eq. 5.2)}$$

5.1.2 Opposite-Direction Crashes: Head-On and Opposite-Direction Sideswipe

The modeling process for opposite-direction crashes indicated that the presence of RPMs was statistically significant only for reducing nighttime opposite-direction crashes, while no significant effect was observed under daytime conditions. Consequently, only the nighttime crash frequency model is presented for implementation. Similarly to the ROR models, geometric roadway features were excluded from the implementation model to enhance interpretability, and the exposure adjustment variable *Months in observation* was incorporated into the model intercept rather than included as a separate predictor.

TABLE 5.2
Implementation Model: Opposite-Direction Crashes.

	Nighttime Crashes		
Dispersion Parameter	**0.6813**		
Random effect LRT (p-value)	**$< 2.2 \times 10^{-16}$**		
Term	Estimate	StdErr	Pr > |t|
Intercept	-10.1443	0.5488	< 0.01
Log (Length)	0.8038	0.0517	< 0.01
Log (AADT)	0.6917	0.0472	< 0.01
RPM presence	-0.2477	0.1379	0.0724
Rumble strips presence [RS]	-0.3683	0.0947	< 0.01
Density of minor intersections [Int]	0.0037	0.0018	< 0.05

$$a = 3.9298 \times 10^{-5} \cdot Length^{0.8038} \cdot AADT^{0.6917} \cdot \exp[-0.2477 * RPM_{presence} - 0.3683 * RS + 0.0037 * Int] \quad \text{(Eq. 5.3)}$$

5.2 Crash Modification Factors

To estimate the CMFs, the expected number of crashes must be first calculated. To determine the CMFs for each design alternative, the expected number of crashes was first computed for an initial (existing) condition without RPMs and then recalculated for a new condition with RPMs installed. The CMF for a specific change in design was then determined using the formula:

$$CMF = \frac{a_{new}}{a_{exist}} \quad \text{(Eq. 5.4)}$$

Where:

a_{new} is the expected crash frequency for the new roadway condition,

a_{exist} is the expected crash frequency for the existing condition.

TABLE 5.1
Implementation Model: Run-Off-Road Crashes.

	Daytime Crashes			Nighttime Crashes		
Dispersion Parameter	**2.3654**			**2.1826**		
Random effect LRT (p-value)	**$< 2.2 \times 10^{-16}$**			**$< 2.2 \times 10^{-16}$**		
Term	**Estimate**	**StdErr**	**Pr > |t|**	**Estimate**	**StdErr**	**Pr > |t|**
(Intercept)	-5.2689	0.2142	< 0.01	-5.0233	0.2040	< 0.01
Log (Length)	0.6180	0.0174	< 0.01	0.5801	0.0188	< 0.01
Log (AADT)	0.2292	0.0179	< 0.01	0.2966	0.0189	< 0.01
RPM presence	-0.1578	0.0476	< 0.01	-0.1102	0.0500	< 0.05
Rumble strips presence [RS]	-0.0620	0.0352	0.0787	-0.1358	0.0372	< 0.01
Density of minor intersections [Int]	0.0026	0.0007	< 0.01	0.0019	0.0007	< 0.01
Shoulder Width: 3–4 ft	-0.1887	0.0689	< 0.01	-0.2390	0.0725	< 0.01
Shoulder Width: 5–6 ft	-0.3865	0.1170	< 0.01	-0.2742	0.1201	< 0.05
Shoulder Width: 7+ ft	-0.3940	0.0920	< 0.01	-0.1611	0.0946	0.0886
Shoulder Width: 0–1–2 ft	0.0000			0.0000		
Lane Width: 7–8–9–10 ft	0.0467	0.0322	0.1475	0.0737	0.0325	< 0.05
Lane Width: 11–12 ft	0.0000			0.0000		
$\sqrt{SW * LW}$	0.0251	0.0071	< 0.01	0.0124	0.0073	0.0900

TABLE 5.3
Crash Modification Factors for Raised Pavement Markers.

		Crash Modification Factor		
Type of Crash	**Time of Day**	**RPM**	**Rumble Strip**	**RPM and Rumble Strip**
Run-off-road	Daytime	0.854	0.939	0.802
Run-off-road	Nighttime	0.896	0.873	0.782
Opposite-direction	Daytime	1.000	1.000	1.000
Opposite-direction	Nighttime	0.781	0.692	0.540

A CMF value below 1.0 indicates a reduction in crash risk after the change, whereas a CMF above 1.0 indicates no safety benefit.

Overall, three CMFs were estimated, each corresponding to a specific scenario considered in the analysis: daytime ROR, nighttime ROR, and nighttime opposite-direction collision. Accordingly, separate CMFs are reported for ROR daytime crashes, ROR nighttime crashes, and opposite-direction nighttime crashes. All the existing conditions scenarios are assumed without the presence of RPMs. In contrast, new conditions are assumed with the presence of centerline RPMs. For the calculations, segment length and traffic volume were assumed to be the average of all the observations. In addition, shoulder and lane width were set to the standard values. The calculated crash modification factors are shown in Table 5.3. The opposite-direction daytime case with no safety benefit is also included to confirm that it was part of the analysis.

The results indicate that, without requiring major infrastructure modifications, the implementation of RPMs leads to an approximate 15% reduction in ROR daytime crashes and an 11% reduction in nighttime crashes. Likewise, nighttime opposite-direction crashes are reduced by nearly 22% following the installation of RPMs.

Moreover, the analysis also considers the potential joint effect of RPMs and rumble strips, as these countermeasures are frequently implemented together in practice and may work jointly to further strengthen the safety benefit. Indeed, the implementation of rumble strips alongside RPMs was demonstrated to reduce the ROR crashes in approximately 20% during the day and 22% during night conditions. The two countermeasures combined are estimated to reduce opposite direction crashes by almost 46%. The combined implementation of rumble strips and RPMs provides a greater safety benefit compared to RPMs alone.

The crash severity analysis presented in Section 4.2 concluded that the presence of rumble strips and RPMs do not affect the severity outcome of crashes. Thus, the obtained CMFs apply to corresponding type of crashes regardless of severity levels.

6. RESULTS IMPLEMENTATION

6.1 Estimating the Safety Effect of RPMs

In general, the method to estimate the safety benefits involves the following steps.

1. Estimate the number of crashes by severity,
2. Multiply the estimates with corresponding CMFs and
3. Finally, multiply the above result with corresponding crash costs to obtain the estimated safety benefits.

A significant challenge emerges when applying this method to ROR crashes, as their severity is highly dependent on roadside hazards. Because detailed information about these hazards is unavailable, it would be challenging studying crash severity with conventional methods that rely on such data.

Therefore, alternate methodology is proposed. First, alternative severity models were developed based on exposure variables only (traffic volume, segment length and density of minor intersections). If one assumes that exposure is not related to roadway cross-section, then only the effect of exposure on severity is grasped through these models. On the other hand, the severity of recorded ROR crashes are affected by the roadside hazard. Combining the model-based estimates with the crash data, preserves (to some extent) the crash severity while reducing the random variability. By applying this approach, INDOT can better assess the safety impact of cross-sectional design changes when complete roadside hazard data is not available at the system level.

The process begins by identifying roadway segments with an excessive number of crashes over the past several years with a focus on road segments where road cross-section improvements are being considered. Once segments are selected, the crashes observed there are classified into two categories: PDO and non-PDO crashes. This distinction is necessary to enable a severity-based analysis that aligns with safety performance objectives and cost estimation frameworks.

After classification, safety performance functions (SPFs) are used to estimate the expected number of crashes under existing conditions. These functions incorporate exposure variables, such as traffic volume and segment length, and are also used to estimate the dispersion parameter required for crash modeling. The EB method is then applied to combine the reported crash counts with the SPF-based estimates, producing expected annual crash frequencies for the segments. This intermediate estimate reflects the typical crash occurrence under current local conditions and is further used to estimate the proportion of PDO and non-PDO crashes.

In the next stage, the full ROR frequency model, previously developed as part of the overall safety analysis, is applied to obtain an estimate of the expected number of ROR crashes on the segments. This model incorporates additional roadway characteristics such as curvature and presence of rumble strips. This estimate is combined with the observed crashes using the EB method to obtain the best estimates of the expected ROR crashes.

To estimate the effect of the RPM installation, the appropriate CMFs are applied to the EB-adjusted crash frequencies. CMFs quantify the expected reduction in crashes associated with the proposed design alternative. The adjusted total number of crashes is then allocated into PDO and non-PDO categories using the proportional distribution obtained previously. The resulting estimates are multiplied by the average crash costs for PDO and non-PDO crashes respectively to quantify the safety benefits.

An example illustrating this procedure is provided in the next section.

6.2 Example Safety Benefit Estimation

A 1.47-mi segment with 10-ft-wide lane, neither shoulders nor rumble strips, was selected for analysis. The other characteristics are shown in Table 6.1.

The analysis covers the 9-year period from 2015 to 2023. The average AADT for the segment during the period of analysis is 3,415 vehicles per day. AADT by year and crash counts by type are provided in Table 6.2.

6.2.1 Daytime and Nighttime Traffic Volumes

Since RPM effectiveness is different during daytime and nighttime, the daytime and nighttime traffic volumes must be calculated from AADT. AADT is first converted to hourly traffic volume for each month separately using appropriate conversion factors. Historical average sunrise and sunset times in Indiana for each month are used to determine nighttime hours and daytime hours. The nighttime traffic volume for a given month is the sum of nighttime hourly volumes for that month. The average nighttime traffic volume for an entire year is obtained by averaging the monthly nighttime traffic volume. The example annual average daytime and nighttime traffic volumes are shown in Table 6.3.

TABLE 6.1
Road Characteristics.

Lane Width [ft]	Shoulder Width	Deflection Angle	No. of Curves	Int. per mile	Rumble Strips	Raised Pavement Markers
10	0	28.874	2.71	0.67	No	No

TABLE 6.2
AADT and Crash History.

		Run-Off-Road (ROR)				Head-On and Opposite-Direction sideswipe (OD)			
		Daytime		Nighttime		Daytime		Nighttime	
Year	AADT	KABC	PDO	KABC	PDO	KABC	PDO	KABC	PDO
2015	7190	1	3	0	0	0	0	0	0
2016	7022	0	0	2	2	0	1	1	1
2017	5706	0	2	0	1	0	0	0	0
2018	5706	0	1	0	0	1	0	0	1
2019	5706	0	2	1	0	0	0	1	0
2020	6250	0	1	0	0	0	0	1	0
2021	6950	0	0	0	0	0	0	1	0
2022	6825	0	0	0	3	0	0	0	0
2023	6948	0	0	0	1	0	0	0	0

TABLE 6.3
Annual Average Daytime and Nighttime Traffic Volumes.

Year	AADT	Annual Average Daytime Traffic Volume	Annual Average Nighttime Traffic Volume
2015	7190	5129	2061
2016	7022	5009	2013
2017	5706	4070	1636
2018	5706	4070	1636
2019	5706	4070	1636
2020	6250	4458	1792
2021	6950	4958	1992
2022	6825	4869	1957
2023	6948	4956	1992
Average	6478	4621	1857

TABLE 6.4
Crash Counts for 9 Years (2015–2023).

	ROR				OD	
	Daytime		Nighttime		Nighttime	
Severity	PDO	KABC	PDO	KABC	PDO	KABC
Count	9	1	7	3	2	4

TABLE 6.5
Cost of Crashes by Severity (in Thousands).

	PDO	KABC
Cost	39.0	1,415.0

6.2.2 Crash Severity Distribution

The total number of ROR and opposite-direction crashes by severity is presented in Table 6.4.

The cost of a crash by severity annualized for 2025 is presented in Table 6.5.

6.2.3 Estimating Safety Benefit

Using three exposure variables namely, traffic volume, segment length, and density of minor intersections, SPFs were developed for ROR PDO crashes and ROR non-PDO (KABC) crashes using a NB model. Separate models were derived for daytime and nighttime crashes (Figure 6.1 through Figure 6.4).

The number of nighttime head-on and opposite-direction sideswipe crashes were far less than ROR crashes. Thus, a reliable NB model could not be fitted to develop a safety performance function based on the above-mentioned exposure variables. Thus, method of moments was used to derive the expected number of annual crashes, variance of expected number of

Covariance Parameter Estimates					
Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	Random_ID_Township	0.3944	0.02237	17.63	<.0001
Scale		0.3007	0.04558	6.60	<.0001

Solutions for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	-3.9575	0.1360	6944	-29.10	<.0001
Ln_Length	0.5590	0.02228	65321	25.09	<.0001
Ln_Day_AADT	0.2441	0.01779	65321	13.72	<.0001
Density_Minor_Inters	0.001842	0.000776	65321	2.38	0.0175

Figure 6.1 ROR Daytime PDO Model Results.

Covariance Parameter Estimates					
Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	Random_ID_Township	0.6903	0.04634	14.90	<.0001
Scale		0.04423	0.06720	0.66	0.2552

Solutions for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	-4.3381	0.1690	6944	-25.67	<.0001
Ln_Length	0.6174	0.03283	65321	18.80	<.0001
Ln_Night_AADT	0.2037	0.02500	65321	8.15	<.0001
Density_Minor_Inters	0.001066	0.001244	65321	0.86	0.3915

Figure 6.2 ROR Daytime KABC Model Results.

annual crashes, and dispersion parameters for PDO and KABC (non-PDO) nighttime head-on and opposite-direction crashes. The results are presented in Table 6.6.

6.2.3.1 Run-Off-Road Crashes. The equations shown in Table 6.7 were derived from the above-mentioned negative binomial models.

The expected number of daytime and nighttime ROR crashes for each classification for the segment considered are calculated as follows:

TABLE 6.6
Estimates for Nighttime Head-On and Opposite-Direction Sideswipe Crashes.

Severity	Mean	Variance	Dispersion
PDO Crashes	0.0115	0.0135	15.3125
KABC Crashes	0.0374	0.0398	1.6984

Covariance Parameter Estimates					
Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	Random_ID_Township	0.3423	0.02364	14.48	<.0001
Scale		0.3128	0.05663	5.52	<.0001

Solutions for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	-4.3185	0.1417	6944	-30.47	<.0001
Ln_Length	0.5131	0.02316	65321	22.16	<.0001
Ln_Day_AADT	0.2728	0.01849	65321	14.75	<.0001
Density_Minor_Inters	0.000783	0.000834	65321	0.94	0.3477

Figure 6.3 ROR Nighttime PDO Model Results.

Covariance Parameter Estimates					
Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	Random_ID_Township	0.6607	0.05818	11.36	<.0001
Scale		0.06925	0.09624	0.72	0.2359

Solutions for Fixed Effects					
Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	-5.4119	0.1961	6944	-27.59	<.0001
Ln_Length	0.6394	0.03653	65321	17.50	<.0001
Ln_Night_AADT	0.3209	0.02883	65321	11.13	<.0001
Density_Minor_Inters	0.002407	0.001287	65321	1.87	0.0615

Figure 6.4 ROR Nighttime KABC Model Results.

$$a_{ROR\_Day_{PDO}} = 1.911 \cdot 10^{-2} \cdot \left(DayVol\right)^{0.2441} \cdot \left(L\right)^{0.5590} \cdot \exp\left[\left(Int\right)^{0.0018}\right]$$
$$a_{ROR\_Day_{PDO}} = 1.911 \cdot 10^{-2} \cdot \left(4621\right)^{0.2582} \cdot \left(1.476\right)^{0.5169} \cdot \left(0.677\right)^{0.0015}$$
$$a_{Day_{PDO}} = 0.1866 \tag{Eq. 6.1}$$

$$a_{ROR\_Day_{KABC}} = 1.306 \cdot 10^{-2} \cdot \left(DayVol\right)^{0.2038} \cdot \left(L\right)^{0.6174} \cdot \exp\left[\left(Int\right)^{0.0011}\right]$$
$$a_{ROR\_Day_{KABC}} = 1.306 \cdot 10^{-2} \cdot \left(4621\right)^{0.2038} \cdot \left(1.476\right)^{0.6174} \cdot \exp\left[\left(0.677\right)^{0.0011}\right]$$
$$a_{Day_{KABC}} = 0.0928 \tag{Eq. 6.2}$$

$$a_{ROR\_Night_{PDO}} = 1.332 \cdot 10^{-2} \cdot \left(NightVol\right)^{0.2728} \cdot \left(L\right)^{0.5131} \cdot \exp\left[\left(Int\right)^{0.0008}\right]$$
$$a_{ROR\_Night_{PDO}} = 1.332 \cdot 10^{-2} \cdot \left(1857\right)^{0.2728} \cdot \left(1.476\right)^{0.5131} \cdot \left(0.677\right)^{0.0008}$$
$$a_{Night_{PDO}} = 0.1268 \tag{Eq. 6.3}$$

TABLE 6.7
Safety Performance Functions Based on Exposure for ROR Crashes.

Time	Severity	SPF	Dispersion (α)
Day	PDO	$1.911 \cdot 10^{-2} \cdot \left(DayVol\right)^{0.2441} \cdot \left(L\right)^{0.5590} \cdot \exp\left[\left(Int\right)^{0.0018}\right]$	0.3007
Day	KABC	$1.306 \cdot 10^{-2} \cdot \left(DayVol\right)^{0.2038} \cdot \left(L\right)^{0.6174} \cdot \exp\left[\left(Int\right)^{0.0011}\right]$	0.0442
Night	PDO	$1.332 \cdot 10^{-2} \cdot \left(NightVol\right)^{0.2728} \cdot \left(L\right)^{0.5131} \cdot \exp\left[\left(Int\right)^{0.0008}\right]$	0.3474
Night	KABC	$4.50 \cdot 10^{-3} \cdot \left(NightVol\right)^{0.3209} \cdot \left(L\right)^{0.6394} \cdot \exp\left[\left(Int\right)^{0.0024}\right]$	0.0693

$$a_{ROR\_Night_{KABC}} = 4.46 \cdot 10^{-2} \cdot (NightVol)^{0.3209} \cdot (L)^{0.6394} \cdot \exp\left[(Int)^{0.0024}\right]$$

$$a_{ROR\_Night_{KABC}} = 1.306 \cdot 10^{-2} \cdot (1857)^{0.3209} \cdot (1.476)^{0.6394} \cdot \exp\left[(0.677)^{0.0024}\right]$$

$$a_{Night_{KABC}} = 0.0642 \qquad \text{(Eq. 6.4)}$$

Thus, the SPF estimated annual daytime number of PDO crashes $a_{Day_{PDO}}$ is 0.1866 while the estimated annual number of injury crashes $a_{Day_{KABC}}$ is 0.0928. Similarly for nighttime, the estimated number of PDO crashes $a_{Night_{PDO}}$ is 0.1268 and the estimated number of non-PDO crashes $a_{Night_{KABC}}$ is 0.0642.

The EB method is used to combine SPF estimates of ROR crashes with observed crashes over 9 years. The calculations are shown below:

$$a_{EB} = \frac{C + \frac{1}{\alpha}}{Y + \frac{1}{\alpha a}} \qquad \text{(Eq. 6.5)}$$

$$a_{EB_{ROR\_Day_{PDO}}} = \frac{9 + \frac{1}{0.3007}}{9 + \frac{1}{0.3007 \cdot 0.1866}} = 0.4596 \qquad \text{(Eq. 6.6)}$$

$$a_{EB_{ROR\_Day_{KABC}}} = \frac{1 + \frac{1}{0.0442}}{9 + \frac{1}{0.0442 \cdot 0.0928}} = 0.0934 \qquad \text{(Eq. 6.7)}$$

$$a_{EB_{ROR\_Night_{PDO}}} = \frac{7 + \frac{1}{0.3474}}{9 + \frac{1}{0.3474 \cdot 0.1268}} = 0.3116 \qquad \text{(Eq. 6.8)}$$

$$a_{EB_{ROR\_Night_{PDO}}} = \frac{3 + \frac{1}{0.0693}}{9 + \frac{1}{0.0693 \cdot 0.0642}} = 0.0746 \qquad \text{(Eq. 6.9)}$$

Where:

a_{EB} is the EB estimate,

C is the number of target crashes in the preceding Y years,

α is the dispersion parameter value from the safety performance function,

a is the safety performance function estimate of annual crashes.

The results for the EB estimate of annual crash frequencies during the observed 9-year period are shown in Table 6.8.

Table 6.8 indicates that ROR daytime PDO crashes are ~83% of the total ROR daytime crashes, whereas daytime injury crashes represent ~17%. Similarly, ROR nighttime PDO crashes are ~81% of the total ROR nighttime crashes whereas injury crashes form the remaining ~19%.

6.2.3.2 Head-On and Opposite-Direction Sideswipe Crashes. For nighttime head-on and opposite direction sideswipe crashes, the EB estimate is obtained using the values shown in Table 6.6, where the mean is equivalent to the expected number of crashes.

$$a_{EB} = \frac{C + \frac{1}{\alpha}}{Y + \frac{1}{\alpha a}} \qquad \text{(Eq. 6.5)}$$

$$a_{EB_{OD\_Night_{PDO}}} = \frac{2 + \frac{1}{0.0115}}{9 + \frac{1}{15.312 \cdot 0.0115}} = 0.1408 \qquad \text{(Eq. 6.10)}$$

$$a_{EB_{OD\_Night_{KABC}}} = \frac{4 + \frac{1}{0.9830}}{9 + \frac{1}{0.9830 \cdot 0.0074}} = 0.0344 \qquad \text{(Eq. 6.11)}$$

The combined EB estimate of annual crash frequencies during the observed 9-year period is shown in Table 6.9.

Thus, the proportion of PDO and non-PDO nighttime opposite direction crashes are ~80% and ~20%, respectively.

TABLE 6.8
EB Method for ROR Crash Estimation and Severity Proportions.

	Daytime			Nighttime		
	PDO	**KABC**	**Total**	**PDO**	**KABC**	**Total**
Observed Frequency	9	1	10	7	3	10
Expected frequency	0.1866	0.0934	0.2734	0.1268	0.0642	0.1910
EB method frequency	0.4596	0.0934	0.5530	0.3116	0.0746	0.3862
Proportion	82.91%	17.09%	100%	80.69%	19.31%	100%

TABLE 6.9
EB Method for Nighttime Opposite-Direction Crash Estimation and Severity Proportions.

	Nighttime		
	PDO	**KABC**	**Total**
Observed Frequency	2	4	6
Expected frequency	0.0115	0.0074	0.0189
EB method frequency	0.1408	0.0344	0.1752
Proportion	80.36%	19.64%	100%

6.2.4 Benefit–Cost Analysis Example

The benefit–cost analysis procedure can be summarized as follows:

1. Identify the existing condition and the proposed design alternative.
2. Estimate the annual crash frequency using the crash frequency model.
3. Combine the estimated annual crash frequency and the observed number of crashes over 9 years using the EB method.
4. Using the appropriate CMF to estimate the change in number of crashes (typically reduction of crashes).
5. Split the estimated crash reduction by severity using the previously obtained proportions.

TABLE 6.10
Existing Conditions and Design Alternatives for a Segment.

	Raised Pavement Markers	Rumble Strip
Existing Conditions	Not installed	Not installed
Design Alternative	Installed	Installed

6. Compute the annual benefits for each severity by multiplying the estimated reduction in crashes and the corresponding crash cost.
7. The sum of reduction in crash costs by severity is the desired total safety benefit.

The above-mentioned procedure is illustrated using the same example explained previously. The existing condition and proposed design alternatives are shown in Table 6.10.

The number of daytime ROR crashes observed over 9-year period is ten and the number of nighttime ROR crashes observed is also ten (Table 6.4) whereas the number of nighttime opposite direction crashes is six. Using the equation derived in the previous chapter (Eq. 5.1), we can calculate the expected number of daytime ROR crashes per year for the existing conditions according to the model.

$$a_{ROR\_Day} = 0.0051 \cdot Length^{0.6180} \cdot AADT^{0.2292} \cdot \exp\left[-0.1578 * RPM - 0.0620 * RS + 0.0026 * Int - 0.1887 * SW_{3-4\,ft} - 0.3865 * SW_{5-6\,ft} - 0.3940 * SW_{7+\,ft} + 0.0467 * LW_{\le 10} + 0.0251 * \sqrt{(LW * SW)}\right] \quad \text{(Eq. 5.1)}$$

$$a_{ROR\_Day} = 0.0051 \cdot 1.476^{0.6180} \cdot 4621^{0.2292} \cdot \exp\left[0.0026 * 0.677 + 0.046 * 1 + 0.0251 * \sqrt{(10 * 0)}\right]$$
$$a_{ROR\_Day} = 0.2101 \quad \text{(Eq. 6.12)}$$

Similarly, the expected number of nighttime ROR crashes are calculated using Equation 5.2 as follows,

$$a_{ROR\_Night} = 0.0066 \cdot Length^{0.5801} \cdot AADT^{0.2966} \cdot \exp\left[-0.1102 * RPM - 0.1358 * RS + 0.0019 * Int - 0.2390 * SW_{3-4\,ft} - 0.2742 * SW_{5-6\,ft} - 0.1611 * SW_{7+\,ft} + 0.0737 * LW_{\le 10} + 0.0124 * \sqrt{(LW * SW)}\right] \quad \text{(Eq. 5.2)}$$

$$a_{ROR\_Night} = 0.0066 \cdot 1.476^{0.5801} \cdot 4621^{0.2966} \cdot \exp\left[0.0019 * 0.677 + 0.0737 * 1 + 0.0124 * \sqrt{(10 * 0)}\right]$$
$$a_{ROR\_Night} = 0.1643 \quad \text{(Eq. 6.13)}$$

The number of nighttime opposite direction crashes are calculated using Equation 5.3 as follows.

$$a_{OD\_Night} = 3.9298 \times 10^{5} \cdot Length^{0.8038} \cdot AADT^{0.6917} \cdot \exp\left[-0.2477 * RPM_{presence} - 0.3683 * RS + 0.0037 * Int\right] \quad \text{(Eq. 5.3)}$$

$$a_{OD\_Night} = 3.9298 \times 10^{5} \cdot 1.476^{0.8038} \cdot 1957^{0.6917} \cdot \exp\left[0.0037 * 0.677\right]$$
$$a_{HO\_ODS\_Night} = 0.0786 \quad \text{(Eq. 6.14)}$$

The model estimated annual crash frequency (Equation 6.12) and the observed number of crashes (Table 6.4) are combined using the EB method to get the best estimate of annual crash frequency for the existing condition.

$$a_{EB} = \frac{C + \frac{1}{\alpha}}{Y + \frac{1}{\alpha a}} \quad \text{(Eq. 6.5)}$$

$$a_{EB_{ROR\_Day}} = \frac{10 + \frac{1}{2.3654}}{9 + \frac{1}{2.3654 \cdot 0.2101}} = 0.9464 \quad \text{(Eq. 6.15)}$$

$$a_{EB_{ROR\_Night}} = \frac{10 + \frac{1}{2.1826}}{9 + \frac{1}{2.1826 \cdot 0.1643}} = 0.8872 \quad \text{(Eq. 6.16)}$$

$$a_{EB_{OD\_Night}} = \frac{6 + \frac{1}{0.6813}}{9 + \frac{1}{2.1826 \cdot 0.2101}} = 0.2699 \quad \text{(Eq. 6.17)}$$

The EB estimates for annual crash frequency are shown in Table 6.11. By multiplying the EB estimates and the appropriate CMFs table shown in Table 5.3, we get the estimate for annual crash frequency after RPMs and rumble strips are installed.

$$a_{EB_{ROR\_Day_{improved}}} = 0.9464 \times 0.8018 = 0.7597 \quad \text{(Eq. 6.18)}$$

The expected reduction in annual crash frequency after the improvement is

$$a_{EB_{ROR\_Day}} - a_{EB_{ROR\_Day_{improved}}} = 0.9464 - 0.7597 = 0.1868 \quad \text{(Eq. 6.19)}$$

This procedure is repeated for the nighttime ROR and opposite-direction crashes to obtain the reduction in crashes. The reduction in annual crash frequency is then split by severity using the crash severity proportions obtained in Section 6.2.3 (Table 6.8 and Table 6.10). The results are shown in Table 6.12.

TABLE 6.11
EB Method for Crash Estimation.

	ROR Daytime	ROR Nighttime	OD Nighttime
a (EB)	0.9464	0.8872	0.2699

TABLE 6.12
Estimated Annual Reduction in Crashes by Severity.

	ROR Day		ROR Night		OD Night	
Crashes	0.1868		0.1935		0.0589	
	PDO	KABC	PDO	KABC	PDO	KABC
	0.1552	0.0316	0.1561	0.0374	0.0473	0.0116

TABLE 6.13
Estimated Annual Savings by Crash Severity (in Thousands).

	ROR Day		ROR Night		OD Night	
Savings	PDO	KABC	PDO	KABC	PDO	KABC
	$6.05	$44.64	$6.09	$52.86	$1.84	$16.36
	$50.70		$58.94		18.21	
Total			$127.85			

Multiplying the reduction in annual crash frequency by severity with its corresponding crash cost shown in Table 6.5 we obtain the estimated savings for each severity level.

The total annual savings for the proposed design alternative of installing RPMs and rumble strips is: $127,850.00.

7. CLOSURE

7.1 Summary

Raised pavement markers are used in Indiana to improve safety on two-lane rural roads. They are designed to provide drivers with enhanced lane guidance, improved visibility, and, in some cases, generate noise to alert drivers about a near-departure. When combined with complementary countermeasures such as rumble strips or wider paved shoulders, RPMs are expected to reduce the likelihood of ROR and opposite-direction crashes, which together represent a major portion of fatal incidents on rural roadways. Given that more than 70% of Indiana's state-administered highway network consists of rural two-lane roads, understanding the joint safety benefits of these countermeasures is critical for guiding infrastructure improvements.

This study developed a crash frequency model using negative binomial regression with random effects, analyzing more than 8,000 segments and 5,000 mi of rural roads across a 9-year period. The model controlled for traffic volume, roadway geometry, intersection density, and safety countermeasures. Results confirmed that RPMs significantly reduce ROR crash frequency during daytime and nighttime, as well as nighttime opposite-direction crashes. Moreover, some other roadway features, like shoulder and lane width, were found to be significant in reducing crash frequency. Additionally, the presence of rumble strips along with RPMs further reduces all types of crashes, reinforcing their value as a complementary measure.

The safety effects were quantified through CMFs. These CMFs provide a practical tool for INDOT and other agencies to evaluate the benefits of proposed design alternatives. To support implementation, the study introduced a methodology for estimating crash severity using SPFs and the EB method. This approach enables agencies to assess expected safety benefits even when detailed, clear zone data are unavailable. The obtained CMFs are then used to quantify the safety benefits of implementing RPMs.

7.2 Limitations, Recommendations and Future Research

While the current research provides valuable insights into the relationship between RPMs and crash frequency and severity, there are still opportunities for further research and improvement.

First, the roadway routine maintenance and the quality of pavement materials is an area that deserves greater attention. Over time, the effectiveness of RPMs may reduce due to the degradation of road surfaces, weather exposure or snowplowing operations. For example, the recommended practices suggest that the markers should be inspected every 2–4 years; however, the marker may be missing or dislodged before the time of scheduled inspection. A regular monitoring of RPMs could lead to maintenance strategies that results in increased safety benefits.

Furthermore, the interaction between roadside hazards and RPM effectiveness presents an important research opportunity. Edgeline RPMs are being considered for implementation in Indiana. The FHWA has established hazard ratings based on clear zone width, side slope steepness, and the presence of obstacles, ranging from fully recoverable zones (Rating 1) to non-recoverable areas with a high likelihood of severe injuries (Rating 7). By incorporating clear zone ratings into safety models along with presence of edgeline RPMs, the model can better assess relationships between RPMs and run off road crash severity.

Moreover, the rapid development of connected vehicle technologies also introduces new research opportunities. Modern vehicles are increasingly equipped with systems such as lane departure warning systems, which have the potential to reduce the likelihood of certain types of crashes. For example, some studies have proposed chip-enabled RPMs to serve as a dynamic information source for autonomous vehicles. This can serve as an alternative to traditional lane marking strategies, which may be subject to paint degradation, modifications due to construction operations, or visibility issues, and consequently represent a safety hazard for autonomous vehicles. Investigating how traditional features, such as RPMs, can interact with emerging technologies is important for a smoother transition.

In summary, while the current research contributes important findings regarding the impact of centerline RPMs on crash frequency and severity, many research possibilities remain open. Expanding the model to cover roadside hazard information, weather information and presence of edgeline RPMs, or exploring the integration of emerging vehicular technologies are all possible next steps.

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APPENDICES

Appendix A. Animal-Related Crash Frequency Model

Appendix A. Animal-Related Crash Frequency Model

As discussed in Section 4.1.2.1, the animal-related crash frequency model results is presented ahead.

Table A.1 Full Model: Animal-Related Crashes

	Daytime Crashes			**Nighttime Crashes**		
Dispersion Parameter	**1.5204**			**0.6826**		
Term	**Estimate**	**StdErr**	**Pr > |t|**	**Estimate**	**StdErr**	**Pr > |t|**
Intercept	-10.6906	0.9255	< 0.01	-8.3749	0.5306	< 0.01
Log (Length)	1.0026	0.0972	< 0.01	0.7974	0.0671	< 0.01
Log (AADT)	0.3485	0.0757	< 0.01	0.2935	0.0552	< 0.01
RPM status: Before	0.1042	0.1725	0.5459	-0.0982	0.1254	0.4337
RPM status: After	-0.5201	0.3000	0.0830	-0.3963	0.1858	< 0.05
RPM status: Control	-0.1653	0.1756	0.3467	-0.3604	0.1234	< 0.01
Rumble strips presence [RS]	0.0015	0.0006	< 0.05	0.0005	0.0006	0.3723
Deflection angle [DA]	0.0019	0.0047	0.6774	-0.0023	0.0033	0.4758
Density of minor intersections [Int]	0.0592	0.0164	< 0.01	0.0284	0.0145	< 0.05
Curvature degree [Crv]	-0.8884	0.2487	< 0.01	-0.6981	0.1519	< 0.01
Covid	0.2275	0.0590	< 0.01	0.1679	0.0310	< 0.01
Months in observation	0.1503	0.0185	< 0.01	0.1378	0.0232	< 0.01

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