SAFETY PERFORMANCE EVALUATION OF INTEGRATED ACTIVE TRAFFIC MANAGEMENT ON FREEWAYS USING CRASH FREQUENCY MODELS

Md Mushtaque Tahmid

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ABSTRACT

This study evaluated the safety performance of an integrated Active Traffic Management system combining Variable Speed Limits, Lane Control Signs, and Part Time Shoulder Use on Central Florida freeways. Freeway segments operating under the integrated system were compared to similar untreated segments, matched on traffic and geometric characteristics, to evaluate total, rear-end, sideswipe, and injury crashes. Crash rates per million vehicle miles traveled were compared between treated and comparison segments, and crash frequency models were estimated to control for traffic exposure, segment configuration, entry and exit presence, and shoulder width. Models confirmed that treated segments experienced significantly lower crash frequencies than comparison segments for total, rear-end, sideswipe, and injury crashes. The Poisson Lognormal model provided the best fit for total crashes and estimated a crash modification factor of 0.596, representing a 40.4 percent reduction in expected total crash frequency associated with the integrated system. Because rear-end and sideswipe crashes were positively related to injury crashes, joint Poisson Lognormal models were also estimated. The joint models produced crash modification factors of 0.609 for rear-end crashes, 0.679 for sideswipe crashes, and 0.463 for injury crashes, corresponding to reductions of 39.1 percent, 32.1 percent, and 53.7 percent, respectively. Model also showed a stronger treatment effect at complex segments (merge, diverge, and weaving) than basic segments, consistent with the crash rate trend. These findings indicate that the integrated system improved freeway safety by helping drivers respond more smoothly to congestion, lane closures, and changing traffic conditions. The study provides practical evidence to support future Active Traffic Management planning and operational decisions.

Keywords: Active Traffic Management, Variable Speed Limits, Lane Control Signs, Safety Performance Function, Crash Modification Factor, Part time Shoulder Use.

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Dedicated to my wife *Sumaya Riza*

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CHAPTER ONE: INTRODUCTION

Freeway safety and traffic operations are closely intertwined. When recurrent demand, incidents, lane closures, or geometric constraints disrupt mainline flow, the resulting speed differentials and abrupt lane-changing maneuvers can produce shockwaves that propagate upstream and increase crash risk. These conditions are especially consequential at merge, diverge, and weaving segments, where vehicles must simultaneously respond to changing speeds, enter or exit the freeway, and compete for limited lane space. Managing these conditions requires more than a static roadway design; it requires real-time strategies that communicate the developing condition to approaching drivers and coordinate their behavior before they reach the conflict area.

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Active Traffic Management (ATM) provides such a strategy by integrating traffic surveillance, dynamic control devices, and operating rules to improve the safety, mobility, and reliability of freeway corridors. Variable Speed Limit (VSL) is among the most widely deployed ATM components because they allow to reduce and harmonize speeds upstream of congestion, incidents, or bottlenecks. By reducing abrupt braking and moderating speed variation, VSLs are intended to lessen the conditions that contribute to conflicts and severe crash outcomes (M. Abdel-Aty et al., 2006; Gu et al., 2025). Lane Control Signs (LCS) serve a complementary function, displaying real-time lane status, open, closing, closed, or move-over, through overhead signal indicators so that drivers can merge out of an affected lane well in advance of reaching it rather than making a last-moment maneuver. When shoulder use is managed as a part-time operating strategy, the system can also provide additional usable capacity while maintaining controlled lane-use guidance. Together, these components form an integrated operational framework rather than a set of independent roadside devices.

Although ATM programs are commonly justified by their potential to reduce congestion and improve incident management, their safety effects can be established using observed crash data. The safety benefit of a dynamic system depends on whether the coordinated system changes the traffic conditions that precede crashes, including speed dispersion, sudden deceleration, late lane changes, and conflicting vehicle paths. A credible evaluation must therefore distinguish the system effect from differences in traffic exposure, roadway geometry, and baseline risk between sites. Crash-frequency modeling is particularly suited to this task because it can estimate the expected crash occurrence while controlling the factors that systematically influence crash opportunity and severity (Lord & Mannering, 2010; Mannering et al., 2016).

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The Central Florida Expressway Authority has deployed a Flex Lane ATM system on selected portions of SR-417 and SR-429 in the Orlando metropolitan area. The system combines VSL, LCS, and Part-Time Shoulder Use (PTSU) to actively manage freeway operations when non-recurrent events or congested conditions require additional control. Under the system's concept of operations, trained Regional Transportation Management Center (RTMC) operators monitor the corridor through CCTV feeds and automated incident-detection algorithms. Figure 1 shows operational components of the system showing sensor inputs, real time monitoring and control devices. When an incident is confirmed, LCS gantries display lane-closure indications over the affected and immediately upstream lanes, while VSL signs across three upstream gantries step the posted speed down in stages from the normal 70 mph limit: drivers first encounter a 60 mph display, then 55 mph at the two gantries nearer the incident. Gantries sit approximately half a mile apart along the corridor, so the speed reduction builds up gradually rather than dropping all at once. The shoulder may be opened as a managed travel lane when operating conditions and the control plan allow. The intended result is a more orderly transition through the affected area, with fewer abrupt speed changes and fewer unexpected lane maneuvers. Figure 2 illustrates progressive speed limit reduction and lane control sign activation of the system as the incident location approaches.

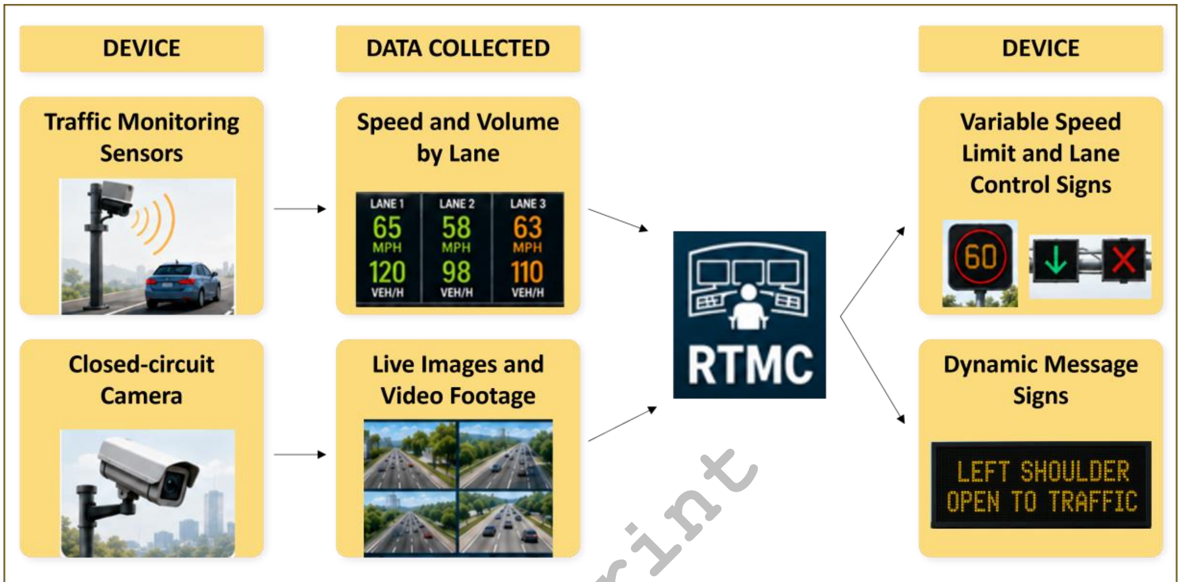

Figure 1 System Components

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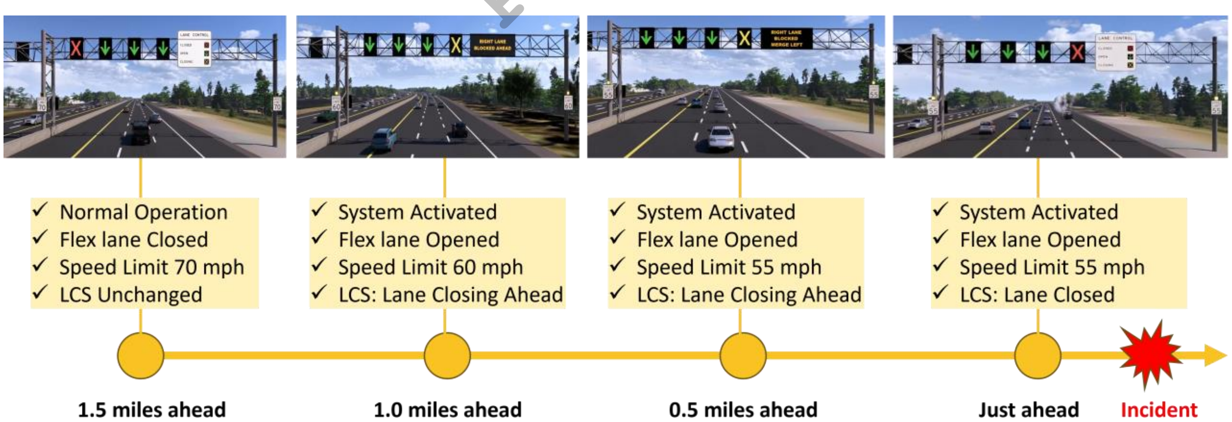

Figure 2 Sequential System Response to a Downstream Incident

The safety rationale for this integrated configuration is particularly strong at locations where the physical roadway creates recurring conflict opportunities. Merge, diverge, and weaving segments concentrate lane-changing activity and often exhibit pronounced speed differences among vehicles pursuing different movements. The beginning and end of managed segments may also create additional transition effects because drivers enter or leave the dynamically controlled environment. Consequently, an evaluation of the Flex Lane system should examine not only overall crash frequency but also whether the system effect varies across segment types and crash outcomes that are closely linked to speed harmonization and lane-use control.

Previous research has shown that VSL deployments can improve freeway safety, particularly by reducing crash risks associated with unstable traffic flow (Khondaker & Kattan, 2015). However, much of the existing evidence evaluates VSL as an individual countermeasure or focuses on a limited set of crash outcomes. In contrast, the Flex Lane configuration considered in this study combines dynamic speed management, lane-use control, and managed shoulder operations. Its safety effect therefore cannot be inferred directly from evaluations of a single component. An assessment is needed to determine whether this integrated operating strategy is associated with lower crash frequency after accounting for traffic exposure and roadway characteristics.

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In addition, crash outcomes are often modeled separately even though collision type and injury severity can be linked through shared unobserved conditions. For example, roadway segments with unstable traffic flow may simultaneously experience more rear-end or sideswipe crashes and more injury crashes. Recent VSL research has demonstrated that jointly modeling related crash outcomes can provide a more informative representation of treatment effects than estimating each outcome independently (Gu et al., 2025).

Finally, descriptive comparisons alone are insufficient for a defensible treatment evaluation. Raw crash counts and crash rates may differ because segments carry different traffic volumes, have different lengths, or contain different geometric features. A cross-sectional Crash Modification Factor (CMF) framework addresses this issue by incorporating a treatment indicator directly into a crash-frequency model and estimating the adjusted difference between treated and comparison segments while controlling exposure and segment-level attributes.

The objective of this study is to evaluate the safety performance of the integrated Flex Lane ATM system deployed on Central Florida freeways. The study pursues the following specific objectives:

1. Estimate crash-frequency models that control traffic exposure, segment configuration, entry and exit presence, and shoulder width, and derive cross-sectional CMFs for the integrated Flex Lane ATM treatment.

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2. Evaluate the dependence between collision type and injury crashes and apply joint bivariate models for the rear-end-injury and sideswipe-injury crash pairs to obtain treatment-effect estimates that recognize shared unobserved heterogeneity.

3. Differentiate the treatment effect at basic segments from its effect at complex (merge, diverge, and weaving) segments and compare the resulting pattern with the trend observed in the crash rate comparison.

The resulting CMFs provide information that can be used directly in transportation engineering practice whenever such a system is implemented. It can also support benefit-cost assessment, system expansion decisions, and operational-plan development.

CHAPTER TWO: LITERATURE REVIEW

The safety benefits of VSL have been examined extensively in literature. Early simulation work on Interstate 4 in Orlando found that VSL strategies reduced real-time crash likelihood under medium-to-high-speed conditions, though the benefit did not extend to already-congested, low-speed regimes (M. Abdel-Aty et al., 2006). Building on this, a dynamic VSL strategy was shown to meaningfully lower real-time crash risk on freeways more broadly (M. Abdel-Aty et al., 2008) and a related evaluation demonstrated safety improvements specifically at congested weaving segments, a geometry of direct relevance to the present study (M. Abdel-Aty & Wang, 2017). More recently, crash prediction models incorporating VSL inputs were developed for freeway corridors, reinforcing the link between dynamic speed control and reduced crash frequency (Hasan et al., 2023), and an optimal VSL control framework was proposed specifically to ameliorate traffic safety risk (Yu & Abdel-Aty, 2014). Collectively, this kind of work establishes VSL as an effective mechanism for reducing crash likelihood under most operating conditions. A general overview of VSL was provided in previous research (Khondaker & Kattan, 2015).

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On Interstate 95 in Virginia, a comparison of crash counts one year before and one year after VSL deployment found reductions in total crash frequency alongside a more pronounced decline in fatal-injury crashes (Cho et al., 2024). A winter-specific evaluation across three highways in British Columbia, comparing three seasons before and after VSL installation using an Empirical Bayes framework, reported 34.4% reduction in serious winter collisions (El Esawey et al., 2022). Using a four-year before and four year after window with logistic segmented regression and generalized estimating equations, total and rear-end crash reductions were identified in Wyoming (34% reduction in total crashes, 65% reduction in rear end crashes) and Georgia (29% reduction in total crashes, 35% reduction in rear end crashes), though no statistically significant safety benefit emerged in Virginia, underscoring that VSL effectiveness is not uniform across jurisdictions (Avelar et al., 2021). A six-year Full Bayes before-after analysis on Interstate 5 in Seattle similarly found a substantial 32.23% reduction in total crashes, with the benefit most pronounced for rear-end crashes and comparatively smaller for sideswipe crashes (Pu et al., 2021). A weather-responsive VSL deployment on a rural mountainous corridor in Wyoming, evaluated using both Empirical Bayes and a Negative Binomial multivariate adaptive regression splines approach over a six-year before and five-year after window, found 22% and 13% reduction in total and property-damage-only crashes (Gaweesh & Ahmed, 2020). European evidence from Belgium, drawn from an Empirical Bayes evaluation spanning three years before and two years after implementation, similarly found VSL associated with reductions in injury, fatal-injury, rear-end, and single-vehicle crashes (De Pauw et al., 2018). Earlier evaluations in Missouri and Portland, using naive before-after and Empirical Bayes methods respectively, reported reductions in total and rear-end crash frequency (Bham et al., 2010; Siddiqui & Al-Kaisy, 2017). Taken together, this body of observational evidence is broadly consistent in direction, total and rear-end crashes decline following VSL deployment in nearly every study reviewed, even as the magnitude of the effect varies considerably with corridor geometry, climate, and evaluation method.

LCS has received comparatively less attention in the safety literature, with much of the existing evidence centered on lane-changing behavior and incident management efficiency. An early evaluation of freeway lane control for incident management found that LCS could produce more orderly lane changes, though sometimes at the cost of longer travel time during the transition (Jha et al., 1999). Beyond the direct VSL and LCS literature, the broader motivation for active traffic management is reinforced by evidence that disabled and abandoned vehicles measurably extend freeway incident duration (Chimba et al., 2014), and that incidents of any kind can produce non-recurring congestion that propagates well beyond the segment where the event originated (Chung et al., 2012).

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Beyond VSL and LCS, the safety effect of Part-Time Shoulder Use has also been examined using high-resolution detector data across six freeway corridors in Georgia, Michigan, and Virginia, where shoulder-running segments were found to experience meaningfully fewer crashes than comparable non-shoulder-running freeway sections, with an average marginal reduction of roughly 0.42 crashes per segment under a Random Parameters Negative Binomial-Lindley framework that outperformed both traditional Negative Binomial and fixed-coefficient mixture specifications (Hasan & Abdel-Aty, 2024). The same study found that the design and operational context of the shoulder lane mattered considerably. Crashes were more frequent when the rightmost lane, rather than the leftmost lane, was used as the part-time shoulder, plausibly due to closer interaction with entrance and exit ramps, while the presence of emergency rest areas for stranded vehicles and shoulder widths beyond a critical threshold were each associated with further reductions in crash frequency. Hotspot analysis in the same study further revealed that the transition zones marking the start and end of the shoulder-running section were disproportionately hazardous.

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Moreover, positive research outcomes have also been seen in the study of reduction in incident duration due to the system application on freeways (Tahmid, 2025). Different statistical and artificial intelligence based study have also been found for evaluation of risk and reliability of different transportation systems (G. A. Noman et al., 2024; M. G. A. Noman et al., 2025; Tahmid et al., 2023; TAHMID et al., 2023; Tahmid et al., 2025).

Critically, nearly every study reviewed evaluates one of these three ATM strategies in isolation, and the existing PTSU literature in particular has not yet examined deployments in which VSL, LCS, and PTSU operate together as a single integrated system, nor has it modeled the statistical dependence between related crash types and severity outcomes that may arise from shared, unobserved segment-level risk factors. The present study addresses this gap by evaluating the safety performance of an integrated VSL, LCS, and PTSU deployment on SR-417 and SR-429 using a cross-sectional crash modification factor framework, and by extending this framework to a joint bivariate modeling approach for correlated crash-type and severity outcomes, an extension motivated directly by the segment-type and crash-type sensitivities documented.

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CHAPTER THREE: DATA PREPARATION

Treated and Comparison Segments

A detailed base map of the study network was first developed, classifying every roadway segment into one of four geometric types, basic, merge, diverge, and weaving, and recording associated geometric attributes such as lane count, lane width, and the posted speed limit. Continuous traffic data from the Microwave Vehicle Detection System (MVDS) covering the study network was then integrated with this base map at the segment level. Each treated segment operating under the Flex Lane system was subsequently matched to one or more comparison segments on the basis of shared geometric characteristics, segment type and number of lanes, posted speed limit, and traffic characteristics, specifically weekday and weekend volume and speed profiles. To confirm that the matched comparison segments carried statistically similar traffic conditions to their treated counterparts, a Mann-Whitney U-test was applied to compare speed distributions and a Kolmogorov-Smirnov test was applied to compare volume distributions between candidate comparison segments and each treated segment. This matching procedure ensured that any difference in crash frequency between the treated and comparison groups could be more confidently attributed to the presence of the Flex Lane system rather than to underlying differences in traffic exposure or roadway geometry. Figure 3 illustrates the steps for finding comparison segments corresponding to the treated segments.

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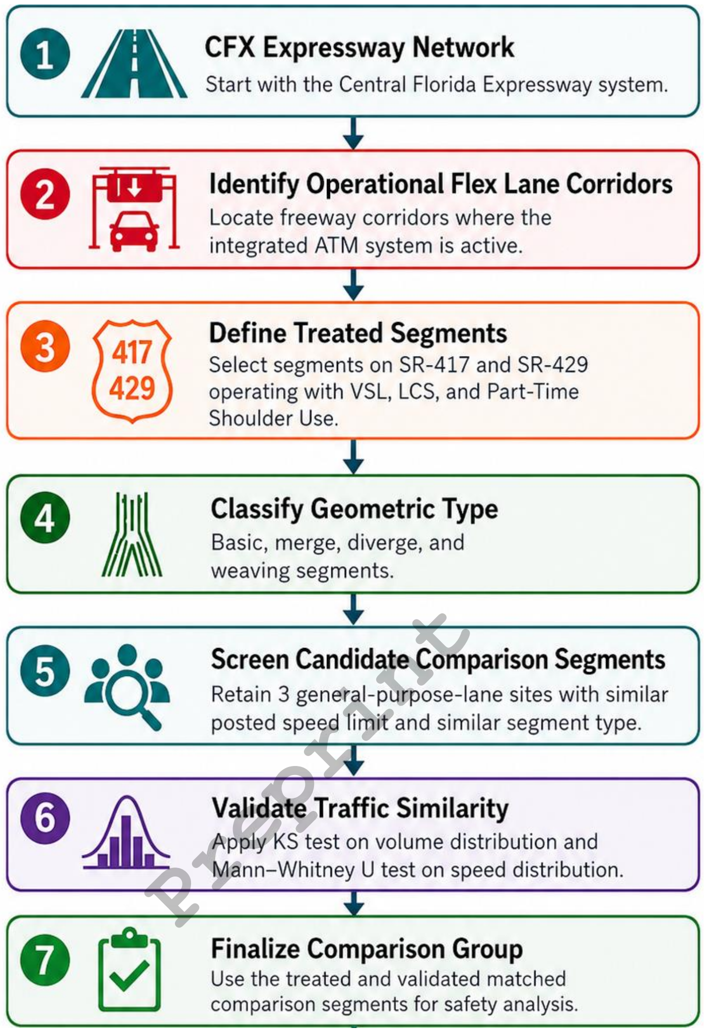

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Figure 3 Steps for Finding Comparison Segments

The treated segments are located on SR-417 and on SR-429, the two corridors on which the integrated VSL, LCS, and PTSU system is operational. Figure 4 illustrates the treated sites of the study area. The comparison segments identified through the matching procedure described above are not confined to the untreated portions of these same two routes; rather, as illustrated in Figure 5, they are distributed across several additional freeways within the Central Florida Expressway network, including SR-414, SR-408, and SR-528, in addition to untreated sections of SR-417 and SR-429 itself. This wider geographic span was necessary to assemble a sufficient number of segments that satisfied the geometric and traffic-condition matching criteria for each of the four segment types, and it is consistent with the cross-sectional comparison framework adopted in this study, in which the treatment effect is estimated by comparing concurrently observed treated and comparison segments rather than the same segments before and after deployment.

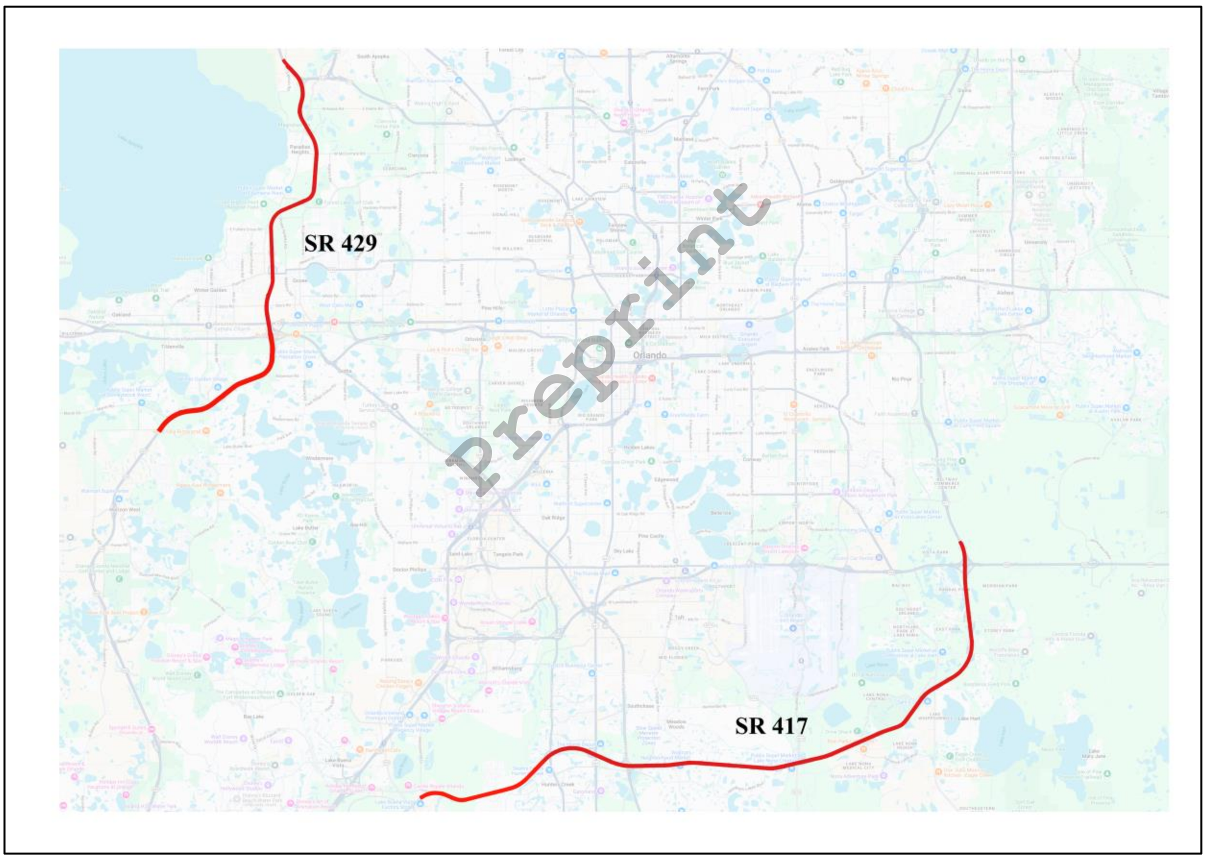

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Figure 4 Treated Sites of The Study Area

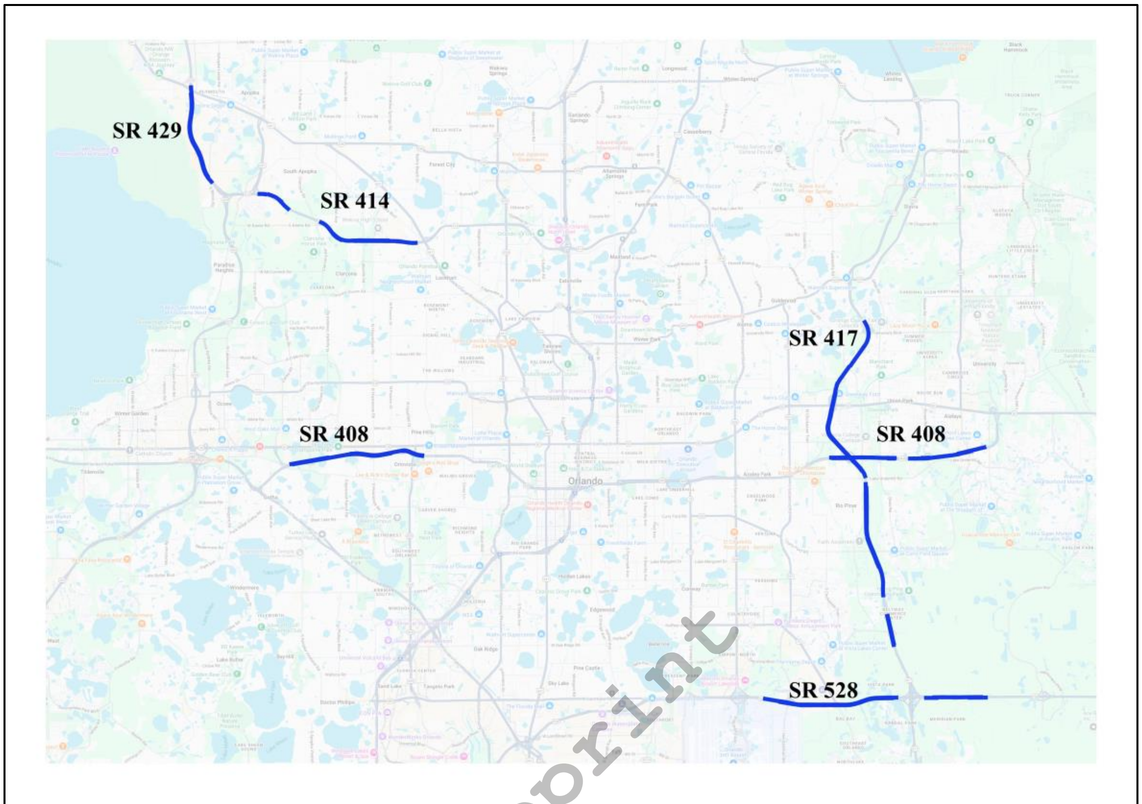

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Figure 5 Comparison Group Sites of The Study Area

Each segment in the study network was classified into one of four geometric types following the definitions of the Highway Capacity Manual, as illustrated in Figure 6. Basic segments consist of uninterrupted mainline freeway with no ramp influence area. Merge segments correspond to the influence area immediately downstream of an on-ramp, where entering traffic accelerates and merges into the mainline flow. Diverge segments correspond to the influence area immediately upstream of an off-ramp, where exiting traffic decelerates and maneuvers toward the deceleration lane. Weaving segments occur where an on-ramp and an off-ramp are sufficiently close together that merging and diverging traffic streams cross paths within a short distance, producing a concentrated zone of lane-changing activity. This four-category classification underlies the segment type variable used throughout the crash frequency models. In the models, segment type was represented by a binary indicator variable, *Basic Segment*, coded as one for basic segments and zero for all *complex segment* types, comprising merge, diverge, and weaving segments, which together serve as the reference category.

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Figure 6 Different Segment Types in the Study Area

Data Structure

The final dataset comprises 235 unique freeway segments. The treated group consists of 135 unique segments, while the comparison group consists of 100 unique segments. A total of 783 crashes were recorded across the full dataset. The comparison group accounts for 491 of these crashes, comprising 184 rear-end, 142 sideswipe, 96 off-road, 156 injury, and 333 no-injury crashes. The treated group accounts for the remaining 292 crashes, comprising 115 rear-end, 92 sideswipe, 36 off-road, 71 injury, and 207 no-injury crashes. Although the treated group contains more unique segments than the comparison group, it accounts for fewer total crashes, consistent with the lower crash rates per million vehicle miles traveled reported later for the treated group.

Crash and traffic data were collected from October 2024 through March 2026, spanning six calendar quarters from Q4 2024 through Q1 2026. Data were aggregated at the quarterly level rather than annually, with each calendar year divided into four three-month quarters (Q1 through Q4), and each segment permitted to contribute one observation per quarter, yielding the segment-season as the unit of analysis used throughout this study. Across the full dataset, Q1 contributes 342 observations, Q2 contributes 107, Q3 contributes 170, and Q4 contributes 244 with the comparison group consistently contributing more observations than the treated group within every quarter. This seasonal structure allows the crash frequency models to account for within-year variation in exposure through the seasonal traffic volume. *Vehicle Miles Traveled (VMT)* was constructed for each segment-season observation as the product of the seasonal average daily traffic volume, and the segment length, in miles.

Binary variable *Treated Segment* was indicator denoting whether the observation belongs to the comparison group or the treated group. *Shoulder Width* that reflects the outside shoulder width in feet was incorporated into models as continuous variable. Another binary variable *Entry/Exit Segment* was indicator denoting whether the segment is initial or terminal segment of the ATM system in the corridor.

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CHAPTER FOUR: METHODOLOGY

Safety Performance Functions (SPFs)

Safety Performance Functions (SPFs) are statistical models that relate the expected number of crashes, or a related safety outcome, to a set of explanatory variables describing traffic exposure, roadway geometry, and operational conditions. The safety outcome modeled by an SPF can be a count, such as crash frequency, or a continuous measure, such as crash rate. In this study, the crash data are non-negative, integer-valued counts recorded across roadway segments, and this data type determines the model family used to estimate the treatment effect.

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Generalized Linear Models (GLMs) employing a Negative Binomial (NB) distribution are the most widely applied SPF specification in highway safety research, owing to their ability to accommodate the overdispersion that is routinely observed in crash count data, where the variance of the observed crash frequency exceeds its mean (M. A. Abdel-Aty & Radwan, 2000; Lord & Mannering, 2010). For a given segment observation *i*, the crash count Y_i is assumed to follow a Negative Binomial distribution with mean μ_i and dispersion parameter α:

$$Y_i \sim \text{Negative Binomial}(\mu_i, \alpha) \tag{1}$$

with the corresponding mean-variance relationship expressed as:

$$\text{Var}(Y_i) = \mu_i + \alpha\mu_i^2 \tag{2}$$

where α > 0 indicates the presence of overdispersion relative to the Poisson assumption of equal mean and variance (Lord, 2006). The expected crash frequency μ_i is related to the covariates through a log-link function, ensuring that predicted crash frequencies remain non-negative:

$$log(\mu_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_p X_{pi} \quad (3)$$

where X_{1i}, X_{2i}, …, X_{pi} represent the explanatory variables for observation *i* and β_0, β_1, …, β_p are the corresponding model coefficients estimated through maximum likelihood estimation. This Negative Binomial SPF specification forms the baseline modeling framework adopted in this study and is extended to incorporate the treatment effect of the integrated Active Traffic Management system, and to alternative distributional assumptions, including the Poisson-Lognormal, Zero-Inflated Negative Binomial, and Hurdle Negative Binomial specifications, each of which addresses a different aspect of the heterogeneity and zero-crash-frequency patterns present in the dataset.

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Crash Modification Factor (CMF)

A cross-sectional modeling framework was used to estimate the safety effect of the integrated system. The cross-sectional approach is appropriate for this study because the treatment effect is estimated by comparing concurrently observed treated and comparison segments rather than the same segments before and after deployment. Similar to the approach used in a prior study for estimating treatment-based modification factors in a cross-sectional framework (Ahsan & Abdel-Aty, 2025), here the treatment effect was incorporated directly into the crash frequency model through a binary treatment indicator. In the present study, this treatment indicator represents whether a freeway segment was located within the deployed Flex Lane Active Traffic Management system. Differences in traffic exposure, roadway geometry, and segment characteristics among the segments are then adjusted for in the crash frequency model.

Let Y_i denotes the observed crash frequency for segment *i,* where crashes may represent total crashes or a specific crash type such as rear-end, sideswipe, off-road, or injury crashes. The expected crash frequency, μ_i was modeled as a function of exposure, geometric characteristics, and treatment status. The cross-sectional CMF estimation method was applied by incorporating the treatment indicator directly into the crash-frequency model. In this framework, the regression model is used to estimate the adjusted treatment effect after controlling for exposure and segment-level characteristics. The crash-frequency model used for CMF estimation can be expressed as:

$$ln(\mu_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_p X_{pi} + \beta_T T_i \tag{4}$$

where, $T_i = \begin{cases} 1, & \text{Treated Flex Lane segment} \\ 0, & \text{Comparison group segment} \end{cases}$

X_{ki} = the *k*th explanatory variable for segment i

β_0 = model intercept

β_k = estimated coefficient for explanatory variable X_{ki}

β_T = estimated treatment coefficient

The Crash Modification Factor was then obtained from the treatment coefficient as:

$$CMF_T = e^{\beta_T} \tag{5}$$

CMF_T value less than 1.0 indicates a reduction in expected crash frequency associated with the treatment, whereas a value greater than 1.0 indicates an increase in expected crash frequency. Thus when CMF_T value is less than 1.0, the corresponding percentage change in crash frequency is calculated as:

$$\text{Crash Reduction} = (1 - CMF_T) \times 100 \tag{6}$$

This formulation allows the safety performance of treated and comparison segments to be evaluated in a model-based manner rather than relying only on raw crash counts or crash rates. Therefore,

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the estimated CMF provides an adjusted measure of the safety effect of the integrated Flex Lane Active Traffic Management system while controlling for exposure and segment-level roadway characteristics.

Crash Frequency Models

While the Negative Binomial specification is the most commonly applied SPF framework in safety research, crash frequency data are frequently characterized by two additional features that the standard Negative Binomial model does not explicitly address: unobserved, continuously distributed heterogeneity across observations, and an excess proportion of zero-crash observations beyond what the Negative Binomial distribution would predict (Mannering et al., 2016; Shankar et al., 1997). To examine the sensitivity of the estimated treatment effect to these alternative distributional assumptions, four count-data model specifications were estimated and compared for each crash type considered in this study: the Negative Binomial (NB) model described above, the Poisson-Lognormal (PLN) model, the Zero-Inflated Negative Binomial (ZINB) model, and the Hurdle Negative Binomial (Hurdle-NB) model. The Negative Binomial model addresses overdispersion through a Gamma-distributed multiplicative error term. The Poisson-Lognormal model instead introduces a Normally distributed random effect on the log scale, allowing for a continuous representation of unobserved, segment-level heterogeneity in crash risk. The Zero-Inflated and Hurdle specifications extend the Negative Binomial framework by explicitly partitioning the zero observations from the positive count process, under the assumption that some portion of recorded zeros may arise from a structurally distinct mechanism.

The Poisson-Lognormal model addresses overdispersion by introducing a continuous, Normally distributed random effect on the log scale, rather than the discrete Gamma mixing distribution underlying

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the Negative Binomial model (El-Basyouny & Sayed, 2009; Park & Lord, 2009). The PLN model can be expressed as:

$$Y_i \sim \text{Poisson}(\lambda_i),\ \log(\lambda_i) = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_p X_{pi} + \varepsilon_i,\ \varepsilon_i \sim N(0, \sigma^2) \tag{7}$$

where ε_i is an observation-level random effect that captures unobserved, segment-level heterogeneity in crash risk not explained by the included covariates, and σ^2 is the variance of this random effect. Because the random effect is continuous rather than discrete, the PLN model can represent a more flexible and gradual range of unobserved risk variation across segments than the Negative Binomial model, and has been shown in several crash-frequency studies to outperform the Negative Binomial model when such continuous heterogeneity is present (Park & Lord, 2009).

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The Zero-Inflated Negative Binomial model extends the standard Negative Binomial framework by explicitly modeling the zero-crash observations as arising from two distinct latent processes: a binary process governing whether a observation belongs to an always-zero state, and a Negative Binomial count process governing crash frequency for observations belonging to the at-risk state (Shankar et al., 1997). The probability mass function of the ZINB model is given by:

$$P(Y_i = 0) = \pi_i + (1 - \pi_i) g(0 \mid \mu_i, \alpha) \tag{8}$$

$$P(Y_i = y_i) = (1 - \pi_i) g(y_i \mid \mu_i, \alpha),\ y_i > 0 \tag{9}$$

where π_i is the probability of belonging to the always-zero state, typically modeled through a logistic regression on a subset of covariates, and g is the Negative Binomial probability mass function with mean μ_i and dispersion α.

The Hurdle Negative Binomial model similarly partitions the data-generating process into a binary component and a count component, but differs conceptually from the Zero-Inflated specification in that all zero observations are assumed to arise exclusively from the binary hurdle process, while the count component is modeled using a zero-truncated Negative Binomial distribution applied only to the positive observations (Yu et al., 2019). The Hurdle-NB model is expressed as:

$$P(Y_i = 0) = 1 - p_i \tag{10}$$

$$P(Y_i = y_i) = p_i \cdot \left[\frac{g(y_i|\mu_i,\alpha)}{1-g(0|\mu_i,\alpha)}\right], \quad y_i > 0 \tag{11}$$

where p_i is the probability of crossing the hurdle, that is, of observing at least one crash in the observation period, typically modeled through a logistic regression.

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The four candidate models were compared using standard goodness-of-fit measures derived from the maximized log-likelihood of each model, allowing the specification providing the best representation of the observed crash data to be identified for each crash type. The log-likelihood of the fitted model is expressed generally as:

$$\log L = \sum_{i=1}^{n} \log P\,(Y_i \mid \mu_i, \alpha) \tag{12}$$

Where $P\,(Y_i \mid \mu_i, \alpha)$ is the probability mass function corresponding to the assumed distribution of the response variable, whether Negative Binomial, Poisson-Lognormal, Zero-Inflated Negative Binomial, or Hurdle Negative Binomial. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to compare the four model specifications while penalizing model complexity, defined respectively as:

$$AIC = 2k - 2\log(L) \tag{13}$$

$$BIC = k \log(n) - 2 \log(L) \quad (14)$$

where k is the number of estimated parameters in the model, n is the number of observations, and log(L) is the maximized log-likelihood. Lower values of AIC and BIC indicate a model specification that achieves a better balance between goodness-of-fit and parsimony, and the model with the lowest AIC and BIC among the four candidates was adopted as the preferred specification for interpreting covariate effects and treatment-related crash modification factors for each crash type in this study.

Joint Model

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The four model specifications described above are conventionally estimated separately for each crash type or severity outcome of interest, an approach referred to throughout this study as univariate modeling. This approach implicitly assumes that the unobserved factors influencing one crash outcome, such as collision type, are independent of those influencing a related outcome, such as injury severity. In practice, a given roadway segment may possess unobserved characteristics, such as driver behavior patterns or sight-distance limitations, that simultaneously elevate the likelihood of a particular collision type and the severity of the resulting crash. When such shared, unobserved heterogeneity exists but is not accounted for, the precision of the estimated treatment effect may be understated, and the true relationship between the deployed countermeasure and crash outcomes may not be fully captured. This concern has been raised directly in recent literature evaluating active traffic management countermeasures. In an evaluation of a variable speed limit system deployed on the I-24 Smart Corridor in Tennessee, it was demonstrated that rear-end crash frequency and the frequency of associated injury and property-damage-only outcomes were strongly and significantly correlated, and showed that jointly modeling rear-end crashes with their associated severity outcomes through a copula-based framework produced more precise treatment-effect estimates than estimating each outcome separately (Gu et al., 2025). Motivated by this evidence, and by the statistically significant correlations observed between collision type and injury frequency in the present dataset, a joint bivariate Poisson-Lognormal modeling framework was adopted in this study for two crash-type pairs of engineering relevance: rear-end and injury crashes, and sideswipe and injury crashes.

Rather than estimating the rear-end (or sideswipe) and injury crash models independently, the joint specification introduces a shared component of unobserved heterogeneity between the two outcomes being modeled together, extending the observation-level random effect to a structure in which the random effects of the two outcomes are permitted to be correlated:

$$\begin{bmatrix}\varepsilon_{1i}\\ \varepsilon_{2i}\end{bmatrix}^T \sim N\left(\begin{bmatrix}0\\0\end{bmatrix}, \Sigma\right), \quad \Sigma = \begin{bmatrix}\sigma_1^2 & \rho\sigma_1\sigma_2\\ \rho\sigma_1\sigma_2 & \sigma_2^2\end{bmatrix} \tag{15}$$

where ε_{1i} and ε_{2i} are the observation-level random effects for the two jointly modeled crash outcomes, σ_1^2 and σ_2^2 are their respective variances, and ρ is the correlation between them, representing the strength of the shared, unobserved heterogeneity linking collision type and injury severity. This approach allows the model to borrow statistical strength across the two correlated outcomes, in principle yielding a more efficient and more precise estimate of the treatment effect than would be obtained from estimating each outcome independently.

The joint and independent model specifications were compared using the same log-likelihood, AIC, and BIC statistics, in addition to a likelihood ratio test of independence, which tests the null hypothesis that the correlation parameter ρ is equal to zero. A statistically significant likelihood ratio test indicates that the joint model provides a meaningfully better representation of the data than the corresponding

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pair of independent univariate models, confirming that the dependence between collision type and injury severity is both present and substantively important for this corridor.

Crash Rate

In addition to the treatment-effect estimates described above, crash rates were also calculated in the study area to account for differences in the exposure, such as traffic volume and road length. Using crash rates instead of raw crash counts allows for a more accurate comparison across segments by normalizing the data based on how much traffic each segment carries and the segment length. The crash rate of segments was calculated based on the following equation:

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$$R = \frac{1{,}000{,}000 \times C}{365 \times N \times AADT \times L} \tag{16}$$

here, R = Crash rate per Million Vehicle Miles Traveled (MVMT)

C = Total number of crashes

N = Number of years

AADT = Average Annual Daily Traffic

L = Length of the roadway segment in miles

Crash-rate comparison was conducted to provide a preliminary, segment-level view of how observed crash frequency differed between treated and comparison segments. Because these rate-based comparisons were not adjusted for confounding differences between segments or evaluated for statistical significance, they were not used to draw conclusions independently. Instead, any pattern identified in the descriptive comparison, particularly differences between basic and complex segment types, was examined for consistency with the corresponding treatment-effect estimates obtained from the crash frequency models.

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CHAPTER FIVE: RESULTS AND DISCUSSION

Total Crash Frequency Model Results

Table 1 presents the estimation results for four candidate crash frequency models applied to total crash counts: the Negative Binomial (NB), Poisson-Lognormal (PLN), Zero-Inflated Negative Binomial (ZINB), and Hurdle Negative Binomial (Hurdle-NB) specifications. These four models were selected to represent the principal strategies available for handling overdispersion and excess zero observations in crash count data, two characteristics that were common in dataset where many segments recorded no crash in each observation period.

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Table 1 Crash frequency models comparison for total crashes

Variables	Negative Binomial (NB)	Poisson Lognormal	Zero inflated NB	Hurdle NB
Intercept	0.133*	-0.644**	0.704**	0.244*
Treated Segment (Ref. Comparison Group Segment)	-0.605**	-0.518**	-0.554**	-0.648**
Basic Segment (Ref. Complex Segment type)	-0.421**	-0.271**	-0.572**	-0.809**
VMT (in 1000)	0.073**	0.078**	0.038**	0.041**
Entry/Exit Segment	1.334**	1.459**	1.059**	0.897**
Shoulder Width	-0.061**	-0.053**	-0.061**	-0.081**
Goodness of Fit				
Log-likelihood	-1085	-1063	-1065	-1078
AIC	2185	2140	2148	2174
BIC	2218	2173	2191	2217

** Significant at 95% confidence level.
* Significant at 90% confidence level.

Based on the goodness-of-fit statistics reported at the bottom of Table 1, the Poisson-Lognormal model provides the best overall fit to the total crash data, achieving the lowest Akaike Information Criterion (AIC = 2,140) and Bayesian Information Criterion (BIC = 2,173) among the four candidates, alongside the highest log-likelihood (-1,063). This result indicates that the continuous, lognormally distributed random effect captured the unobserved variation in crash risk across segments more effectively than either the discrete Gamma mixing assumed by the standard Negative Binomial model or the explicit zero-generating mechanisms assumed by the Zero-Inflated and Hurdle specifications. The zero observations largely reflected short observation windows combined with naturally low crash frequencies at individual segments, a pattern more consistent with continuous heterogeneity than with a discrete zero-generating process. The Poisson-Lognormal specification was therefore adopted as the primary model for subsequent interpretation.

The estimated coefficients were broadly consistent in sign and statistical significance across all four models, lending confidence to the interpretation that follows. The treated segment coefficient is negative and statistically significant at the 95th percent confidence level in every specification. Exponentiating the Poisson-Lognormal coefficient yields a crash modification factor of approximately 0.596, indicating that, holding all other covariates constant, segments operating under the integrated Active Traffic Management system were associated with a 40.4 percent reduction in expected total crash frequency relative to comparison segments. This finding is consistent with the descriptive crash rate comparison (later discussed) and provides model-based confirmation that the observed reduction in crash rates was not attributable solely to differences in traffic volume or segment geometry between the treated and comparison groups.

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The basic segment coefficient is also negative and significant across all models, equal to -0.271 under the Poisson-Lognormal specification, corresponding to a 23.8 percent lower expected crash frequency at basic freeway segments relative to complex segments like diverges, merges, and weaving, after controlling for traffic volume, shoulder width, and the presence of an entry or exit. This result is intuitive from a traffic engineering perspective, since complex segments inherently contain a greater number of conflict points arising from vehicles entering, exiting, or changing lanes, whereas basic segments carry continuous mainline flow without these maneuvers.

The entry/exit segment coefficient is the largest in magnitude among all covariates, at 1.459 under the Poisson-Lognormal model, corresponding to an exceptionally large increase in expected crash frequency at segments where the system starts or ends. These are high-risk locations due to the speed differential and lane-change maneuvers near these locations. The shoulder width coefficient is negative and significant, at -0.053, indicating that wider shoulders are associated with modestly lower crash frequency, plausibly by providing additional recovery space for errant vehicles and a clear area for disabled vehicles. Finally, the vehicle miles traveled coefficient is positive and significant, at 0.078 per thousand vehicle-miles, reflecting the expected exposure relationship in which segments carrying higher traffic volume experience a correspondingly higher absolute crash frequency.

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Joint Model Results

Crash frequency models are conventionally estimated separately for each crash type or severity, an approach commonly referred to as univariate modeling. While this strategy is straightforward to implement, it implicitly assumes that the unobserved factors influencing one crash outcome, such as collision type, are independent of those influencing a related outcome, such as injury severity. In practice, this assumption is unlikely to hold. A given roadway segment may possess unobserved characteristics that simultaneously elevate the likelihood of a particular collision type and the severity of the resulting crash. When such shared, unobserved heterogeneity exists but is ignored, the precision of the estimated treatment effect may be understated, and the true strength of the relationship between countermeasure deployment and safety outcomes may not be fully captured.

This concern has been raised in recent literature evaluating active traffic management countermeasures. In a study evaluating the safety effects of a variable speed limit system on the I-24 Smart Corridor in Tennessee, it was demonstrated that rear-end crash frequency and the frequency of associated injury and property-damage-only outcomes were strongly and significantly correlated, with pearson correlation coefficients reported in excess of 0.85 between collision type and consequence (Gu et al., 2025). Building on this evidence, the present study also examined the analogous relationship for the Flex Lane system evaluated here. As shown in Figure 7, a statistically significant positive correlation was observed between rear-end crash frequency and injury crash frequency (Pearson $r = 0.61$, $p < 0.001$), and between sideswipe crash frequency and injury crash frequency (Pearson $r = 0.43$, $p < 0.001$). Bubble size here reveals number of observations. The consistent direction and statistical significance of both correlations support the conclusion that rear-end and sideswipe crash frequencies are not independent of injury crash frequency, and that a joint modeling framework is therefore both statistically justified and methodologically preferable to estimating these outcomes in isolation.

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Motivated by this evidence of dependence, a joint bivariate Poisson-Lognormal model was estimated for two crash-type pairs: rear-end and injury crashes, and sideswipe and injury crashes. The joint specification retains the Poisson-Lognormal structure identified as the best-fitting univariate model, while introducing a shared component of unobserved heterogeneity between the two outcomes being modeled together. This approach allowed the model to borrow statistical strength across the two correlated outcomes, yielding more precise estimates of the treatment effect than would be obtained from estimating each outcome independently.

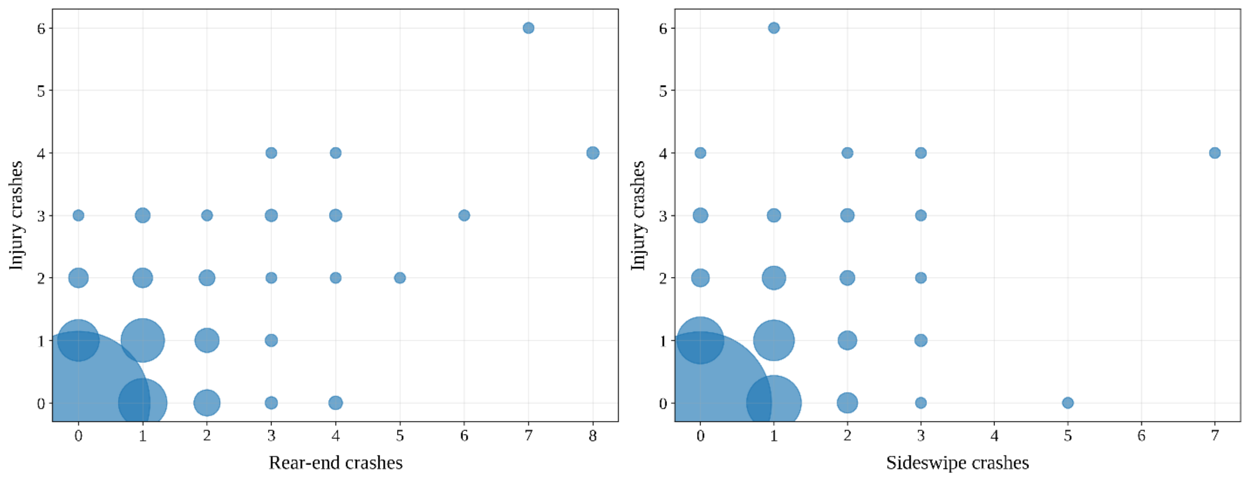

Figure 7 Injury Crash, Rear end, and Sideswipe Crash Scatters

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Table 2 reports the estimated coefficients for the univariate and joint Poisson-Lognormal models applied to the rear-end and injury crash pair, and separately to the sideswipe and injury crash pair. Across both pairings, the sign and statistical significance of the covariates are consistent with the total crash model presented in Table 1 and with the interpretation, providing internal consistency across the modeling framework.

For the rear-end crash outcome, the treated segment coefficient is -0.461 under the univariate model and strengthens to -0.496 under the joint model, corresponding to crash modification factors of 0.631 and 0.609, respectively. This indicates that the integrated Active Traffic Management system is associated with reductions in rear-end crash frequency of 36.9 percent and 39.1 percent under the univariate and joint specifications. The basic segment indicator is not statistically significant for rear-end crashes in either specification, suggesting that, after accounting for entry/exit presence, traffic volume, and shoulder width, rear-end crash risk does not differ between basic and complex segments. Rear-end collisions are influenced by following-distance and braking behavior rather than of the geometric configuration of the segment itself.

For the injury crash outcome estimated jointly with rear-end crashes, the treated segment coefficient strengthens from -0.746 under the univariate model to -0.769 under the joint model, corresponding to crash modification factors of 0.475 and 0.463, or reductions of 52.5 percent and 53.7 percent, respectively. When injury crashes are instead estimated jointly with sideswipe crashes, the treated segment coefficient strengthens from -0.746 to -0.777, corresponding to a slightly larger crash reduction under the joint specification. In both pairings, the basic segment coefficient for injury crashes remains negative and significant, reinforcing that complex interchange geometry is associated with materially higher injury crash risk than basic segments.

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For the sideswipe crash outcome, the treated segment coefficient is -0.378 under the univariate model and -0.387 under the joint model, corresponding to crash modification factors of 0.685 and 0.679, or reductions of 31.5 percent and 32.1 percent. The basic segment coefficient for sideswipe crashes is negative and significant in both specifications, indicating that, similar to total and injury crashes but unlike rear-end crashes, sideswipe risk was elevated at complex segments relative to basic segments, consistent with the higher frequency of lane-changing maneuvers that occur in merge, diverge, and weaving segments.

Table 2 Univariate and joint model coefficients for rear-end, sideswipe, and injury crashes

Variables	Rear End Crashes		Injury Crashes	
	Univariate Poisson Lognormal	Joint Poisson Lognormal	Univariate Poisson Lognormal	Joint Poisson Lognormal
Intercept	-1.798**	-1.89**	-2.049**	-2.315**
Treated Segment (Ref. Comparison Group Segment)	-0.461**	-0.496**	-0.746**	-0.769**
Basic Segment (Ref. Complex Segment type)	-	-	-0.491**	-0.4052**
VMT (in 1000)	0.059**	0.067**	0.097**	0.109**
Entry/Exit Segment	1.291**	1.424**	0.751*	1.079**
Shoulder Width	-0.062*	-0.065*	-	-
Variables	**Sideswipe Crashes**		**Injury Crashes**	
	Univariate Poisson Lognormal	**Joint Poisson Lognormal**	**Univariate Poisson Lognormal**	**Joint Poisson Lognormal**
Intercept	-1.878**	-2.132**	-2.049**	-2.004**
Treated Segment (Ref. Comparison Group Segment)	-0.378**	-0.387**	-0.746**	-0.777**
Basic Segment (Ref. Complex Segment type)	-0.458**	-0.459**	-0.491**	-0.492**
VMT (in 1000)	0.075**	0.087**	0.097**	0.104**
Entry/Exit Segment	1.177**	1.242**	0.751*	0.879**
Shoulder Width	-	-	-	-

** Significant at 95% confidence level.
* Significant at 90% confidence level.
- indicates the variable was not statistically significant

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Table 3 Goodness-of-fit comparison between independent and joint model

Goodness of Fit	Rear End and Injury Crashes		Sideswipe and Injury Crashes	
	Independent Model	Joint Model	Independent Model	Joint Model
Log-likelihood	-1134	-1066	-1057	-1022
AIC	2296	2160	2142	2072
BIC	2362	2226	2209	2139

Accounting for the shared unobserved heterogeneity between collision type and injury severity, the joint specification recovers a treatment effect that is, in every instance, at least as strong as that obtained when the two outcomes are modeled in isolation. The improvement in the treated segment coefficient is most evident for the rear-end and injury pairing, where the joint model produces a meaningfully larger reduction in both crash types relative to the univariate estimates, suggesting that ignoring the dependence between these two outcomes would have led to an understatement of the true safety benefit attributable to the system.

This improvement in the precision and strength of the treatment effect estimate is corroborated by the model performance statistics reported in Table 3. For the rear-end and injury crash pairing, the joint model achieves a substantially higher log-likelihood (-1,066) than the corresponding independent model (-1,134), accompanied by a reduction in AIC from 2,296 to 2,160 and in BIC from 2,362 to 2,226. Improvement is observed for the sideswipe and injury crash pairing, where the joint model log-likelihood improves from -1,057 to -1,022, with AIC decreasing from 2,142 to 2,072 and BIC decreasing from 2,209 to 2,139. In both cases, the magnitude of improvement in AIC, exceeding 70 points for the sideswipe and injury pairing and exceeding 135 points for the rear-end and injury pairing, providing strong statistical confirmation that the joint specification is preferred over the independent estimation of these crash outcomes.

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In addition to the improvement in goodness-of-fit, the estimated dependence parameters further confirm the presence of shared unobserved heterogeneity between collision type and injury crashes. The estimated correlation parameter was $\rho = 0.91$ for the rear-end and injury crash pair and $\rho = 0.65$ for the sideswipe and injury crash pair, with both parameters statistically significant. These positive and significant estimates indicate that unobserved segment-level risk factors contributing to rear-end or sideswipe crashes are also strongly associated with injury crash occurrence. Therefore, modeling these outcomes independently would ignore an important source of dependence in the data, whereas the joint Poisson-Lognormal specification explicitly accounts for this correlation.

The integrated Active Traffic Management system is associated with a statistically significant safety benefit across all examined crash types, with the largest proportional reduction observed for injury crashes, followed by total crashes, and with rear-end and sideswipe crashes showing comparatively more modest, though still substantial and statistically significant reductions.

Differentiating Treatment Effect by Segment Geometry

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To examine whether the treatment effect on total crashes differed by segment type, the Poisson Lognormal model was extended by introducing a single interaction term between the treatment indicator and the Basic Segment dummy variable, with complex segments (merge, diverge, and weaving) serving as the reference category. The interaction term (Treated Segment * Basic Segment) is statistically significant ($\beta = 0.465$, $p = 0.04$), indicating that the treatment effect at basic segments is meaningfully weaker than at complex segments. For complex segments, the CMF derived from the treatment coefficient alone is $e^{-0.7853}$= 0.456, corresponding to a 54.4 percent reduction in expected total crash frequency. For basic segments, the combined coefficient (−0.785 + 0.465) yields a CMF of $e^{-0.7853+0.4645}$ = 0.726, corresponding to a 27.4 percent reduction. All other covariates retain their expected direction and significance. Model results are shown in Table 4. Whether this pattern of a stronger treatment effect at complex segments relative to basic segments is consistent with the descriptive crash rate comparison is examined in the subsequent discussion.

Table 4 Poisson Lognormal model with interaction variable

Variables	Coefficient	p value
Intercept	-0.526	0.015
Treated Segment (Ref. Comparison Group Segment)	-0.785	<0.001
Basic Segment (Ref. Complex Segment type)	-0.425	0.008
VMT (in 1000)	0.074	<0.001
Entry/Exit Segment	1.411	<0.001
Shoulder Width	-0.054	0.021
Treated Segment * Basic Segment	0.465	0.04
Goodness of Fit		
Log-likelihood	-1061	
AIC	2138	
BIC	2177	

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Table 5 summarizes the crash rate per million vehicle miles traveled (MVMT) for each segment type before and after deployment of the integrated Active Traffic Management system, disaggregated across total, rear-end, sideswipe, off-road, and injury crash categories. Across every segment type and crash category, the treated group crash rates were less relative to that of the comparison group, indicating a broadly consistent safety benefit associated with the Flex Lane system. The magnitude of this benefit, however, varied systematically with segment geometry. Diverge segments exhibited the largest overall reduction in total crash rate, at 58.4 percent, followed by weaving segments at 45.7 percent, merge segments at 30.6 percent, and basic segments at 18.8 percent. Diverge and weaving are normally locations of concentrated lane-changing activity and speed differential, the conditions that variable speed limit harmonization and lane control signals are designed to mitigate. Because the variable speed and lane-control signs activate in response to downstream congestion or incidents, their influence is naturally most pronounced at the geometric features where conflicts originate, rather than along basic segments.

Off-road crashes showed the steepest decline of any crash type at every segment, ranging from 43.1 percent at basic segments to 82.6 percent at weaving segments. Injury crashes likewise declined substantially across all segment types, with the largest reduction again observed at diverge segments (75.1 percent), suggesting that the treatment is not only reducing the frequency of collisions but also moderating their severity, consistent with the broader premise that speed harmonization reduces both the likelihood and consequence of a crash.

Rear-end and sideswipe crashes, which are closely tied to stop-and-go congestion and lane-changing, show comparatively smaller reductions at merge segments (11.3 percent for rear-end) than at diverge or weaving segments. Merge segments experience continuous, gradual lane-changing rather than the abrupt directional separation found at diverge or weaving segments. Basic segments, which lack the complex geometry of interchange areas, consistently showed the smallest percentage reductions across all crash types. It is expected since these segments were the least likely to benefit from components of the system, even though they still benefited from the corridor-wide variable speed limit and lane control signs.

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Table 5 Crash rate (per million vehicle miles traveled) by segment type and treatment status

Type of Segment	Group	Total Crash Number	Total Crash Rate	Rear End Crash Rate	Sideswipe Crash Rate	Off Road Crash Rate	Injury Crash Rate
Diverge	Comparison	104	2.034	0.821	0.450	0.391	0.567
	Treated	42	0.846	0.322	0.242	0.121	0.141
	Crash rate % Change		**-58.4%**	**-60.8%**	**-46.2%**	**-69.1%**	**-75.1%**
Merge	Comparison	47	0.894	0.247	0.342	0.247	0.304
	Treated	34	0.620	0.219	0.219	0.055	0.128
	Crash rate % Change		**-30.6%**	**-11.3%**	**-36.0%**	**-77.7%**	**-57.9%**
Weaving	Comparison	83	0.669	0.250	0.250	0.121	0.226
	Treated	17	0.363	0.149	0.107	0.021	0.149
	Crash rate % Change		**-45.7%**	**-40.4%**	**-57.2%**	**-82.6%**	**-34.1%**
Basic	Comparison	257	0.346	0.132	0.094	0.065	0.112
	Treated	199	0.281	0.113	0.089	0.037	0.071
	Crash rate % Change		**-18.8%**	**-14.4%**	**-5.3%**	**-43.1%**	**-36.6%**
Overall	Comparison	491	0.506	0.190	0.146	0.099	0.161
	Treated	292	0.340	0.134	0.107	0.042	0.083
	Crash rate % Change		**-32.8%**	**-29.5%**	**-26.7%**	**-57.6%**	**-48.4%**

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The convergence of the descriptive crash rate comparison and the model-based treatment-effect estimates reinforces the finding that the Flex Lane system delivered greater safety benefits at complex freeway segments than at basic segments.

CHAPTER SIX: CONCLUSIONS

This study evaluated the safety performance of an integrated Flex Lane Active Traffic Management system consisting of Variable Speed Limits, Lane Control Signs, and part-time shoulder use on selected freeway corridors in Central Florida. Using matched comparison segments and crash-frequency modeling approaches, the study examined total crashes as well as key crash outcomes, including rear-end, sideswipe, and injury crashes. The results indicate that the integrated system got CMF = 0.596 from Poisson-Lognormal model for total crashes (40.4% reduction), after controlling for exposure, geometry, entry/exit, and shoulder width. Joint bivariate Poisson-Lognormal models confirmed shared heterogeneity between collision type and injury crashes, producing stronger treatment effects than univariate models. Moreover, the treatment effect differs by segment geometry. Model with interaction variable shows a markedly stronger effect at complex segments (CMF = 0.456) than at basic segments (CMF = 0.726). System helps drivers negotiate complex segments more safely. The findings further demonstrate that the safety effects were not uniform across crash outcomes, highlighting the value of evaluating multiple crash types rather than relying only on total crash frequency.

From a practical transportation engineering perspective, the results support the use of integrated ATM strategies as a proactive approach for improving safety on urban freeways. By harmonizing speeds upstream of disturbances, providing advance lane-use guidance, and using the shoulder as an operational resource when needed, the Flex Lane system can help reduce abrupt braking, lane-changing conflicts, and unstable traffic conditions that often contribute to freeway crashes. The study has the ability to provide transportation agencies with an evidence-based framework for evaluating similar ITS deployments, and refining operational strategies to maximize the safety benefits of future ATM investments.

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