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Advancing Self-Enforcing Streets Phase 1: The Relationship between Roadway Environment and Crash Severity

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Advancing Our Understanding of Self-Enforcing Streets and the Use of Target Speeds to Improve Safety

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16. Abstract

The concept of self-enforcing roadways (SER) has been proposed as a speed management strategy to achieve harmony in drivers' speed selection and to address safety issues associated with excessive speeding. While numerous examples of SER implementation exist outside of the United States (particularly in European countries), this concept is fairly new in the United States. Only a few states in the U.S. have explored the possibility of implementing SER and evaluated its potential impacts on roadway safety. Accordingly, this study aims at (1) providing a comprehensive review of the literature on SER implementation and impact assessment across the world and (2) examining how roadway elements influence operating speeds and, consequently, crash outcomes, in Illinois, shedding light on the potential impact of roadway design and features on crash severity. A specific before-and-after study is required to analyze carefully the impacts of various SER strategies on safety in the state of Illinois.

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EXECUTIVE SUMMARY

The concept of self-enforcing roadways (SER) has been proposed as a speed management strategy to promote harmony in drivers' speed selection and to address safety issues related to excessive speeding. While numerous examples of SER implementation exist outside the United States, particularly in European countries, this concept is fairly new in the U.S. Only a few states have explored the possibility of implementing SER and have evaluated its potential impact on roadway safety. Accordingly, this study aims to (1) provide a comprehensive review of the literature on SER implementation and impact assessment globally, and (2) explore the possible relationship between roadway elements and speed-related crash severity in Illinois. This study serves as a preliminary analysis of the impacts of roadway elements on crash severity. A specific before-and-after study is needed to thoroughly assess the safety effects of various SER strategies in Illinois.

To achieve the first objective, this report examined literature focused on enhancing roadway safety under prevailing conditions, drivers' perception of their surroundings, and other environmental factors. The main findings highlighted the effects of visual guiding facilities, road layouts, and design elements on speed perception, reaction time, and general driving behavior. Overall, the findings underscore the need for a systematic approach to road design that aligns with drivers' cognitive processes and expectations.

To achieve the second objective, this study analyzed traffic crash data from Illinois between 2019 and 2022 to identify trends in crash severity and contributing factors. The findings indicated that crashes were notably more severe under darker conditions and more frequent on weekends, while non-injury crashes were more common on weekdays. The leading cause of fatal crashes was "Failing to Reduce Speed to Avoid a Crash," highlighting the crucial role of SER strategies in managing speed-related crashes. This conclusion was drawn based on the "Primary Cause" attribute recorded in the Illinois Traffic Crash data. This attribute reflects the most significant factor contributing to the crash, as determined by the investigating officer's judgment.

To gain a deeper understanding of the impacts of roadway environments on crash severity, the study utilized geospatial data to retrieve Google Street View images of crash sites, providing visual context for analyzing factors such as road conditions and visibility. The exact coordinates of each crash site were linked to front and rear views from a 135-degree field of view, simulating what drivers might have seen at the time of the incident.

To enhance the analysis, a deep learning-based image segmentation algorithm was applied to each image. The model, pre-trained on the CityScapes dataset, was fine-tuned to align with the traffic scenarios relevant to this study. Each pixel in the images was classified into one of the commonly observed categories in urban or rural contexts, including road, vegetation, buildings, and other relevant elements. For modeling purposes, the road or vegetation percentage was defined as the ratios of pixels labeled as "road" or "vegetation" to the total number of pixels in each image. These metrics provide a quantitative representation of the visual environment at crash sites, facilitating a robust exploration of the relationship between roadway elements, visibility, and crash severity.

The study analyzed data from over 1.15 million crashes, categorized by injury severity, and used statistical models to assess how road and vegetation percentages at crash sites influenced crash severity. Multinomial logit (MNL) modeling, based on segmentation results, revealed a significant association between road surface percentage and crash severity. A unit increase in road surface percentage was associated with a 55.3% increase in the likelihood of fatal crashes. Vegetation percentages showed a more complex relationship, mitigating minor injuries but slightly increasing the odds of severe outcomes.

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CHAPTER 1: INTRODUCTION

In recent decades, the state of Illinois has introduced numerous programs aimed at reducing the number of fatal and injury crashes through speed management. Most of these programs either rely on preventive measures, such as speed enforcement, or conventional educational efforts to influence roadway users' behavior. While these approaches have shown to be effective to a certain degree (Wakefield et al., 2010), data from the past five years (2018–2022) still show approximately 2,500 speeding-related fatalities in Illinois (Illinois Department of Transportation, 2022). This indicates a need for more innovative strategies to reduce fatal and injury crashes to zero. Considering that speeding was involved in about 45% of fatalities, a key focus of these strategies should be on harmonizing the roadway design with human behavior to reduce speeding (Singh et al., 2016). Achieving such harmony requires innovative design approaches.

One example of an innovative approach involves strategically designing road environments to encourage drivers to adopt operating speeds that align with posted limits, thereby enhancing overall roadway safety. Traditional design guidelines focus on maximizing the throughput without considering the negative consequences of fast-moving vehicles in the traffic flow. In fact, the design process excludes only the fastest 15% of drivers, potentially leading to a wide standard deviation in speed, which can cause safety issues, such as fast-moving vehicles encountering slower traffic. Simply removing the 85th-percentile rule without further interventions can exacerbate these issues by increasing speed variability. Accordingly, self-enforcing roadways (SER) have been proposed as a speed management strategy to achieve harmony in drivers' speed selection and to address safety concerns related to excessive speeding. The aim of SER is to ensure that drivers adhere to the desired operating speed (i.e., target speed) through effective roadway design, thereby minimizing potential speed violations and collisions. SER design incorporates various behavioral, geometric, and environmental factors, including the speed feedback loop, inferred design speed, design consistency methods, geometric design criteria, signage, and pavement markings, and rational speed limits (Donnell et al., 2018). Integrating these elements into the design process is essential to align intended speed with drivers' perceptions.

While numerous examples of SER implementation exist outside of the United States, particularly in European countries, this concept is fairly new in the U.S. Accordingly, this report provides a detailed analysis of the potential impacts of SER implementation on roadway safety in Illinois. Specifically, it investigates the relationship between various roadway design features and crash severity across the state. It is important to note that while the methods employed in this study were not developed specifically for SER evaluation or implementation, their inclusion is relevant and essential to the successful application of SER approaches.

The remainder of this report is organized as follows. The next chapter presents a comprehensive review of the literature related to SER implementations. This is followed by a detailed explanation of the methodology used to evaluate the impact of roadway features on crash severity and a discussion on the data used in this report. The report continues with a presentation of the results and detailed discussions of the study's findings. Finally, the report concludes with a summary and recommendations for future SER implementations.

CHAPTER 2: REVIEW OF RELEVANT LITERATURE

This section reviews studies focused on enhancing roadway safety under various conditions, examining how drivers perceive the surroundings and different road environments. The main findings demonstrate the effects of visual guiding facilities, road layouts, and design elements on speed perception, reaction time, and general driving behavior. Several studies emphasize the need for self-explaining and self-enforcing design principles in creating safer road systems. These studies also highlight the importance of a systematic approach to road design that aligns with drivers' cognitive processes and expectations. As explained in a Federal Highway Administration (FHWA) report, self-enforcing roadways are intended to encourage road users to select speeds comparable to the posted speed limits. This goal is achieved through the use of geometrical design features that convey the desired speed. The report recommends six approaches to facilitate self-enforcing roadways: the speed feedback loop, inferred design speed, design consistency techniques, existing geometric design criteria, and the combination of signs and pavement markings (Donnell et al., 2018). By using these methods throughout different stages of planning and design, engineers can ensure that intended speeds closely match operating speeds, and existing roads can be retrofitted with appropriate signs and markings to produce the desired outcomes. The ultimate aim is to reduce speeding-related crashes and improve roadway safety.

Paliotto et al. (2022) introduced a methodological approach for reviewing roadway design features from a human factors perspective. Their methodology, developed qualitatively through review procedures based on checklists derived from available literature, was structured using the Delphi method. The study evaluated Italian design standards against human factors requirements outlined by the Permanent International Association of Road Congresses. The analysis showed that, despite some consideration of human factors principles in highway design, many additional elements—particularly those related to the road environment and driver perception—needed to be included. The authors suggested that future reviews of design standards incorporate detailed guidelines on human factors to ensure adequate road safety and SER development. They also suggested that this methodology could be applied to road safety audit procedures.

Jiao et al. (2022) investigated how visual guiding facilities, as a form of SER, affect drivers' speed perception and reaction time in urban tunnel sections. The authors created six different visual guiding scenarios using 3D Max software: no facility, horizontal stripe, edge marker, retroreflective arch, vertical stripe, and multiple facilities. The "multiple facilities" scenario combined elements from the other scenarios. Two metrics, stimulus of subjectively equal speed (SSES) and perception reaction time (PRT), were used to evaluate the scenarios. The results revealed two key points. First, the multiple facilities scenario led to an SSES closest to the standard speed, followed by the vertical stripe, retroreflective arch, horizontal stripe, and no facility. The most significant overestimation of speed occurred in scenes with edge markers. Second, PRT was the longest in the multiple facilities and vertical stripe scenarios.

In a picture-sorting task and driving simulation experiment, van der Horst and Kaptein (1998) examined how road design influences perceptual road categorization and the resulting driving behavior. They found that roads designed using SER principles were more consistently categorized by subjects into official road classifications, leading to more uniform driving speeds. This study argued that the systematic application of road design elements could significantly improve road categorization. However, it did not provide conclusive evidence on how these findings could be applied to real-world driving conditions.

Török (2013) examined the simplification of road transport infrastructure layouts to enhance roadway safety. The study aimed to make roads more self-explanatory, thereby adjusting driver behavior and preventing collisions. Statistical analysis was done after studying the cross-section design of the roadway infrastructure. From the driver's perspective, this design was crucial for choosing the appropriate speed and resulted in proper driving behavior. Yu et al. (2020) devised a simulation-based experiment with 10 distinct intersection scenes and 20 participants to investigate features of intersections associated with the SER concept. The study used both post-experiment questionnaires and driving performance metrics, including speed choice and vehicle trajectories, to summarize the results. The findings revealed that community islands, roundabouts, and specific road markings, such as deceleration lines, significantly influenced driver behavior by reducing speed and improving trajectory consistency without substantially increasing cognitive load. However, the study's low number of participants limited the validity of its conclusions.

Wang et al. (2020b) focused on evaluating the safety of SER by analyzing the impact of visual information on driver behavior. They used a driving simulator and eye tracker to collect data on trajectories, velocities, and eye movements under various traffic visual conditions and self-explaining features. The results showed that SER designs could improve driving behavior by aligning drivers' expectations with road conditions, thereby enhancing safety. Additionally, they discovered that converting two-way, two-lane intersections into roundabouts with self-explaining designs improved trajectory consistency. However, they did not find a statistically significant impact on driving speed or cognitive load. In a related study, Wang et al. (2020a) focused on analyzing the cognitive states of drivers within various self-explaining intersections to improve road safety. A driving simulation experiment was done to assess cognitive workload and driving intentions using a Hidden Markov Model. This model evaluated different intersection designs, comparing traditional and self-explaining intersections to measure their effect on driver cognition. The study demonstrated that self-explaining intersections, such as those with roundabouts and diversion lines, enhanced driver's awareness of chaotic driving behavior. Consequently, improving driver awareness through self-explaining road design could contribute to increased traffic safety.

Godthelp (2020) highlighted the serious problem of traffic crashes in low- and middle-income countries (LMICs) and advocated for the "safe system approach" to roadway safety. This study introduced Generic User Interface for Driving Evolution (GUIDE), an affordable driver assistance system that integrates vehicle and roadway characteristics to help drivers navigate both safe and unsafe roads. The aim was to improve global roadway safety by using intelligent transport systems and in-car guidance, with a particular focus on benefiting LMICs. While these findings may not be directly applicable to the United States, they introduced a concept very similar to SER. In another related study, Godthelp (2023) emphasized the urgent need for improved roadway safety in LMICs through the safe system approach. The author recommended the development of sustainable and effective road systems, along with fitting vehicles with affordable technology to guide drivers in making safe choices regarding travel, route, and speed. The study supported the use of affordable technology to assist drivers in enhancing road safety.

Ghorbani et al. (2023) developed a crash prediction model for self-enforcing characteristics on rural highway curves in Iran. The results showed that SER significantly reduced crashes, making it an effective, low-cost measure for improving roadway safety. This study suggested that increasing the field of view was an economical method to enhance roadway safety on horizontal curves of two-lane, two-way rural highways. The construction of self-explaining horizontal curves on these roadways was four times more efficient in reducing crashes compared to improving road uniformity and 33% more effective than enhancing superelevation.

An Institute of Transportation Engineers report detailed the construction of a self-enforcing road in Golden, Colorado. The redesign of South Golden Road addressed concerns related to speeding, safety, and access. The project involved the installation of roundabouts and center medians, which significantly lowered the 85th-percentile speed from 48 to 33 mph. Additionally, injury-producing crashes were reduced by 97%, leading to a 36% decrease in total monthly crashes. Bike-related crashes dropped from 78 over five years to 4 in 3.5 years following construction. The improvement in pedestrian accessibility also positively impacted local businesses (Institute of Transportation Engineers & United States Department of Transportation Federal Highway Administration, 2020).

Marshall (2018) conducted a comparative analysis of the factors contributing to the higher safety levels of Australian roads compared to those in the United States. The results highlighted the design philosophy behind self-enforcing roads in Australia, where physical characteristics like narrow lanes and curved streets encourage safe driving. These approaches aim to integrate safety directly into road design, reducing the need for active enforcement and decreasing the likelihood of crashes.

De Brucker et al. (2014) employed a multi-actor multi-criteria analysis to explore strategies and preferences of different stakeholders, including transportation service users, policymakers, and manufacturers, on improving traffic safety. The findings suggested that self-enforcing roads hold promise as they benefit multiple key stakeholders. However, the successful implementation and adoption of such safety measures require a thorough understanding of and integration with the diverse preferences of these stakeholders.

Ivan and Koren (2013) showed that an online picture-show survey was an effective method for assessing drivers' speed choices based on road scenes. Additionally, they found that motorways and regular two-lane primary roads were more self-explanatory than other road types. This critical finding suggests that additional effort is needed to ensure the successful implementation of SER on less-traveled roadways.

Yan et al. (2024) investigated how an "environment's self-explaining design" affects drivers' safety by focusing on drivers' situational awareness. They developed a situational awareness model and conducted a simulation experiment using 3D Max software. The results showed that colored pavements and light-colored sidewalls enhanced safety by improving drivers' understanding of their surroundings. These findings underscore the importance of self-explaining designs, particularly in tunnels, for improving safety by aligning with drivers' cognitive processes.

Theeuwes and Godthelp (1995) investigated traffic safety improvements by re-evaluating road layouts to minimize potential driver errors. They discussed the concept of SER, which aligns road design with drivers' expectations to promote safer behavior. Their study explored categorizing road users and establishing criteria for designing rural roads, concluding that SER can reduce crashes by meeting drivers' intuitive expectations.

Stiles et al. (2022) examined how urban street characteristics influence road crash frequencies by utilizing segmented street view imagery to study the built environment's impact on driving behavior in Columbus, Ohio. They automated image processing of segmented street view images into identifiable elements like roads, trees, and buildings, which they then analyzed in relation to crash data. This study discovered that the visibility of the sky and the roadway, along with signage in the "open road" street areas, was strongly correlated with increased collisions, suggesting that such environments may encourage faster and less cautious driving due to their visual similarity to highways.

Stelling-Konczak et al. (2011) aimed to understand which road layouts made rural road categories most recognizable. Their findings suggested that physical separation of driving directions was more recognizable than current lane markings. Generally, they found that explicit information positively affected the recognizability of road category transitions.

Goldenbeld and van Schagen (2007) examined the suitability of an 80 km/h speed limit for different rural roads, focusing on roadway and environmental features, along with personal traits, such as age, sensation-seeking tendencies, prior speeding tickets, and regional location (Goldenbeld and van Schagen, 2007). Their findings suggested that features like the presence or absence of curves and field of view significantly impacted preferred driving speeds and their relationship with the posted speed limit.

Theeuwes and Diks (1995) conducted two experiments to explore road user categorization outside built-up areas. The results revealed that the "freeway" category was subjectively perceived, while other "official" categories did not align with drivers' subjective categorizations. The second experiment demonstrated a connection between subjective categorization and driving speed choices with road elements like side markings and road width influencing speed decisions.

Utilizing a meta-analytic approach, Davidse et al. (2004) researched the effect of altered road markings on driving speed. They found that adding markings to previously unmarked roads led to increased driving speed. Their findings suggested that appropriate road markings should be selected carefully to ensure the effective implementation of SER principles.

Kosztolányi-Iván et al. (2015) explored how drivers recognize road types. Their study included a picture-sorting exercise and an online speed choice survey to assess how drivers recognize different road types and select their speeds. The study revealed that ambiguous road designs led to greater variations in speed choices, which posed safety risks.

Yao et al. (2020) used a questionnaire to examine the credibility of current legal speed limits in various UK road environments. Their findings revealed that road layout and roadside features influence perceived speed limits, often causing drivers to choose speeds 8 to 20 mph higher than the legal limits. Specifically, factors such as curved sections, number of lanes, road width, road markings, and roadside vegetation or buildings affected drivers' chosen speeds and perceived safe speed limits, which frequently differed from the posted legal limits.

Theeuwes (2021) analyzed the psychological principles underpinning the SER concept, explaining how, through statistical learning, drivers engage in a cognitive process that allows them to extract the optimal driving speed directly from the road environment with minimal cognitive effort. This study is among the first to focus on the human factors that make SER implementations effective.

Kosztolányi-Iván et al. (2019) studied the SER concept and investigated how many road categories people could recognize. Their research concluded that there is a limitation to the number of roadway types people can distinguish based on their speed choices and picture-sorting tasks using photographs of roads. They found that drivers can typically distinguish between 5 and 6 roadway types based on speed choices and road image classification, including freeways, expressways, main roads, minor roads, and roads within built-up areas.

Charlton et al. (2010) implemented a project in Pt. England/Glen Innes, Auckland, to create safer urban roads by making various types of roads look and feel distinctly different. The project increased the number of trees and community islands on local roads, reducing driver sight distances and removing road markings. On collector roads, the project added clear lane markings and bike lanes. The result was a reduction in vehicle speeds and a smoothing out of speed variability. Moreover, residents reported feeling better about the roads' aesthetics and functionality, which also helped distinguish local roads from collector roads. The project was inexpensive and used local cues, making the design appear natural to the region rather than introducing unfamiliar elements.

Kaptein and Claessens (1998) explored the impact of cognitive road classification on driving speed through picture-sorting tasks and a driving simulator. Participants consistently categorized SER road designs into official categories more accurately than they did with current road designs. Although no direct effect on speed was observed, their findings suggested that a consistent SER design correlated with more uniform driving speeds.

A further study by Keptein et al. (2002) used a picture-sorting task and a driving simulator to examine how cognitive road classification influenced driving behavior. Participants drove faster on higher-quality roads and showed significantly higher speeds in specific categories. With repetition, overall driving speeds increased, and participants noted the influence of environmental factors and road design on their speed selection. The study was significant as it partially addressed a key question in the implementation of SER: whether driver behavior changes over time in response to different SER implementation strategies.

Weller (2008) focused on how rural roads can be classified based on subjective impressions and their influence on driving behavior. Factor analysis identified three key factors: demand, comfort, and monotony. The study found that subjective impressions of road comfort and monotony significantly influenced drivers' speed choices, highlighting these as essential factors in roadway design to enhance safety. The study also emphasized the importance of developing behaviorally relevant road categories to improve rural road safety.

Baas and Charlton (2005) discussed how road markings influence driver behavior and improve roadway safety and traffic flow. They emphasized the importance of the perception-decision-action cycle in driving, discussing how visual cues from road markings affect drivers' perceptions of speed and decision-making, leading to safer driving. Their study concluded by highlighting the potential of SER, which uses intuitive design and markings to guide drivers toward appropriate actions.

Theeuwes et al. (2024) investigated how road environments influence travelers' speed choices by exposing participants to images of distinct environments. The results suggested that road users often determine their speed based on road signs. More importantly, the findings were more aligned with the concept of SER than with official road categorization, reinforcing the effectiveness of environment-based speed decisions.

Mackie et al. (2013) examined the impact of SER interventions in Auckland, New Zealand. These interventions involved reducing traffic speeds, incorporating visual elements such as trees and community islands, and removing road markings to create a less formal driving environment. The results showed positive outcomes, including reduced vehicle speeds, decreased traffic volume, and increased pedestrian activity on local roads, indicating a successful trial. Additionally, the intervention resulted in lower costs and fewer collisions, reinforcing the effectiveness of the SER approach in enhancing roadway safety.

Ryan et al. (2018) investigated children's perceptions of self-enforcing roads in Auckland, New Zealand. The results showed that children appreciated the SERs for providing safer and more enjoyable play areas, whereas parents expressed contrasting opinions, finding the SERs to be inconvenient due to slowed traffic and the removal of parking spaces. The study also highlighted a need for clearer communication about the safety features and benefits of SERs to help both children and adults understand and appreciate the design's intentions.

The TU Berlin's project, "Safe Design of Rural Roads by Normalized Road Characteristics," investigated how road design affects driving behavior and safety. Through empirical analysis covering over 10,000 km of road tracking and driving simulations, the project aimed to create SER types to enhance roadway safety. The findings highlighted the positive impact of specific road designs, such as the single-lane cross-section for less busy roads, which significantly reduced average driving speeds and improved lane-keeping (Richter & Zierke, 2009).

Ambros et al. (2017) introduced a framework for applying SER principles to Czech national roads. They divided the roadway into horizontal curves and straight stretches, collected vehicle data, created multivariate speed estimation models, applied these models across the network, and identified substandard curves to optimize traffic control devices or road reconstructions. The study analyzed 992 pairs of straight and curved road sections, covering approximately 380 miles. It found that roads with the smallest speed differences (i.e., the most consistent speeds) had the highest speed limits. The researchers identified 117 curves in need of improvement. Their method, which utilizes several years of crash data, was approved for use by the Czech National Road Agency.

Porter et al. (2012) studied the relationship between geometric design, speed, and safety. They analyzed how design speed has evolved over time and noted the challenges in aligning it with operating speeds. The study explored the concept of managing speed through roadway geometry for self-enforcing design, raising questions about its implementation and impact on safety.

Qin et al. (2020) developed a speed choice model using visual information and proposed an innovative approach to designing SER. The key factors regulating drivers' speed included the curvature of the near-scene and middle-scenes, as well as the number of trees and houses along the roadside.

Walker et al. (2013) discussed SER and its effect on drivers' situational awareness (SA). They investigated how different road types influence drivers' SA by examining verbal feedback from drivers navigating various road environments. The study emphasized that the interaction between the driver, vehicle, and road is essential and that SA is highly dependent on road classification. Furthermore, it stated that motorways/freeways are most aligned with drivers' cognitive styles, while SA diminishes on less structured, minor roads.

Chowdhury (2014) suggested that SA made SERs more effective. SA helps drivers remain aware of their surroundings and better understand road conditions, thereby keeping them engaged with changing environments. This study was the first to combine SER and SA, with its main contribution being the development of a "road drivability tool" to predict potential danger zones and provide a framework for designing safer roads.

Ambros et al. (2021) explored the relationships and differences between various speed metrics, including official speed limits, perceived speed limits, and preferred speed. The study aimed to identify how the types of roads and personality traits influence these metrics. The findings revealed that road design characteristics—such as road classification, speed limits, road width, and the presence of additional elements like vegetation, pavements, and pedestrian crossings—affected both drivers' beliefs about speed limits and their speed choices, as well as the discrepancies between them.

Gitelman et al. (2016) investigated the infrastructure characteristics that likely influence drivers' speed choices in Israel. Significant features included (1) the width of the road shoulder and recovery-zone, with narrower widths leading to slower speeds, and (2) higher junction density and road curvature, which altered speed more significantly.

Johnson (2023) emphasized that multi-lane roundabouts should be designed to exact geometric design principles, particularly entry and left-view angles, which are considered essential for enhancing road safety. The study examined the high variance in property-damage-only crash rates in the U.S. and postulated that the root cause of high crash rates is driver confusion stemming from designs that do not adhere to these principles. Three case studies in Ohio showed that roundabouts designed with the correct Phi and left-view angles experienced fewer crashes. These findings indicate the importance of a comprehensive approach to roundabout design to achieve optimal safety. Properly aligning the roundabout's geometry with these principles provides drivers with clear visual cues, reducing confusion and, consequently, crash rates.

CHAPTER 3: DATA DESCRIPTION

This report analyzes crash data from Illinois between 2019 and 2022, encompassing all recorded crashes during these four years. The dataset includes 1,156,509 crashes, categorized by the severity of injuries sustained. Injury classifications follow the standard definitions used in traffic safety reporting. Fatal injuries refer to crashes that resulted in the death of one or more individuals. A-Injury refers to incapacitating injuries, which are severe enough to prevent the injured person from continuing normal activities such as walking or driving and often require hospitalization. B-Injury is defined as non-incapacitating but evident injuries, such as fractures or visible wounds, which necessitate medical attention but are not life-threatening. C-Injury includes injuries where there are reported symptoms, such as pain or discomfort, but no visible injury is immediately apparent. Lastly, there are crashes where no injuries were reported.

From 2019 to 2022, 4,387 crashes, or 0.38% of the total, resulted in fatal injuries. Crashes involving A-injuries totaled 29,593, accounting for 2.56% of all crashes. B-injuries were recorded in 123,204 crashes, representing 10.65% of the total, while C-injuries were observed in 84,334 crashes, which represents 7.29%. Finally, crashes where no injuries occurred comprised 914,991 incidents, or 79.12% of the total. Figure 1 presents the annual comparison of total and speed-related crashes in Illinois from 2019 to 2022, categorized into two groups: fatal and injury versus no injury. Figure 2 is a detailed breakdown of fatal, A-Injury, B-Injury, and C-Injury crashes compared to the overall total and speed-related crashes in Illinois from 2019 to 2022. This figure provides a detailed view of the severity distribution.

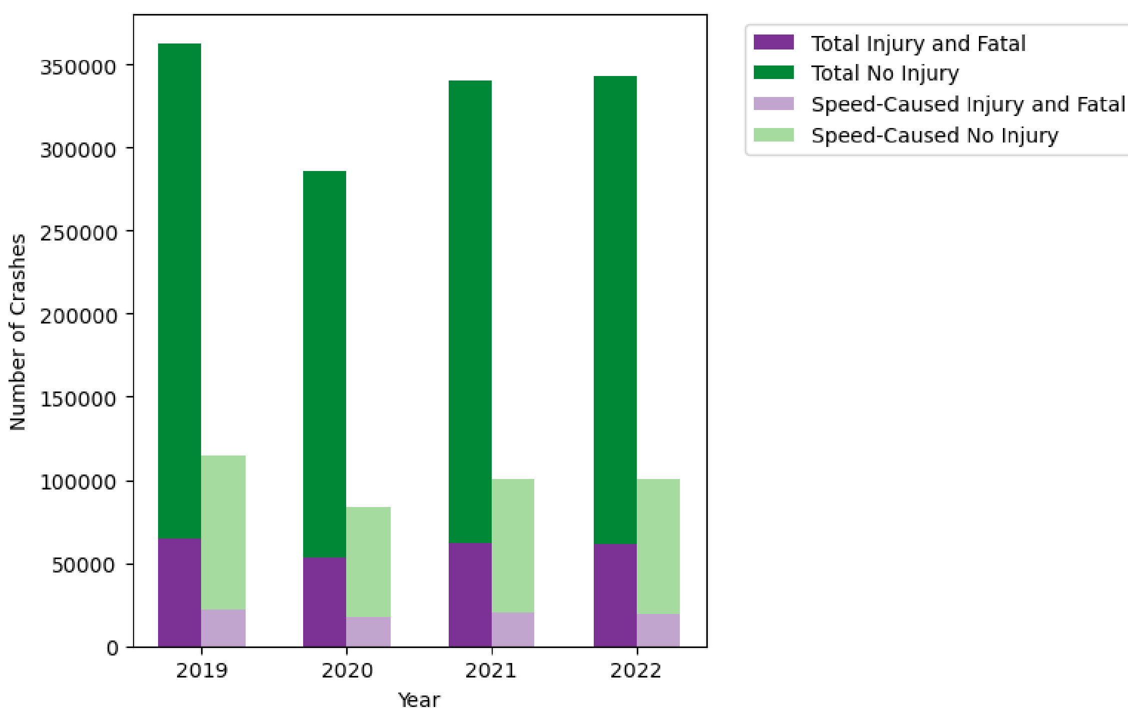

Figure 1. Graph. Yearly comparison of total and speed-related crashes in Illinois from 2019 to 2022, categorized by injury and no injury.

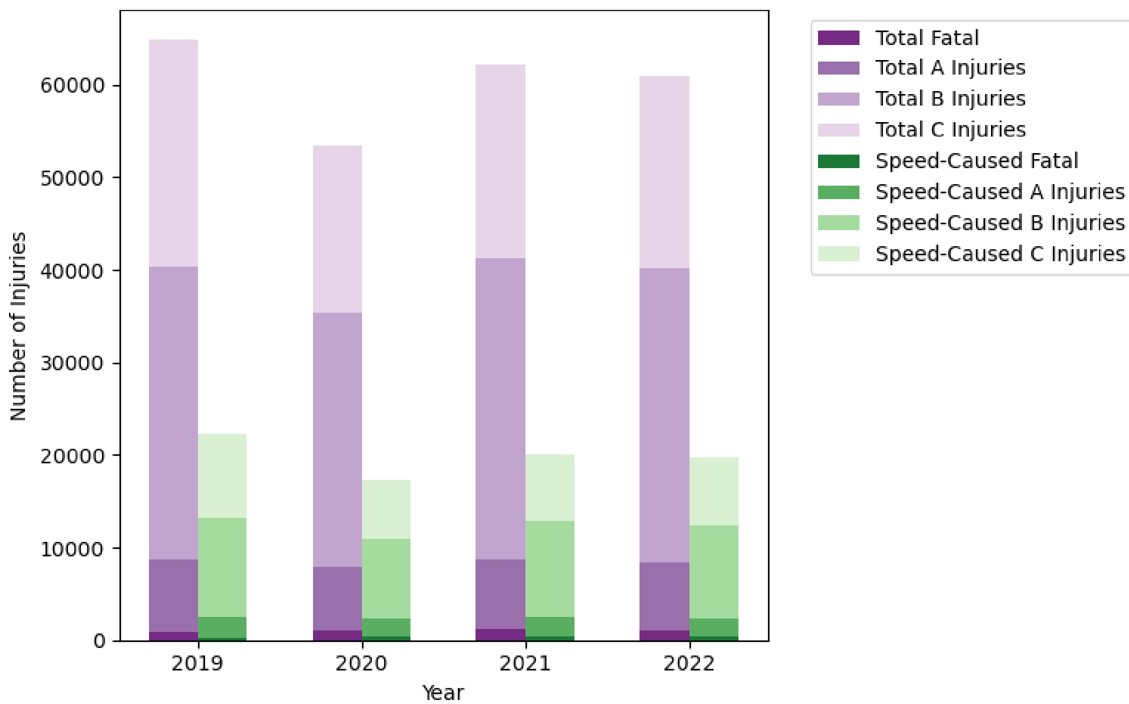

Figure 2. Graph. Yearly comparison of total and speed-related fatal and injury crashes in Illinois from 2019 to 2022.

Table 1 illustrates the distribution of crash causes across different types of crashes in Illinois. Notably, “Failing to Reduce Speed to Avoid Crash” is the leading cause in all crashes, accounting for 15.80% of fatal incidents. In injury crashes, “Failing to Yield Right of Way” is a significant factor, representing 12.08% of cases, while “Following Too Closely” is more common in property damage crashes, comprising 6.38% of these incidents. Additionally, “Driving Under the Influence of Alcohol/Drugs” is notably associated with fatal crashes, with a percentage of 2.81%, reflecting its impact on severe outcomes.

Figure 3 displays a color-coded map of Illinois, where counties are shaded according to the number of fatal crashes recorded. Darker colors indicate higher numbers of fatal crashes, highlighting regions with more severe crash occurrences.

Figure 4 presents the distribution of crash severities across various lighting conditions. It shows that severe crashes, such as fatal and A-Injury, are more frequently associated with darker conditions, while less severe crashes (B-Injury and C-Injury) are relatively more common in well-lit environments.

Figure 5 reveals an interesting pattern in the distribution of crash severity categories throughout the week. Notably, fatal and A-Injury crashes occur more frequently on weekends, while no-injury crashes are less common on these days. This trend suggests that weekend traffic dynamics differ from those on weekdays, potentially contributing to variations in crash severity.

Table 1. Distribution of Crash Causes by Type of Crash (Fatal, Injury, Property Damage) in Illinois

Crash Cause	FATAL (%)	INJURY (%)	PROPERTY DAMAGE (%)
Unknown	38.38	33.67	40.46
Failing to reduce speed to avoid crash	15.80	16.35	14.17
Improper lane usage	10.33	4.65	5.95
Failing to yield right of way	6.48	12.08	7.24
Operating vehicle in reckless manner	3.23	1.05	0.63
Under influence of alcohol/drugs	2.81	2.04	0.75
Driving skills/knowledge/experience	2.70	4.60	4.57
Driving on wrong side/wrong way	2.63	0.65	0.30
Disregarding traffic signals	2.36	3.12	1.08
Physical condition of driver	2.32	2.06	0.68
Disregarding stop sign	2.12	1.73	0.79
Had been drinking	1.57	0.51	0.22
Weather	1.55	2.61	3.03
Improper overtaking/passing	1.44	1.08	2.03
Following too closely	0.92	4.71	6.38
Improper turning/no signal	0.74	1.90	1.88
Equipment — vehicle condition	0.63	0.92	0.89
Distraction — from inside vehicle	0.63	1.43	0.95
Vision obscured	0.56	0.97	0.65
Disregarding other traffic signs	0.48	0.31	0.16
Disregarding road markings	0.39	0.13	0.11
Animal	0.33	0.75	3.35
Distraction — from outside vehicle	0.22	0.57	0.45
Road engineering/surface/marking defects	0.15	0.19	0.17
Cell phone use other than texting	0.14	0.24	0.13
Exceeding safe speed for conditions	0.13	0.27	0.30
Road construction/maintenance	0.11	0.13	0.16
Improper backing	0.10	0.33	1.78
Texting	0.06	0.07	0.04
Exceeding authorized speed limit	0.06	0.06	0.03
Disregarding yield sign	0.06	0.09	0.05
Motorcycle advancing legally on red light	0.02	0.01	0.00
Turning right on red	0.02	0.09	0.09
Related to bus stop	0.02	0.04	0.03
Obstructed crosswalks	0.02	0.02	0.01
Passing stopped school bus	0.01	0.01	0.01

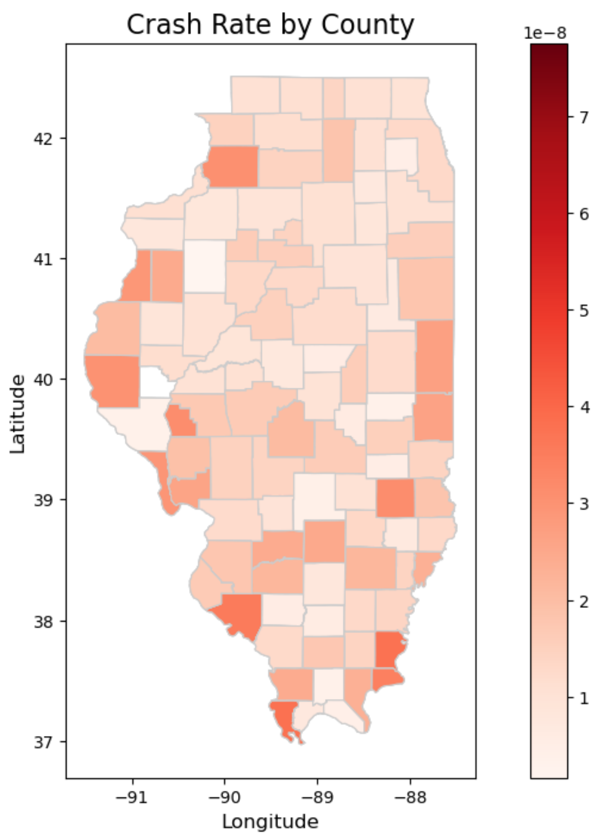

Figure 3. Illustration. Map of Illinois color-coded by the number of fatal crashes per county normalized based on vehicles miles traveled.

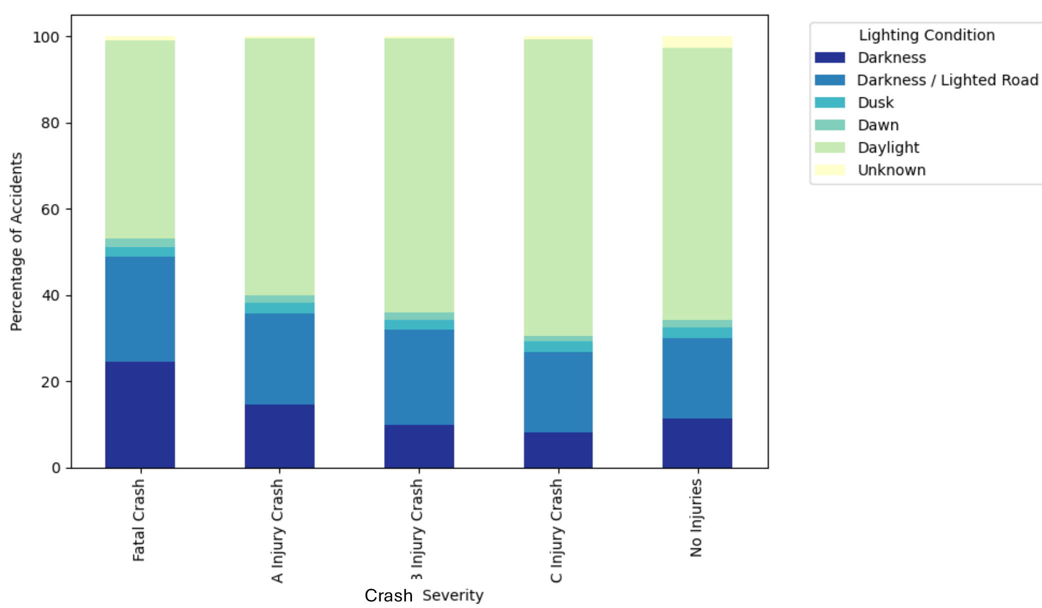

Figure 4. Graph. Distribution of lighting conditions for different crash severity.

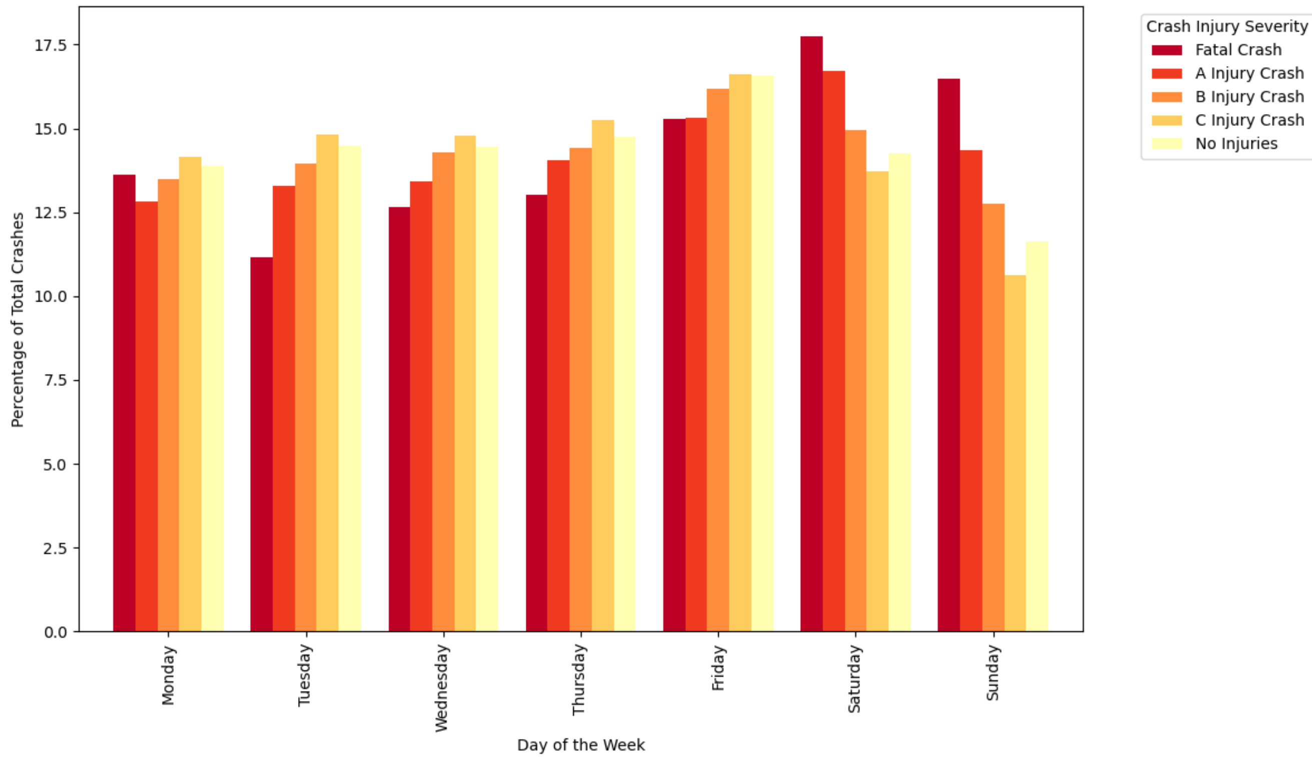

Figure 5. Graph. Distribution of crash severity categories over the weekdays.

CHAPTER 4: METHODOLOGY

This chapter presents the methodologies used to assess the impacts of roadway features on crash severity.

IMAGE DOWNLOADING PROCESS

The exact latitude and longitude coordinates of each crash location in Illinois were used to retrieve the corresponding front and rear views of each crash site through Google's Street View API. A 135-degree field of view, consistent with human vision, was applied to replicate what the driver might have seen at the time of the crash. For geospatial querying and image retrieval, the *streetview module* (Python Package Index, 2023) was utilized to automate the process of locating and downloading the images. In total, 153,690 images from speed-related crash sites involving fatalities or injuries were downloaded using the Google Street View API. These images were subsequently analyzed to examine the impact of roadway elements on speed management and crash outcomes, providing a comprehensive dataset for evaluating the relationship between road design and crash severity.

IMAGE SEGMENTATION PROCESS

A key step in the analysis is characterizing the scenes and roadway features at crash locations. To achieve this, the downloaded images were segmented using the DeepLabv3+ model with a ResNet-101 backbone. Figure 6 shows the structure of the DeeplabV3+ semantic segmentation model, highlighting its core module of atrous spatial pyramid pooling (ASPP), proposed by Chen (2017). This model is specifically designed for semantic segmentation, which involves classifying each pixel in an image into predefined categories. Unlike standard models trained on datasets like the COCO dataset (Lin, 2014), which may not perform well for this task, a model pretrained on the CityScapes dataset (Cordts, 2015) was utilized. This model, sourced from HuggingFace's model zoo (Lhoest, 2021), was found to be more effective for our needs. The model identifies 19 distinct segment types, corresponding to the following classes: road, sidewalk, building, wall, fence, pole, traffic light, traffic sign, vegetation, terrain, sky, person, rider, car, truck, bus, train, motorcycle, and bicycle. Each class is represented by a unique color to facilitate the visualization of the segmentation results.

To prepare the images for segmentation, preprocessing was performed by converting the images to tensor format and normalizing them using mean and standard deviation values derived from the dataset on which the model was trained. The segmentation process involved loading the images from the designated folder, converting them into tensors, and then passing them through the DeepLabV3+ model. The model's output, which consists of class predictions for each pixel, was transformed into color-coded images for easier interpretation. The segmentation outputs were decoded into RGB images using the predefined color mappings for each class. Figure 7 shows two sample images and their corresponding segmentation outputs.

Following the segmentation, the color-coded images were saved to a specified directory. Additionally, the percentage of pixels corresponding to each class was calculated for every image and recorded.

The tools and libraries employed in this process included PyTorch for model implementation and execution, PIL (Python Imaging Library) for handling image input and output operations, and NumPy for array operations and calculations.

For modeling purposes, the road or vegetation percentage was defined as the ratios of pixels labeled as “road” or “vegetation” to the total number of pixels in each image. These metrics provide a quantitative representation of the visual environment at crash sites, facilitating a robust exploration of the relationship between roadway elements, visibility, and crash severity.

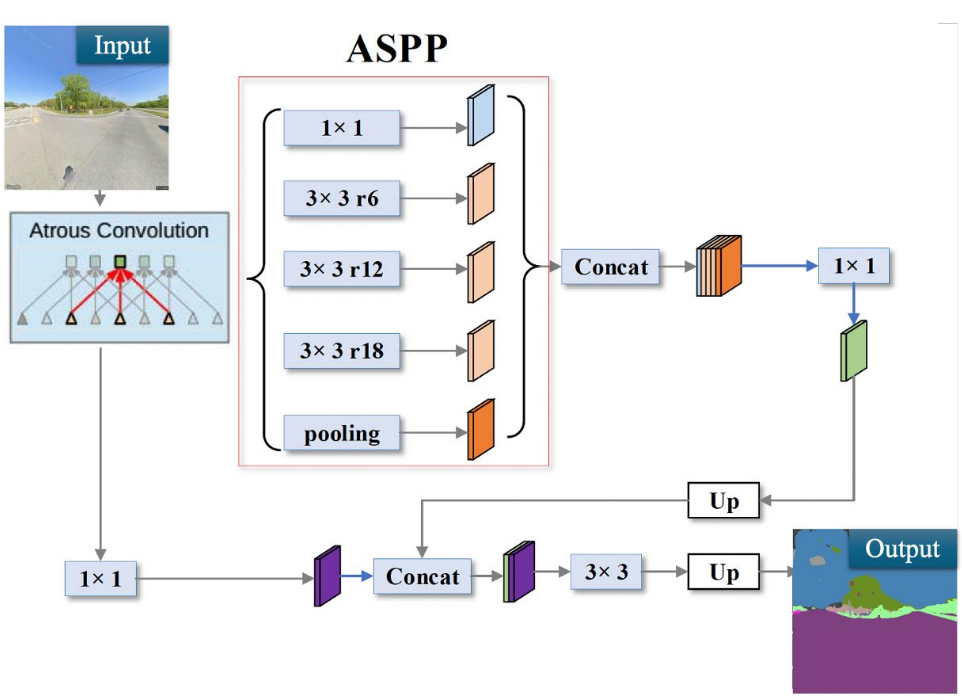

Figure 6. Diagram. Schematic of DeeplabV3+, adapted from Quan et al. (2021).

Figure 7. Diagram. Examples of image segmentation results.

The results, including both the segmented images and the statistical data on class percentages, were saved in the designated folder and a corresponding CSV file.

MULTINOMIAL LOGIT MODEL WITH OVERSAMPLING

This study employs the multinomial logit (MNL) model (Train, 2009) to examine the relationship between speed-related crash severity and roadway features. The explanatory variables include the percentage of road and vegetation derived from image segmentation at the crash site. The MNL model, a widely used discrete choice model, estimates the probability of different outcomes from multiple categories. It has also been applied to analyze injury severity in vehicle crashes (Xie et al., 2012). In this study, crash severity is classified into four levels based on the highest injury severity: C-Injury (possible), B-Injury (non-incapacitating), A-Injury (incapacitating), and fatal. The C-Injury category serves as the reference group for this analysis, and the model predicts the likelihood of the other severity levels relative to this baseline.

The MNL model constructs a utility function for each possible outcome, as shown below.

$$U_{ij} = V_{ij}(\beta) + \epsilon_{ij}$$

Figure 8. Equation. Utility function for each possible outcome in multinomial logit model.

$$V_{ij}(\beta) = \beta_{0,j} + \beta_{road,j} \cdot road_i + \beta_{vegetation,j} \cdot vegetation_i$$

Figure 9. Equation. The deterministic part of the unitality function in multinomial logit model.

where U_{ij} is the utility for the *j*-th possible outcome of the *i*-th crash observation, $V_{ij}(\beta)$ is the deterministic part of the utility function, and ϵ_{ij} is a random error term that contains all unobserved determinants of the utility function following a Gumbel distribution.

The vector β represents the coefficients corresponding to the explanatory variables. In this study, road and vegetation segmentation are included as explanatory variables for modeling crash severity. The coefficients $\beta_{road,\, j}$ and $\beta_{vegetation,\, j}$ indicate how changes in road and vegetation segmentation affect the log-odds of crash severity categories *j* relative to the reference category (C-Injury, in this case). The intercept $\beta_{0,\, j}$ adjusts for baseline differences in severity outcomes independent of road and vegetation segmentation.

The probability of outcome *j* over any other outcome *m* for observation *i* is given by:

$$P(j \mid \beta) = \frac{\exp\left(V_{ij}(\beta)\right)}{\sum_{m=1}^{k} \exp\left(V_{im}(\beta)\right)}$$

Figure 10. Equation. Probability of one outcome over any other outcome in multinomial logit model.

where *k* is the number of severity categories. The coefficients β are estimated using maximum likelihood estimation (MLE), which maximizes the likelihood that the observed outcomes match the predicted probabilities.

Due to the imbalanced nature of the crash severity data, Jeong et al. (2018) suggested that resampling strategies are necessary to enhance the performance of the MNL model. In this study, the fatal and A-Injury categories are underrepresented, with only 1.7% of cases classified as fatal and 10.8% as A-Injury, compared to 50.5% for B-Injury and 37.1% for C-Injury. To address this imbalance, the synthetic minority over-sampling technique (SMOTE) (Pears et al., 2014) is applied. SMOTE generates synthetic samples for the minority classes by interpolating between existing samples within the same class, resulting in a more balanced dataset and reducing bias toward the majority classes.

Finally, the coefficients (β) are interpreted in the next chapter to quantify the relationship between the explanatory variables and crash severity levels. For each unit increase in the independent variables (road and vegetation segmentation), the log-odds of a given crash severity level, relative to the reference category (C-Injury), are calculated. This approach allows us to evaluate how roadway features, such as road and vegetation, influence the likelihood of more severe crashes, offering valuable insights for safety designs.

CHAPTER 5: RESULTS AND DISCUSSION

This chapter presents a descriptive analysis of the relationship between road segmentation percentages and crash severity, followed by the results of the MNL model. The analysis provides both qualitative and quantitative insights into how road and vegetation percentages, as observed at crash sites, influence crash severity. The MNL model quantitatively links crash severity with road design elements, highlighting the role of self-enforcing road designs in speed-related crashes.

Figure 11 presents the crash frequency distributions for four categories of crash severity—fatal, A-Injury, B-Injury, and C-Injury—based on the road percentage in the segmentation. The vertical grey line at 40% serves as a reference to observe the distribution alignment across categories. The distribution of crashes is notably concentrated between 40% and 60% for all severity levels, with means ranging from 45.70% for C-Injury to 48.87% for fatal crashes.

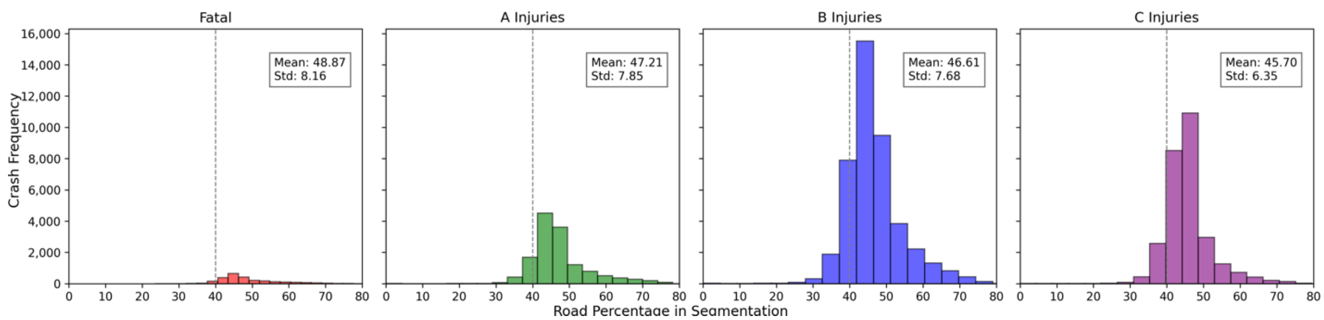

Figure 11. Graph. Crash frequency histograms by road segmentation percentage among four crash severity categories.

Figure 12 compares the density of crashes in each severity category based on road percentage in the segmentation. Figure 12-A reveals notable trends in the relationship between road environments and crash outcomes. The distribution of fatal crashes (red curve) demonstrates a distinct skew toward larger road segmentation percentages. In contrast, the distributions for A-Injury (green), B-Injury (blue), and C-Injury (purple) exhibit more symmetric patterns, with lower densities at higher road percentages. The shift in the distribution of fatal crashes suggests that road environments with higher road percentages may be more prone to more severe outcomes.

Figure 12-B through Figure 12-D further examines the pairwise comparisons between fatal crashes and other severity types. In particular, the comparison between fatal and A-Injury shows that fatal crashes have a higher likelihood of occurring at road percentages exceeding 50%. A similar pattern is observed when comparing fatal crashes with B-Injury and C-Injury, where fatal crashes consistently show a higher density in areas with a more significant road percentage. This pattern suggests an increasing trend in crash severity as road percentage in segmentation increases, indicating a potential link between wider road and higher crash severity outcomes.

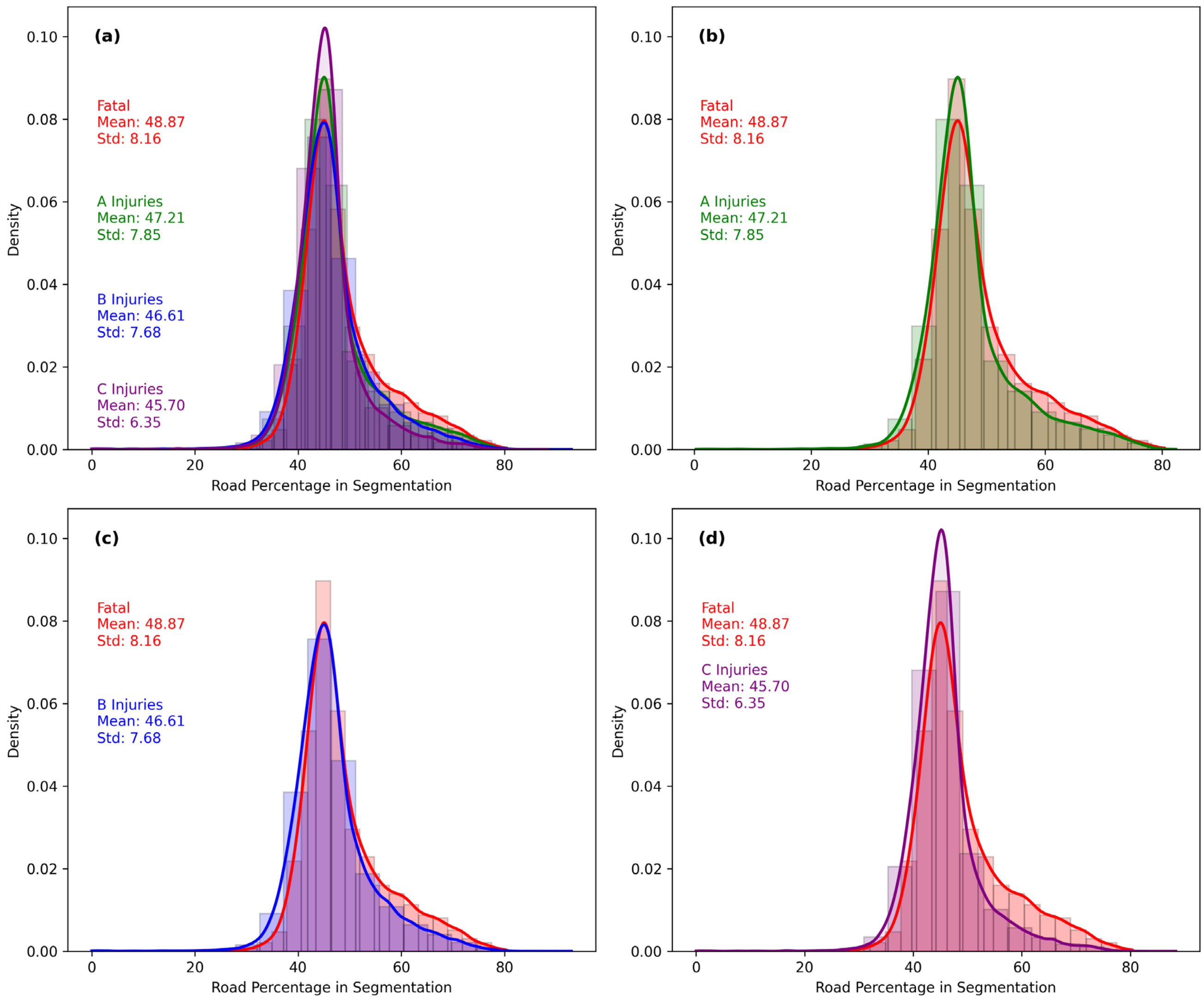

Figure 12. Graph. Comparison of the density distribution of crashes over road percentage in segmentation by severity category.

Figure 13 illustrates the distribution of road percentage in segmentation across different crash severity categories: fatal, A-Injury, B-Injury, and C-Injury. The violin plot represents the kernel density estimation of the data distribution for each severity level, while the black bar within each violin indicates the interquartile range (IQR). The red dashed line marks the median road percentage for each severity category, with the exact median value annotated in red text.

From the plot, the median road percentage is slightly higher for fatal crashes (46.4%) compared to the other categories. For A-Injury, the median road percentage is 45.4%, while B-Injury and C-Injury crashes share a similar median road percentage of 45.1%. The overall distribution shows some variation in road percentage, but the median values are relatively close across the different severity levels, with the distribution for fatal crashes showing slightly more variation compared to the other severity categories. This suggests that higher road percentages might be associated with more severe crashes, although the differences are not very pronounced in the median values.

In addition to the distribution analysis, statistical significance markers (***) indicate that there are statistically significant differences in the road percentages between fatal and A-Injury, fatal and B-Injury, as well as fatal and C-Injury, with *p*-values smaller than 0.001. These results suggest that the observed variations in road percentage between fatal crashes and the other injury categories are not drawn from the same distribution. The higher road percentages are likely contributing factors to more severe crash.

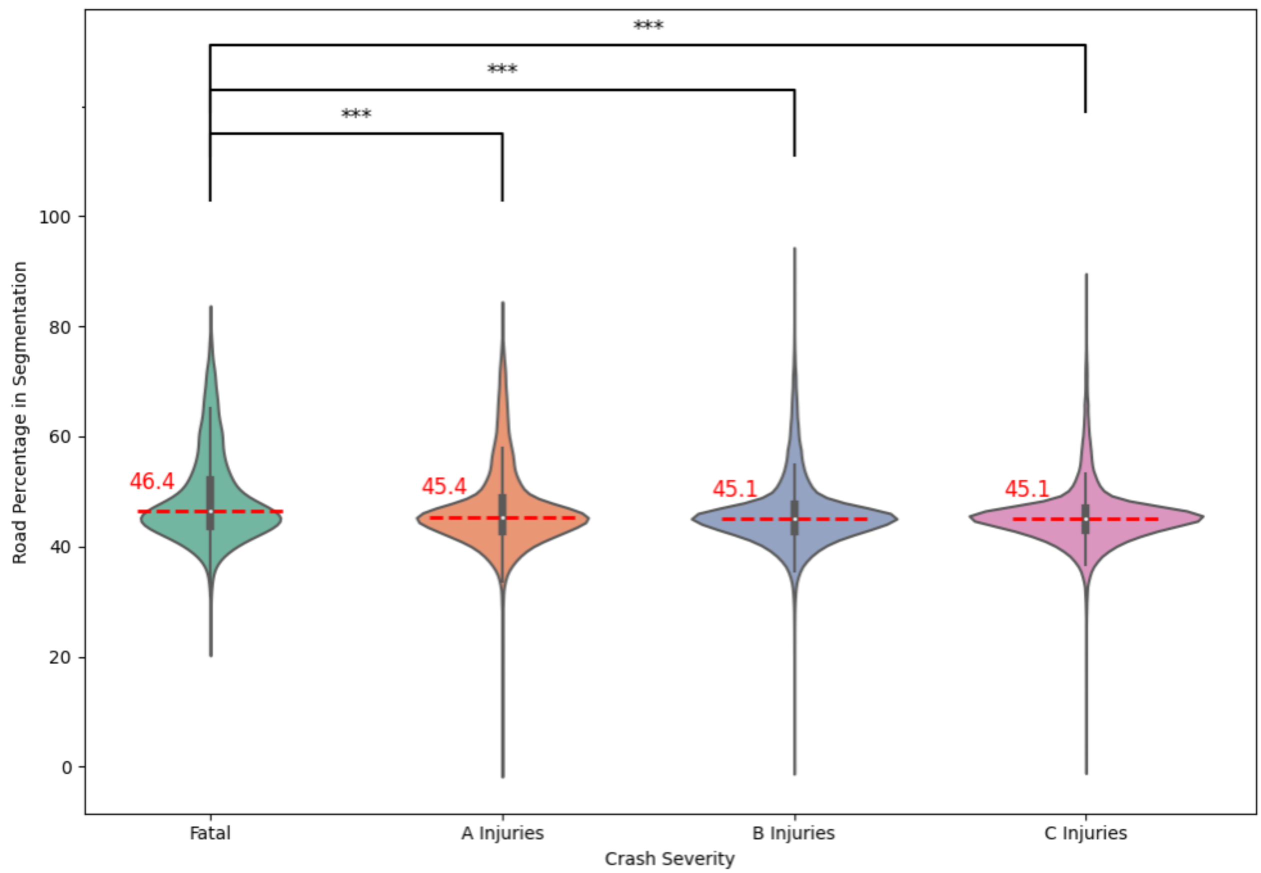

Figure 13. Graph. Violin plots of the road percentage in segmentation among crash severity categories. Above the plots, statistical significance markers with asterisks (***) indicates p-values smaller than 0.001.

Table 2 presents the estimation results of the MNL model to investigate the effects of road and vegetation percentages on crash severity outcomes, specifically comparing B-Injury (Severity 1), A-Injury (Severity 2), and fatal (Severity 3) relative to C-Injury (reference category). The coefficients obtained from the model represent the change in log-odds for each crash severity outcome compared to the reference category. For clearer interpretation, these coefficients were exponentiated to obtain odds ratios in the following analysis. Additionally, the *p*-values and confidence intervals for the coefficients were analyzed to assess their statistical significance.

Table 2. The Multinomial Logit Model Estimation Results

Severity	Variable	Coefficient	Std Err	Z-value	P>|z|	[0.025	0.975]
Severity=1 (B-Injury)	const	0.0027	0.005	0.529	0.597	−0.007	0.013
Severity=1 (B-Injury)	road	0.0719	0.005	13.572	0.000	0.062	0.082
Severity=1 (B-Injury)	vegetation	−0.0387	0.005	−7.393	0.000	−0.049	−0.028
Severity=2 (A-Injury)	const	−0.0111	0.005	−2.159	0.031	−0.021	−0.001
Severity=2 (A-Injury)	road	0.2398	0.005	46.466	0.000	0.230	0.250
Severity=2 (A-Injury)	vegetation	0.0573	0.005	11.068	0.000	0.047	0.067
Severity=3 (Fatal)	const	−0.0745	0.006	−14.170	0.000	−0.085	−0.064
Severity=3 (Fatal)	road	0.4404	0.005	88.222	0.000	0.431	0.450
Severity=3 (Fatal)	vegetation	0.0230	0.006	4.270	0.000	0.012	0.033
No. Observations:		309848					
Df Residuals:		309848					
Df Model:		6					
Log-Likelihood:		-4.2406e+05					
LLR p-value:		0.000					

For B-Injury (non-incapacitating), the road percentage coefficient is 0.0719, corresponding to an odds ratio of 1.0746. This indicates a 7.46% increase in the odds of B-Injury for each unit increase in road percentage, with a *p*-value of less than 0.001, demonstrating high statistical significance. The confidence interval (0.062 to 0.082) further supports this finding. In contrast, the vegetation coefficient is −0.0387, implying a 3.79% decrease in the odds of B-Injury with each unit increase in vegetation percentage, also statistically significant ($p < 0.001$, confidence interval: −0.049 to −0.028).

For A-Injury (incapacitating), the road percentage coefficient rises to 0.2398, yielding an odds ratio of 1.271, meaning a 27.1% increase in the odds of A-Injury per unit increase in road percentage. This result is statistically significant ($p < 0.05$) with a confidence interval of 0.230 to 0.250. Similarly, the vegetation coefficient (0.0573) suggests a 5.9% increase in the odds of A-Injury for each unit increase, with significance confirmed by a *p*-value of less than 0.05 and a confidence interval between 0.047 and 0.067.

For fatal crashes, road percentage shows the strongest effect, with a coefficient of 0.4404 and an odds ratio of 1.553, indicating a 55.3% increase in the odds of a fatal crash per unit increase in road percentage. This is highly significant ($p < 0.001$) and supported by a confidence interval of 0.431 to 0.450. Vegetation has a smaller, but still significant effect (coefficient: 0.0230, odds ratio: 1.023), indicating a 2.3% increase in the odds of a fatal crash per unit increase in vegetation percentage, with a p-value of less than 0.001 and a confidence interval of 0.012 to 0.033.

Overall, the road percentage consistently shows a significant positive relationship with crash severity, with its impact growing as severity increases, particularly in fatal outcomes. Conversely, vegetation shows a more complex effect: it reduces the likelihood of B-Injury but increases the odds of A-Injury and fatal crashes, suggesting that while vegetation may mitigate lower-severity crashes, it could be linked to more severe outcomes in certain scenarios. Further investigation into other potential underlying factors is needed before drawing definitive conclusions.

CHAPTER 6: CONCLUSION

This study presented a comprehensive review of the literature related to self-enforcing roadways (SER), including studies on the impacts of various SER strategies on roadway safety and crash severity. Furthermore, this study demonstrated the significant relationship between roadway design elements, particularly road and vegetation percentages derived from image segmentation, and the severity of speed-related crashes. The results from the multinomial logit model, supported by the application of oversampling techniques, indicate that an increase in road percentage is positively correlated with higher crash severity, with the impact being most pronounced in fatal crashes. The analysis shows that for each unit increase in road percentage, the odds of fatal crashes increase by 55.3%, highlighting the critical influence of road design features on crash severity. Furthermore, vegetation was found to have a more nuanced effect, reducing the likelihood of B-Injury but increasing the odds of both A-Injury and fatal crashes. These findings suggest that while vegetation might mitigate non-incapacitating injuries, it could contribute to more severe outcomes under certain conditions. The insights gained from this study provide valuable evidence for improving SER design to enhance safety.

Future research could include a time-series analysis of the impacts of various roadway features on crash severity. Incorporating property damage into the analysis may also offer additional insights into how crash severity changes based on roadway factors. Finally, a before-and-after study is necessary to test the impacts of various SER strategies on crash frequency and severity. The findings of this study can help refine SER strategies and identify locations where SER can have the greatest impact on roadway safety.

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