Collaborative Sciences Center for ROAD SAFETY

FINAL REPORT

R43: Applying AI to data sources to improve driver-pedestrian interactions at intersections

July 2023

Subhadeep Chakraborty (Principal Investigator)

Asad Khattak

Zach Nelson

A. Latif Patwary

Nastaran Moradloo

Iman Mahdinia

University of Tennessee, Knoxville

Krista Nordback

University of North Carolina, Chapel Hill

THE UNIVERSITY OF TENNESSEE KNOXVILLE | Berkeley UNIVERSITY OF CALIFORNIA | FAU FLORIDA ATLANTIC UNIVERSITY | Duke UNIVERSITY | THE UNIVERSITY of NORTH CAROLINA at CHAPEL HILL

US DOT Disclaimer

Acknowledgment of Sponsorship

This project was supported by the Collaborative Sciences Center for Road Safety, www.roadsafety.unc.edu, a US Department of Transportation National University Transportation Center promoting safety.

1. Report No. CSCRS-R43	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle: Applying AI to data sources to improve driver-pedestrian interactions at intersections		5. Report Date July 15, 2023 6. Performing Organization Code DUNS: 608195277
7. Author(s) Subhadeep Chakraborty (ORCID: 0000-0001-5035-9925) Asad Khattak (ORCID: 0000-0002-0790-7794) Zach Nelson (ORCID: 0000-0001-8111-0444) A. Latif Patwary (ORCID: 0000-0001-8917-4928) Nastaran Moradloo (ORCID: 0000-0002-0724-1005) Iman Mahdinia (ORCID: 0000-0003-1199-7398) Krista Nordback (ORCID: 0000-0001-7967-1998)		8. Performing Organization Report No.
9. Performing Organization Name and Address The University of Tennessee Center for Transportation Research, Knoxville, TN 37996 The University of North Carolina, Chapel Hill, NC 27599 Oak Ridge National Lab, Oak Ridge, TN 37831		10. Work Unit No. 11. Contract or Grant No. Collaborative Sciences Center for Road Safety (Grant #: 69A3551747113)
12. Sponsoring Agency Name and Address University Transportation Centers Program Office of the Assistant Secretary for Research and Technology US Department of Transportation 1200 New Jersey Avenue, SE, Washington, DC 20590-0001		13. Type of Report and Period Covered Final Report (May 2021 – July 2023) 14. Sponsoring Agency Code Office of the Assistant Secretary for Research and Technology-RDT 30
15. Supplementary Notes Conducted in cooperation with the US Department of Transportation, Federal Highway Administration.		

16. Abstract

Tragically, roadway crossings sometimes act as killing fields, especially for pedestrian-vehicle collisions, with intersections accounting for 40% of transportation crashes in the US. This emphasizes the importance of effectively addressing pedestrian safety at intersections to mitigate such incidents. The first chapter of this report incorporates pedestrian safety into the optimization of traffic signals by collecting and linking data from traffic signals (cameras) and analyzing the behaviors of pedestrians and drivers at intersections using Artificial Intelligence techniques, i.e., a decentralized Dyna Q-Learning environment. The results indicate that AI agents may safely prioritize pedestrian service even with longer waiting times or reduce pedestrian delays at the expense of vehicle delay performance. The report's second chapter explores rare pedestrian crashes at intersections, called "corner cases," using Fatality Analysis Reporting System (FARS) data and applying text analytics and the K-means unsupervised learning approach. Such crashes are likely to be triggered by a combination of factors, including poor visibility, severe weather, impaired pedestrian or driver behaviors, and dark lighting conditions. The final chapter of the research investigates the determinants of nighttime pedestrian crash injury severity in pedestrian-involved crashes on intersections using the Random Forest algorithm and ordered logit models. The analysis results reveal that alcohol impairment, foggy weather, elderly pedestrians, a speed limit of 50-55 mph, and motorists not yielding to pedestrians are more likely to contribute to severe pedestrian injuries at intersections. The implications of the findings are discussed in each chapter.

17. Key Words Intersection crashes; driver-pedestrian interaction; Artificial Intelligence; edge cases; nighttime crashes		18. Distribution Statement No restrictions. This document is available through the Collaborative Sciences Center for Road Safety (roadsafety.unc.edu), Chapel Hill, NC.	
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 28	22. Price

Table of Contents

1. Introduction

1.1 Overview

The increasing number of injuries and fatalities among vulnerable road users is a grave concern. Pedestrian fatalities have increased by over 80% from 2009 to 2021 (IIHS 2021). In 2021, 84% of fatal pedestrian-involved crashes occurred in urban areas, with 77% and 23% at non-intersections and intersections, respectively (NSC 2021). Roadway crossings are often deadly due to the variety of conflict points. Decades of research have led to roadway design transformations and traffic mobility enhancement; however, pedestrians are often ignored in optimization considerations (Mongkolluksamee *et al.* 2015). Investigating and improving driver-pedestrian interactions, especially in high-risk areas such as intersections, is necessary to improve transportation safety and reach the vision zero goal of eliminating all traffic fatalities and severe injuries. This CSCRS project first contributes by exploring strategies for improving pedestrian safety at non-intersections. Second, the project contributes by integrating new data sources and AI techniques to reduce negative driver-pedestrian interactions at intersections while optimizing traffic flow. Overall, the key objective of this research is to enhance pedestrian safety at intersections. In this regard, the following activities were undertaken.

1. Collect Data Elements: Link the accessible GridSmart camera feed from 8 monitored intersections. These intersections are located at the Chattanooga Shallowford Road corridor (between Lee Highway and Gunbarrel Road intersections) with geometric and other detector data to observe the queue lengths of vehicles.
2. Develop an Algorithm for Safe Traffic Optimization: Use the data about vehicle queues and estimated pedestrian volumes to develop an AI-based decentralized algorithm for scalable optimization of traffic flow that is engineered to treat pedestrian safety as one of its priorities with mobility as an optimization constraint.
3. Create a digital representation: Create a digital replica of the Shallowford corridor in SUMO (macro) with data links to the physical testbed.

In addition, the study investigates real-life crashes at intersections using artificial intelligence methods. In this regard, the study investigates extreme and rare cases of pedestrian-involved crashes and nighttime crashes at intersections. In order to speed dissemination of findings, this report is organized as research papers, ready for publication:

- Application of Pedestrian Traffic in Decentralized Dyna Q-Learning Environment: Assessing the Integration of Pedestrian Crossing Traffic in Decentralized Dyna Q-Learning Environment
- Identifying Extreme Cases in Fatal Pedestrian-involved Crashes at Intersections: Application of Text Mining and Unsupervised Machine Learning Approaches
- A Comparative Analysis of Nighttime Pedestrian Crash Injury Severity at Crossroads and Mid-blocks

1.2 Research Outputs

Publications and presentations

- Nelson Z., A. Khattak, K. Nordback & S. Chakraborty. (2024) Application of Pedestrian Traffic in Decentralized Dyna Q-Learning Environment (Assessing integration of

Pedestrian Crossing Traffic in Decentralized Dyna Q-Learning Environment), Submitted, Transportation Research Board 103rd Annual Meeting.

- Nelson Z., R. Graves, A. Berres, J. Sanyal, & S. Chakraborty. (2024) Queue length prediction leveraging local camera based monitoring and traffic-flow data communicated between intersections, http://dx.doi.org/10.2139/ssrn.4252262 Submitted, Transportation Research Board 103rd Annual Meeting.
- Harris L., N. Ahmad, A. Khattak, A., & Chakraborty, S. (2023). Exploring the Effect of Visibility Factors on Vehicle–Pedestrian Crash Injury Severity. Accepted for Publication in Transportation Research Record, https://doi.org/10.1177/03611981231164070.
- Moradloo N., I. Mahdinia, A. Khattak, M. SafariTaherkhani. (2023) Identifying Corner Cases in Fatal Pedestrian-involved Crashes: Application of Unsupervised Machine Learning Approach. TRBAM-23-03592.
- Usman S., A. Khattak, & A. Latif Patwary. (2024) Exploring the Determinants of Nighttime Pedestrian Crash Severity in Disadvantaged Communities: Application of Statistical and Machine Learning Techniques, Submitted, Transportation Research Board 103rd Annual Meeting.
- Usman S., & A. Khattak. (2024) A Comparative Analysis of Nighttime Pedestrian Crash Injury Severity at Crossroads and Mid-blocks, Submitted, Transportation Research Board 103rd Annual Meeting.

2. Application of Pedestrian Traffic in Decentralized Dyna Q-Learning Environment: Assessing the Integration of Pedestrian Crossing Traffic in Decentralized Dyna Q-Learning Environment

2.1 Authors

Zach Nelson, Asad Khattak, Krista Nordback, and Subhadeep Chakraborty

2.2 Abstract

As new developments to traffic signal controllers through machine learning can allow for less traditional signal schedules, this work tries to optimize the service and safety of all entities, both vehicular and pedestrians, who may utilize a traffic intersection. A traffic signal controller strategy using a reinforcement learning algorithm is modified to include the service of pedestrian crossings and maintain safe crossing for pedestrian traffic. The algorithm consists of a method of Dyna-Q learning to improve the learning rate and allow for the capacity to negotiate with neighboring intersections with a similar configuration. Results point towards an outcome where AI agents can service pedestrians safely even when they are at a lower priority than passenger vehicles but with elevated waiting times. Alternatively, the additional delays for pedestrians can be reduced but at the cost of vehicle delay performance. This points to a tunable traffic control system that can be programmed to maintain the requisite safety for vulnerable road users but maintain an optimum flow of vehicular and pedestrian traffic. Moreover, this method is reactive, adaptive, and scalable. This method may benefit future work by applying improved models and being assessed against real-life data or multi-intersection environments.

2.3 Introduction

When designing the behavior of a traffic signal, the safety of all users must be accounted for in the design. One of the advantages introduced by a traffic signal operated by a machine learning algorithm is that an intersection does not need to repeat the same signal in a predetermined cycle with only minor changes in duration based on external sensors. While this can be considered disorienting for some individuals who may be accustomed to the traditional timing sequence, many individuals might be open to a more unorthodox timing strategy if it means that they may be serviced at an intersection more frequently. While a large focus in designing machine learning-influenced traffic lights is the regulation and improvement of traffic, it is also important to consider pedestrian traffic and ensure their general safety when crossing an intersection. While a traffic signal controller may benefit from ignoring certain rules or parameters to optimize traffic flow, it is still important that safety parameters continue to be enforced, even at the cost of efficiency. It is important, especially in urban areas or any other intersections with a large amount of foot traffic, that the algorithms governing the decisions and phases of the intersections maintain a healthy balance between the needs of the drivers and the needs of the pedestrians. Otherwise, an intersection may only focus entirely on the demand for vehicles to be serviced and leave pedestrians waiting for an unreasonable length of time, potentially contributing to unsafe crossing behavior.

2.4 Methodology

A Reinforcement Learning (RL) algorithm manages the traffic signal controllers in our work. RL is a machine learning (ML) technique that does not require abundant data sources. Instead, RL can learn from previous experiences and adjust its logic and behavior based on how its decisions have changed the surrounding environment. In this environment, the states for the RL agent are based on whether a lane is considered “Full” or “Empty”, resulting in a total of 256 (2^8) unique permutations (RL states) of being “Full” and “Empty” considering all eight directions of travel that require a traffic light to allow for travel. The reward, the RL parameters that influence decisions wherein the best decisions create the highest reward value, is entirely focused on an approximate measurement of delays. Delay values are recorded by estimating the total duration that a vehicle has been waiting at an intersection, with a set of weights following an exponential curve model to increase the penalty and cost of not servicing a vehicle for prolonged periods, partly as a safeguard to ensure a degree of fairness to ensure lanes with less traffic are not left idle for prolonged periods in favor of more dense lanes. The actions and traffic phases that the RL agent can alternate between to impact traffic queues, reflect the eight standard traffic phases that occur at a common traffic signal intersection. Each action is set at a uniform duration of 13 seconds to guarantee that at least four vehicles per lane can cross an intersection from idle. All actions are the same duration, as this can allow multiple RL agents in a traffic network to communicate and strategize an optimal decision between each other in a decentralized manner. The method by which the actions are selected is based on an array containing the quality value, or Q-values, for each possible state/action combination, resulting in a size 256 x 8 matrix.

While RL does not require historical information sets to learn, it can be helpful to bolster and improve performance, especially if the environment is more stochastic than deterministic. Dyna-Q Learning is a form of RL that runs simulated experiences between actual actions to estimate the most optimal action to take without spending real-time learning through trial and error. This requires that probabilistic models be created to estimate the likelihood of various stochastic transitions for each state/action pair. This model tests the results multiple times, often utilizing the resultant state from a state/action pair to better train and assess the outcome of long-term behavior and actions, as some decisions may have short-term gains but long-term consequences. Additionally, the simulated outcomes generate their own unique set of Q-values that are later applied to the real-world Q-values at a discounted weight, as the simulations can always carry some degree of inaccuracy. To further improve performance, the actions can often include a small set of tests that include the estimations and predictions of the traffic state to anticipate better and train the behavior for what may be the next traffic phase, utilizing delay weights that account for the expected delays brought by either the action or inaction of the RL agent. Figure 1 illustrates how real data is applied directly to the Q-values and simulated experiences generated through a model.

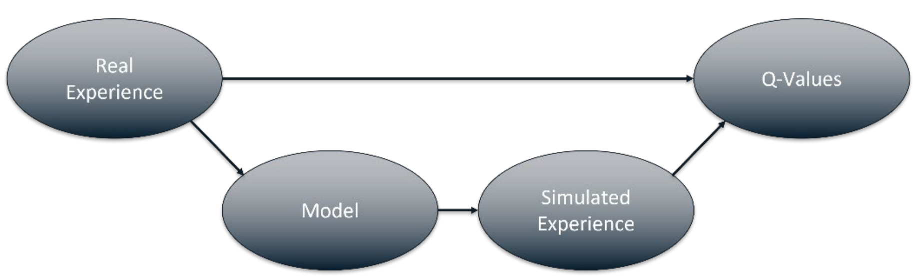

Fig. 1. Representation of Dyna-Q Learning

The simulations are performed through a microscopic and continuous-scale simulation platform known as the Simulation of Urban Mobility (SUMO). Through the application of built-in SUMO packages, we were able to re-create the traffic and roadway layout for a modest length of Shallowford Road, located in Chattanooga, Tennessee. To properly test the environment, a handshake program called TracI4MATLAB allowed for a series of MATLAB commands to observe the SUMO environment, interpret information, and give commands back to SUMO to change traffic light behavior to reflect the decisions and suggested actions made by the RL agent. Through collaboration with the Oak Ridge National Lab staff, we acquired historical data for the timing sequences of the intersections along Shallowford Road and the recorded flow of traffic for prolonged periods. For the flow of pedestrian traffic, the Highway Capacity Manual (HCM) definition of grading pedestrian sidewalks was applied, following the assumption that the roadways meet a Class A Level of Service (LOS) definition for density along sidewalks (HCM 2000).

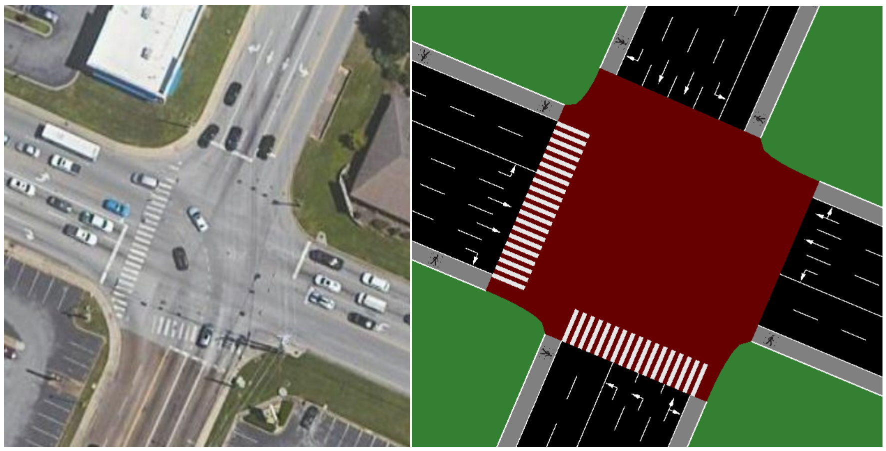

Fig. 2. Simulation Environment (Chattanooga, TN)

Pedestrians could be included in the algorithm by having their importance weight and headcount measured through localized sensors. The relative weight their delays would incur upon the algorithm is associated with the flow of vehicular traffic that is parallel to the flow of pedestrians, ensuring that pedestrians may be serviced while minimizing any additional computational complexity that would normally occur by adding further actions. Suppose the duration of an action does not last long enough to ensure the safe transition of pedestrians across an intersection. In that case, the algorithm will be restricted in the phases it may choose to enact during the next decision cycle to ensure enough time for all pedestrians to safely cross, as illustrated in Figure 3. Following the Federal Highway Administration guidance, the pedestrian crossing signal provides a WALK indicator for a minimum of 7 seconds with the necessary amount of time required for the Change Interval, which is ensured through image recognition software and safety features coded in the agent's architecture (MUTCD 2009).

In previous test cases where there was no pedestrian traffic, the RL agent could transition from action to action with no safety issues regarding vehicles, as a 3-second yellow phase was applied whenever a phase was discontinued in favor of another phase. However, the inclusion of pedestrian traffic will result in some phases being artificially extended an additional action, resulting in modifying the previous Dyna-Q model to reflect this consequence to the RL agent when training that the penalty for not helping a lane associated with pedestrian traffic is more severe than not servicing the other lanes for the next two or more decision cycles.

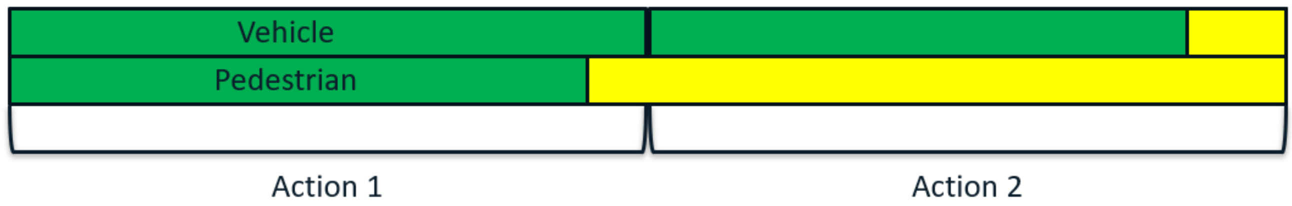

Fig. 3. Study Framework

2.5 Results

Testing was conducted on the SUMO re-creation of the intersection of Shallowford Road and Gunbarrel Road in Chattanooga, TN. The vehicular data is a re-creation of information provided by Oak Ridge National Labs and reflects the flow of traffic collected from 6 AM to 7 AM. The lighter flow at this hour allows the AI agent to exploit some gaps in traffic flow to reduce vehicular delay. However, no historical data for pedestrian crossings were available and had to be approximated based on the assumption that pedestrian traffic correlates with the Level of Service, resulting in a flow of 800 pedestrians per hour traveling along both crosswalks, respectively. Only two crosswalks were created as the respective environment only has two crosswalks, as seen in Figure 2, However, it should be noted that the other two approaches without crosswalks are legal crossings, and it is likely that some pedestrians do cross at these unmarked crosswalks, though they are not included in our study.

Comparisons are made between the performance of the actuated traffic light and the RL-controlled traffic light. Separate measurements were taken for both vehicular traffic as well as pedestrian traffic. Delay measurements begin for a vehicle as soon as the velocity decreases to less than 90% of the given speed limit, suggesting that the vehicle has had to decelerate and either join a queue or form one of its own. This delay value will continue to increase for the vehicle, even after accelerating to the allowable speed limit, until it crosses the intersection. The total delay for any instance is measured as the quotient of the cumulative waiting time for all vehicles in each cardinal direction, and the number of vehicles delayed. The same metric applies to pedestrian traffic, with delays measured as soon as they slow down and continue until they can cross the intersection.

The comparison is made against actuated traffic controllers using a modified version of the signal logic that is currently deployed at the Shallowford and Gunbarrel road intersection (Berres *et al.* 2021). The actuated signals were modified such that if a pedestrian is interested in crossing, abstractly representative of a pedestrian pushing a button to show interest in crossing, the signal duration would allow for the crossing of pedestrians and the necessary time needed for minimum green crossing time. It is important to note that beyond the pressing of a button, the pedestrian levels play no significant factor in the duration of the green phase, as the actuated controller does not have any embedded sensors to extend phases for pedestrians but only for oncoming vehicles that may be able to cross the intersection threshold if the signal is extended by a few seconds.

Table 1. Vehicular Delays Results of Optimal Models for Pedestrians

Directional Flow	Average Vehicle Delay [sec/veh]	Percent Difference
Westbound Left (RL)	0.45	56%
Westbound Left (Actuated)	1.02	
Westbound Through (RL)	7.21	47%
Westbound Through (Actuated)	13.77	
Northbound Left (RL)	11.25	18%

Northbound Left (Actuated)	13.80	
Northbound Through (RL)	9.22	30%
Northbound Through (Actuated)	13.08	
Eastbound Left (RL)	2.74	0%
Eastbound Left (Actuated)	2.73	
Eastbound Through (RL)	4.87	35%
Eastbound Through (Actuated)	7.54	
Southbound Left (RL)	2.16	-11%
Southbound Left (Actuated)	1.93	
Southbound Through (RL)	7.42	-26%
Southbound Through (Actuated)	5.86	
Total RL Improvement	24.10%	

Table 2. Pedestrian Delays Results of Optimal Models for Pedestrians

Directional Flow	Average Pedestrian Delay [sec/ped]	Percent Difference
Northbound (RL)	40.15	-63%
Northbound (Actuated)	24.62	
Eastbound (RL)	28.99	-63%
Eastbound (Actuated)	17.68	
Southbound (RL)	17.73	23%
Southbound (Actuated)	22.90	
Westbound (RL)	9.56	33%
Westbound (Actuated)	14.28	
Total RL Improvement	-21.31%	

Table 3. Vehicular Delays Results of Optimal Models for Vehicles

Directional Flow	Average Vehicle Delay [s/veh]	Percent Difference
Westbound Left (RL)	0.22	78%
Westbound Left (Actuated)	1.02	
Westbound Through (RL)	7.14	48%
Westbound Through (Actuated)	13.77	
Northbound Left (RL)	5.06	63%
Northbound Left (Actuated)	13.80	
Northbound Through (RL)	4.63	64%
Northbound Through (Actuated)	13.08	
Eastbound Left (RL)	2.54	7%
Eastbound Left (Actuated)	2.73	
Eastbound Through (RL)	3.08	59%
Eastbound Through (Actuated)	7.54	
Southbound Left (RL)	2.83	-46%
Southbound Left (Actuated)	1.93	
Southbound Through (RL)	6.28	-7%
Southbound Through (Actuated)	5.86	
Total RL Improvement	46.77%	

Table 4. Pedestrian Delays Results of Optimal Models for Vehicles

Directional Flow	Average Pedestrian Delay [s/ped]	Percent Difference
Northbound (RL)	39.05	-58%
Northbound (Actuated)	24.62	
Eastbound (RL)	27.68	-56%
Eastbound (Actuated)	17.68	
Southbound (RL)	34.60	-51%
Southbound (Actuated)	22.90	
Westbound (RL)	15.58	-9%
Westbound (Actuated)	14.28	
Total RL Improvement	-47.07%	

The outcome from assessing vehicular and pedestrian performance shows that all vehicles' average waiting time decreases by approximately 24%. In comparison, the average waiting time for pedestrians increases by approximately 21%. The penalties applied to the RL agent are influenced by arbitrary weights that increase or decrease the priority of vehicular or pedestrian traffic. These penalties, the total number of vehicles and pedestrians waiting at an intersection, and the most optimal subsequent action determine the agent's behavior during every decision cycle.

Visual analysis of the delay values for vehicles and pedestrians indicates that while some pedestrians may need to wait a long time, they are eventually serviced. Moreover, it may be observed from Figures 4 and 5 that while pedestrian delays during most cycles are observed to stay below a minute, a few instances of about 100-second delay are observed. This is due to an artifact of how SUMO phases the pedestrian movement in a steady stream rather than all at once. This causes some pedestrians not to be able to use a particular walk signal and wait for the next one, which is unrealistic from a practical standpoint. In real life, we expect the entire group of pedestrians to start crossing the street on a given walk signal. This essentially points to the fact that our assessment of the pedestrian delays in the RL algorithm may be artificially inflated.

Even with this artificial shortcoming, an exponentially growing weight on the delay values ensures a degree of fairness for pedestrians at the cost of a potential decrease in efficiency for higher-density vehicular traffic.

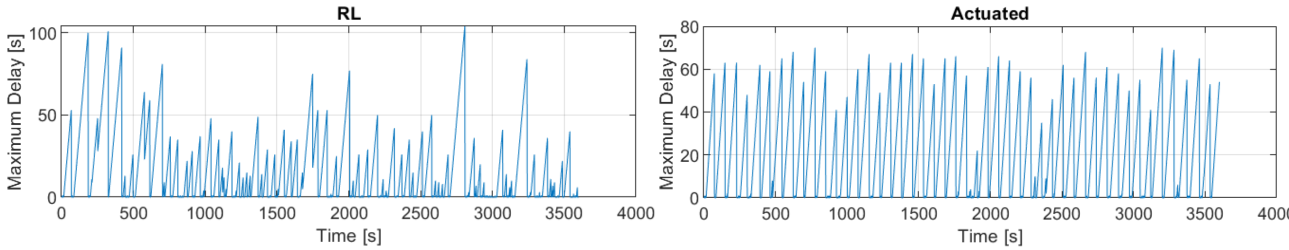

Fig. 4. Pedestrian Delay (Southbound Flow)

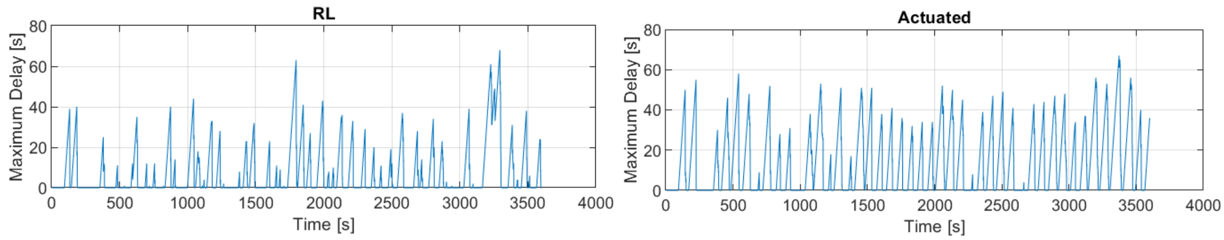

Fig. 5. Vehicular Delay (Westbound Through Flow)

2.6 Conclusion

Analysis of the data suggests that while pedestrian waiting times may increase (both as a result of safety-efficiency compromise as well as due to artificial inflation related to SUMO), a traffic signal controller governed by a machine learning algorithm, specifically a reinforcement learning algorithm with Dyna-Q learning and an image recognition system, can potentially improve the safe crossing of pedestrians and maintain its initial purpose of reducing the delay of vehicular traffic. Also, more beneficial results may be observed at intersections in an urban environment where there may be fewer lanes and thus a need for a shorter clearance time, reducing the likelihood of the agent being restrictive in its decision-making process. While the experiment primarily focused on an average walking speed that correlates with less elderly groups, the image recognition and safety metrics could ensure, if they are implemented correctly and are functional and maintained, that the agent takes necessary actions to extend a phase if pedestrians are on the road, regardless of efforts to optimize efficiency.

3. Identifying Extreme Cases in Fatal Pedestrian-involved Crashes at Intersections: Application of Text Mining and Unsupervised Machine Learning Approaches

3.1 Authors

Nastaran Moradloo, Iman Mahdinia, Asad J. Khattak

Author affiliations:
Civil & Environmental Engineering, The University of Tennessee, Knoxville, TN, USA

This chapter presents a brief version of an unpublished paper that focuses on identifying extreme cases of fatal crashes involving pedestrians. The US Department of Transportation supported the research through the Collaborative Sciences Center for Road Safety (CSCRS), a consortium led by The University of North Carolina at Chapel Hill in partnership with The University of Tennessee. A paper with the same title was presented at the 102nd Annual Meeting of the Transportation Research Board. The paper was submitted for publication in a transportation safety journal, Accident Analysis & Prevention, and is currently under review.

3.2 Abstract

The increase in fatalities of vulnerable road users, such as pedestrians, is a worrying trend. In 2021 there were 7,342 pedestrian deaths, a 12.7% increase from the 6,516 deaths in 2020. Although all fatal pedestrian-involved crashes are critical, some occur in rare and extreme circumstances, called "corner cases," which present a formidable challenge to the safe operation of Automated Vehicles (AVs). These corner cases have a high risk of fatalities and severe injuries, making it essential to identify them to achieve the transportation administration's vision zero goal. This study identifies corner cases in fatal pedestrian-involved crashes at intersections using the Fatality Analysis Reporting System (FARS) 2020 data, which consists of 1,000 one-pedestrian one-vehicle crashes. The authors present a systematic procedure to extract corner cases from these crashes, which involves text analysis of existing literature and applying an unsupervised machine-learning technique called the K-means approach. The results show that nine crashes (1% of the population) are corner cases where a combination of critical factors triggers the crash. These factors include poor visibility, severe weather, impaired pedestrian or driver behaviors, and dark lighting conditions. Some manifestations of these factors are more likely to occur, such as poor visibility, severe weather, dark lighting conditions, pedestrian intoxication, and pedestrians' failure to obey traffic rules. The findings of this study can help road safety practitioners and AV manufacturers prepare for and overcome such extreme circumstances by improving roadway infrastructure and developing AV technologies that operate safely in corner cases.

3.3 Introduction

The number of fatal crashes has increased, and pedestrian fatalities are a primary concern in the transportation system (NHTSA 2023). Research has identified factors affecting crash severity and implemented countermeasures to improve pedestrian safety (USDOT 2021). However, rare traffic crashes that are highly unlikely to happen, called "corner cases," have received less attention but are critical to transportation planners from different perspectives (Cai *et al.* 2016, Sze *et al.* 2019, Kalisvaart *et al.* 2021). Identifying corner cases can help transportation administrations reach the vision zero goal and improve the safety of Automated Vehicles (AVs), which are anticipated in the future transportation system. This study presents a systematic procedure to extract corner cases from car-pedestrian fatal crashes at intersections using text analysis of existing literature and unsupervised machine learning techniques. The study identifies critical phenomena that could result in corner cases, such as extreme values or criticality phenomena, resulting in a condition that challenges the capabilities of the whole system. Countermeasures, such as improving illumination, pedestrian signals, and implementing raised crosswalks, can reduce the crash severity.

3.4 Methodology

Using text analysis and an unsupervised machine learning approach, the study aims to identify corner cases in fatal pedestrian-involved crashes to improve pedestrian safety. This study identifies critical events in rare and extreme pedestrian-vehicle crash scenarios by text-mining 20 fatal pedestrian crashes. Text analysis reveals that darkness and poor visibility are the most frequent topics, followed by the off-peak hour, land use, high-speed limit, visual obstruction, and roadway classification. K-means clustering is an unsupervised machine learning method that partitions observations into prespecified clusters with mean values, and it seeks to minimize the within-cluster variation by calculating the distance between observations and centroids. The elbow method can be used to determine the ideal number of clusters, and it is important to scale and standardize variables before clustering by adding indicator variables for categorical variables. Fig. 6 shows the study framework.

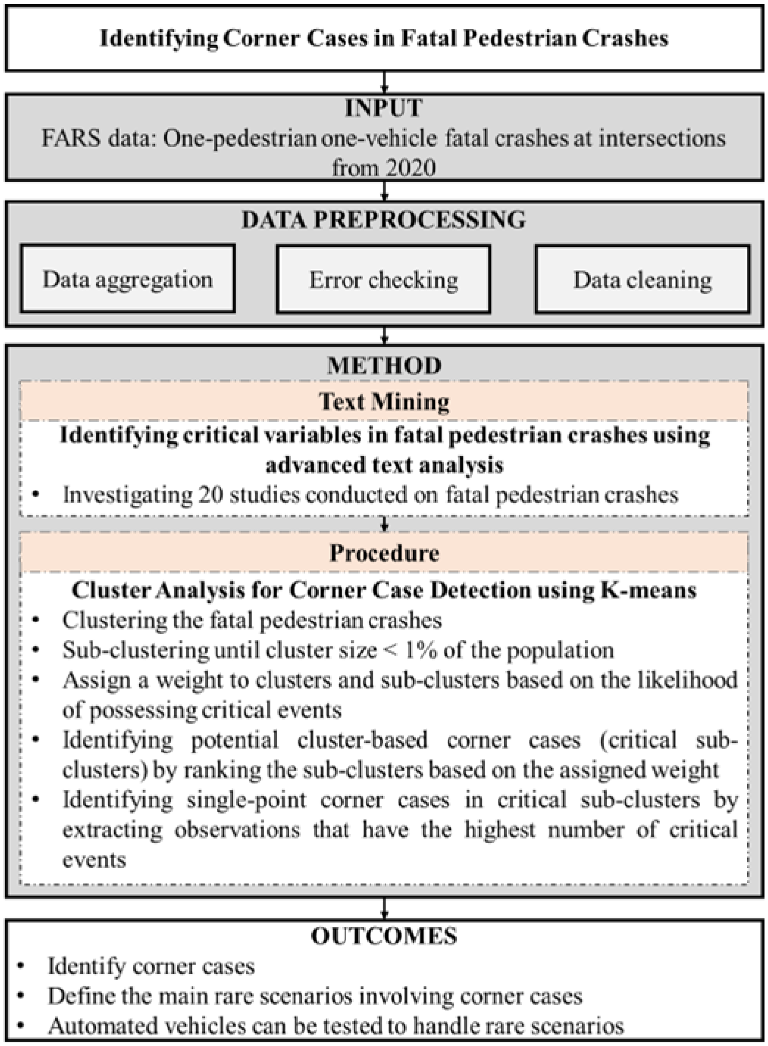

Fig. 6. Study Framework.

To identify corner cases in a study, the following steps should be followed: (1) perform clustering on all observations, (2) continue sub-clustering until the cluster size is less than 1% of the whole population size, (3) assign a total weight to each cluster based on the likelihood of possessing critical variables, (4) identify sub-clusters with potential corner cases if the assigned total weight is higher than 6, and (5) rank the observations in identified clusters based on the number of critical variables they include to identify single-point corner cases. The procedure is illustrated in Fig. 7 and involves systematically adding steps to detect corner cases.

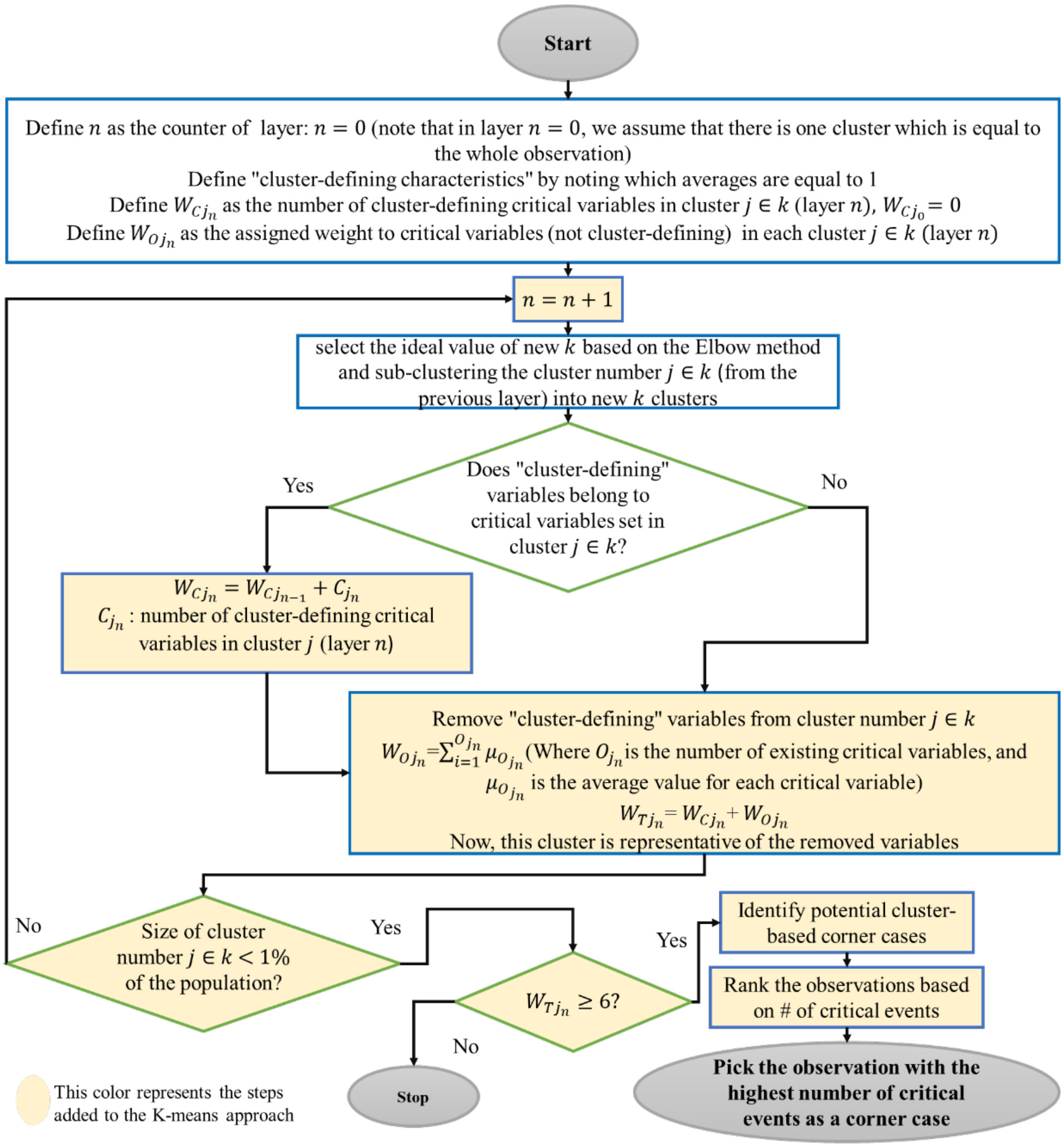

Fig. 7. Overview of the corner cases detection procedure in this study

The study utilized the FARS 2020 dataset, which gathers fatal crashes from the US Department of Transportation National Highway Traffic Safety Administration's National Center for Statistics and Analysis (FARS 2020). The study focused on one-pedestrian one-vehicle crashes at intersections, with a total of 1,000 fatal pedestrian-vehicle crashes after data pre-processing. Variables were categorized into pedestrian, driver, environmental, and roadway characteristics, and those that were frequently used in previous studies and can result in critical conditions were selected. Factors that can cause critical conditions include jaywalking, driver visual obstruction, severe weather, pedestrian or driver impairment, and failing to obey the traffic rules (e.g., traffic signals, signs, and right of way).

3.5 Results

The authors select K = 4 clusters based on the cluster elbow plot and their judgment. Figure 8 illustrates the clustering overview from layers 0 to 4 for cluster three and sub-clusters with the highest weight of critical variables for a demonstration. As the results show in the final layer, cluster 2 in layer 4 possesses the highest weight of critical variables, indicating the possibility of rare and extreme observations in this sub-cluster is higher than others. Tables 5 and 6 present the identified corner cases in clusters three and clusters one, two, and four, respectively. Bold variables indicate the critical events present during the crash. For example, in corner case #1 in cluster three, the collision occurred on an urban interstate road with a traffic signal, and the pedestrian was intoxicated and failed to obey the traffic signal. The pedestrian was not visible in severe weather and dark-lighted condition.

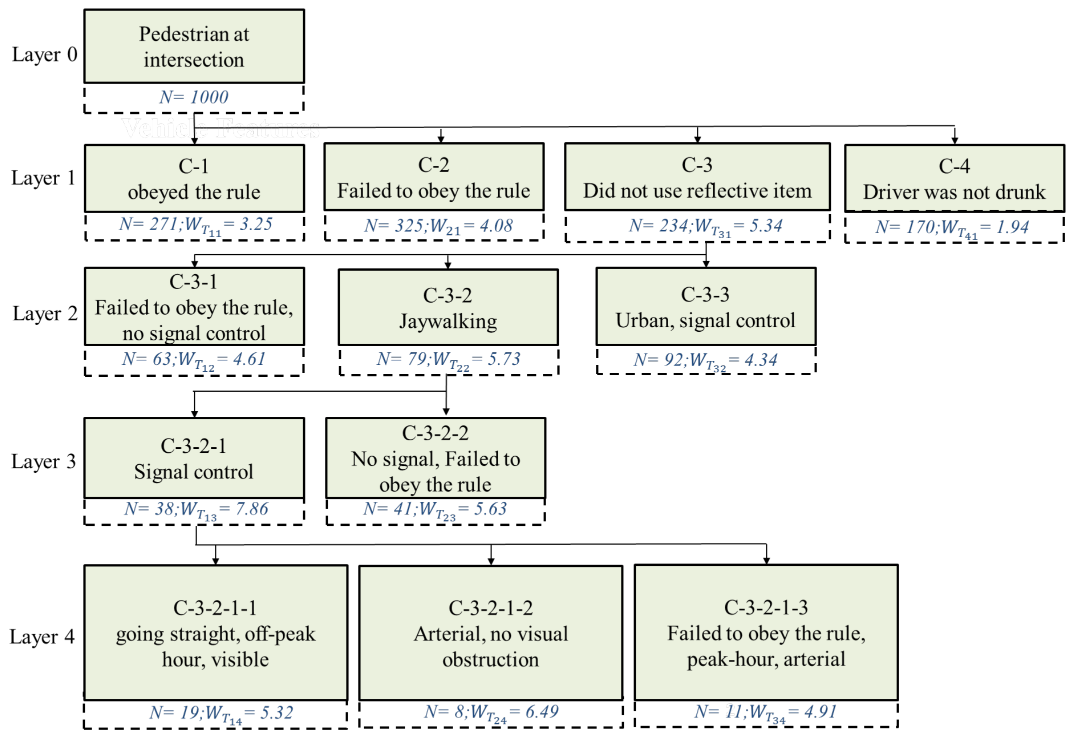

Fig. 8. Clustering overview from layers 1 to 4 for cluster three and sub-clusters with the highest weight of critical variables

The study analyzed nine corner cases (1% of the population) in fatal pedestrian-vehicle crashes at intersections. In 89% and 56% of corner cases, the pedestrian was intoxicated, and the driver was under the influence of drugs, alcohol, or medicine, respectively. The pedestrian was jaywalking and failed to obey the traffic signal, signs, or right of way in 89% of corner cases. All identified corner cases occurred in dark or dark-lighted conditions. Critical events that can result in corner cases include unusual pedestrian behaviors, low visibility conditions, extreme weather conditions, unusual driver behaviors, and visual obstruction. The results suggest that corner cases represent uncommon or extreme scenarios that can pose challenges for preventing or mitigating the severity of pedestrian-vehicle crashes. The study examines critical events that may lead to corner cases in fatal vehicle-pedestrian crashes based on the FARS data. They refer to uncommon or extreme scenarios, including unusual pedestrian or driver behaviors, low visibility or extreme weather conditions, and visual obstruction. Previous studies suggest AVs may not handle rare and extreme scenarios (NTSB 2019) (Mahdinia *et al.* 2022), such as those identified as corner cases in this study. The study's limitations include excluding non-fatal crashes and the absence of impact speed and ADS-related variables in the data.

Table 5. Corner cases in cluster three

Variable	# corner case			
	1	**2**	**3**	**4**
Failure, ROW, Signs	**Failed to Obey the traffic signal**	**Failed to Obey the traffic signal**	**Failed to Obey the traffic signal**	**Failed to Obey the traffic signal**
Land use	Urban	Urban	Urban	Urban
Light	**Dusk/Dawn or Dark-lighted**	**Dusk/Dawn or Dark-lighted**	**Dark**	**Dark**
Speed limit	**>=45 mph**	35-40 mph	**>=45 mph**	35-40 mph
Jaywalking	**Jaywalking**	No Jaywalking	**Jaywalking**	**Jaywalking**
Pedestrian intoxication	**Intoxicated**	**Intoxicated**	**Intoxicated**	**Intoxicated**
Movement	**The pedestrian or driver failed to yield**	**The pedestrian or driver failed to yield**	**The pedestrian or driver failed to yield**	**The pedestrian lost control**
Peak hour	Off-peak hour	Off-peak hour	Off-peak hour	Peak-hour
Driver impairment	Not drunk	Not drunk	**Drunk and under the influence**	Not drunk
Roadway Functional System	Arterial	Arterial	Arterial	Arterial
Pre-crash	Going straight	Going straight	Speeding	Going straight
Visual obstruction	No visual obstruction	**Other motor vehicles**	No visual obstruction	No visual obstruction
Weather	**Severe weather**	Clear	clear	clear
Pedestrian-reflective item	**Did not use a reflective item or cloth**	**Did not use a reflective item or cloth**	**Did not use a reflective item or cloth**	**Did not use a reflective item or cloth**
Visibility	**Not visible**	**Not visible**	Visible	**Not visible**
Signal	Yes	Yes	Yes	Yes

Table 6. Corner cases in clusters one, two, and four

Variable	# corner case				
	1	**2**	**3**	**4**	**5**
Failure, ROW, Signs	**Failed to Obey the rule**	**Failed to Obey the rule**	**Failed to Obey the rule**	Obeyed the traffic rule	**Failed to Obey the rule**
Land use	Urban	Urban	Rural	Urban	Urban

Light	**Dark**	**Dusk/Dawn or Dark-lighted**	**Dark**	**Dark**	**Dusk/Dawn or Dark-lighted**
Speed limit	25-30 mph	25-30 mph	**>=45 mph**	35-40 mph	25-30 mph
Jaywalking	**Jaywalking**	**Jaywalking**	**Jaywalking**	**Jaywalking**	**Jaywalking**
Pedestrian intoxication	**Intoxicated**	**Intoxicated**	**Intoxicated**	Not intoxicated	**Intoxicated**
Movement	**The pedestrian or driver failed to yield**	**Walking or running along the roadway**	**The pedestrian or driver failed to yield**	**Dash or dart**	**The pedestrian or driver failed to yield**
Peak hour	peak hour	peak hour	peak hour	Off-peak hour	Off-peak hour
Driver impairment	**Drunk and was under influenced**	Not drunk	**Physical impairment but not drunk**	**Drunk and was under influenced**	**under the influence of medicine**
Roadway Functional System	Arterial	Local	Arterial	collector	arterial
Pre-crash	Going straight	Going straight	Going straight	**Changing lanes and passing**	Turning
Visual obstruction	No visual obstruction	**External reasons (Rain, Snow, Fog)**	No visual obstruction	**Other motor vehicles**	No visual obstruction
Weather	Clear	**Severe weather**	Clear	Clear	**Severe weather**
Pedestrian-reflective item	**Did not use a reflective item or cloth**	**Did not use a reflective item or cloth**	**Did not use a reflective item or cloth**	**Did not use a reflective item or cloth**	Unknown
Visibility	**Not visible**	**Not visible**	Visible	Visible	Visible
Signal	No	No	No	No	Yes

3.6 Conclusion

The number of fatal pedestrian crashes is increasing every year, and some occur in rare and extreme cases called "corner cases," which may require specific safety countermeasures to be avoided or mitigate the severity level. This study presents a novel idea that provides a systematic procedure to detect corner cases in vehicle-pedestrian fatal crashes at intersections. Through analyzing the FARS 2020 data, an unsupervised machine learning method, the K-means approach, is utilized to develop a procedure to identify corner cases. Nine observations (1% of the population) were identified as corner cases, and the findings imply that identifying corner cases in fatal pedestrian-involved crashes is critical for reaching the vision zero goal and improving the performance of AVs. There are several areas for future research, including investigating other types of crashes and utilizing other methods to identify corner cases.

4. A Comparative Analysis of Nighttime Pedestrian Crash Injury Severity at Crossroads and Mid-blocks

4.1 Authors

Sheikh M. Usman, Asad J. Khattak

Author affiliations:
Civil & Environmental Engineering, The University of Tennessee, Knoxville, TN, USA

This chapter presents a brief version of an unpublished paper, which analyzes the contributing factors of nighttime pedestrian crashes at intersections and non-intersections. The US Department of Transportation supported the research through the Collaborative Sciences Center for Road Safety (CSCRS), a consortium led by The University of North Carolina at Chapel Hill in partnership with The University of Tennessee. The paper will be submitted for a conference presentation at the 103rd Annual Meeting of the Transportation Research Board. It will also be submitted for publication in a transportation safety journal titled *Accident Analysis & Prevention*.

4.2 Abstract

Intersections, or crossroads, present a trade-off between road user safety and mobility. Pedestrians are highly vulnerable to road traffic crashes at such locations. This study analyzed the determinants of nighttime pedestrian crash injury severity in pedestrian-involved crashes on intersections and non-intersections in North Carolina using pedestrian crash data extracted from a comprehensive police-reported crash database created using a crash typing method known as Pedestrian and Bicyclist Crash Analysis Tool (PBCAT). Separate Ordered Logit Models were estimated to analyze pedestrian injury severity in pedestrian crashes at intersections and non-intersections. Owing to its enhanced predictive performance, a powerful machine learning algorithm called Random Forest was also employed to classify the pedestrian injury outcomes in crashes at intersections and non-intersections. The analysis results reveal that nighttime pedestrian crashes at intersections involving alcohol impairment, foggy weather, elderly pedestrians (over 60 years), a speed limit of 50-55 mph, and motorists not yielding to pedestrians were more likely to contribute to severe pedestrian injuries. At non-intersection locations, pedestrian crashes involving pedestrian behaviors such as crossing at midblock non-crosswalk locations, dash and dart behavior, walking along the roadway, etc., were found to be positively associated with fatal and severe injuries to pedestrians. The study findings are expected to assist policymakers and safety practitioners in implementing roadway-specific pedestrian safety countermeasures to mitigate pedestrian crash injury severity.

4.3 Introduction

Pedestrians are most vulnerable to traffic crashes as they are the least protected among all road users. In the United States, pedestrian fatalities have increased by more than 50% from 2009 to 2019, with more than 85% occurring at night (FARS 2019). Pedestrians are at a higher risk of being involved in crashes at night than during daytime and regular light conditions (Uttley and Fotios 2017). In addition to human and vehicle characteristics, roadway geometric characteristics have a major impact on the occurrence of pedestrian-vehicle crashes and the resulting injury severity. In 2018, around 25% of the fatal pedestrian crashes in the US occurred at intersections or near-intersection locations. Pedestrian crashes can occur on various roadway features such as mid blocks, intersections, driveways, and parking lots; however, intersections demand more focus from transportation safety planners and researchers due to the higher proportion of fatal pedestrian crashes associated with them. This higher share of fatal pedestrian crashes at intersections warrants a comprehensive investigation of various human, roadway, and crash-specific factors that influence pedestrian crash injury severity in vehicle-pedestrian crashes at intersections and non-intersection locations. This study compares the roles of pedestrian or driver behaviors, traffic control measures, and roadway geometric characteristics on pedestrian injury severity in nighttime vehicle-pedestrian crashes at intersections and non-intersections. The motivation behind this study is to determine appropriate pedestrian safety countermeasures that can assist in mitigating pedestrian injury severity at intersections and non-intersection locations. This study provides valuable insights into the major differences between pedestrian crash attributes on intersections and non-intersections. Findings from this study can assist transportation safety practitioners and planners in implementing roadway-specific pedestrian safety countermeasures to mitigate pedestrian crash injury severity.

4.4 Methodology

To analyze pedestrian crash injury severity at intersections and non-intersections, pedestrian crash information for the state of North Carolina was obtained from a comprehensive database known as the Pedestrian and Bicycle Crash Analysis Tool (PBCAT). The key variables present in the PBCAT database include driver and pedestrian impairment (due to alcohol or drugs), the position of pedestrians at the time of a crash, roadway factors (roadway types/classes and configuration), lighting conditions, speed limit, land use, types of surrounding developments, weather conditions, geocoded locations of crashes, demographics details (e.g., age, gender, and race) of pedestrians and drivers, and the risky behaviors of drivers and pedestrians involved in pedestrian-vehicle crashes. Pedestrian injury severity, reported on a five-level KABCO scale in the PBCAT database, was selected as the dependent variable for the analysis. The dataset consists of 2329 nighttime pedestrian crash observations in North Carolina from 2016 through 2019. The study employed segmented ordered logit models to analyze nighttime pedestrian crash injury severity in vehicle-pedestrian crashes at intersections and non-intersections. The dataset for pedestrian crashes at intersections had 794 crash observations, while the dataset for non-intersection pedestrian crashes consisted of 1535 crashes. Separate ordered logit models were estimated to analyze pedestrian injury severity in pedestrian crashes on intersections and non-intersections in addition to the overall model. A likelihood ratio test was also performed to determine the statistical significance of the segmented modeling approach. The study framework is presented in Figure 9.

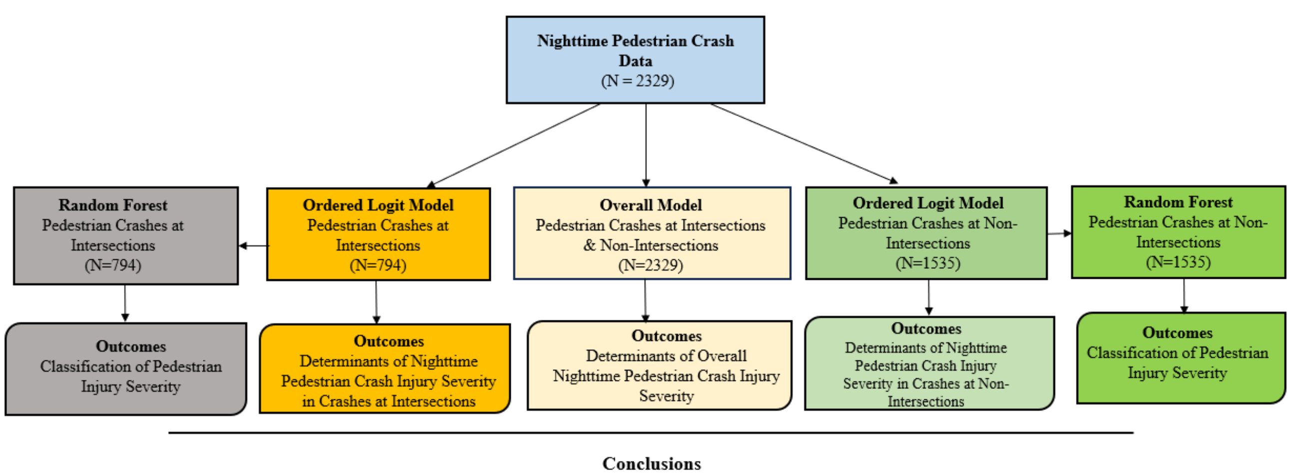

Fig. 9: Overall Study Framework

4.5 Results

Tables 7 and 8 present the results of the estimated ordered logit models for pedestrian crashes at intersections and non-intersections, respectively. Both models were compared to determine the statistical significance of the segmentation using a likelihood ratio test, which shows the segmented models are statistically significantly different from each other, thus providing evidence supporting the segmented modeling approach. All the explanatory variables included in the models were found to be statistically significant at a 95% and higher confidence level. Referring to Table 7, left-turning vehicles at intersections were positively associated with higher levels of pedestrian injury severity. The marginal effects of the left-turning vehicles indicator suggest that the variable is associated with an increase of 0.0752 and 0.1143 units in the probability of incapacitating and fatal injury to pedestrians, respectively. Similarly, nighttime pedestrian crashes at intersections involving alcohol impairment, foggy weather, elderly pedestrians (aged above 60 years), a speed limit of 50-55 mph, and motorists not yielding to pedestrians were found more likely to result in more severe injuries, while pedestrian crashes involving pedestrian road crossing at designated crosswalks and presence of traffic signs at intersections were found less likely to result in more severe injuries to the pedestrians.

Referring to Table 8, pedestrian crossing at non-crosswalk indicator at non-intersections was positively associated with higher levels of pedestrian injury severity. The marginal effects for the indicator suggest an increase in the probability of incapacitating injury by 0.0498 and fatal injury by 0.0878 units. Furthermore, nighttime pedestrian crashes at non-intersections involving pedestrian alcohol impairment, pedestrians walking along the road, pedestrian dash and dart behavior, and male drivers were found more likely to result in more severe injuries. Nighttime pedestrian crashes on local streets, multi-lane roads, roads without proper lights, and roads with a speed limit of 60-75 mph were positively associated with more severe pedestrian injuries. Hit and Run crashes at non-intersection locations were associated with an increase of 14.60% in the chance of fatal pedestrian injury. In comparison, a Stop-and-Go signal at midblock and non-intersection locations was associated with a decrease of 3.62% in the possibility of fatal injury to pedestrians.

Table 7. Results of Ordered Logit Model for Nighttime Pedestrian Crashes at Intersections (N=794)

Variables	Parameter Estimate	p-value	Marginal Effects				
			No Injury	Possible Injury	Minor Injury	Incapacitating Injury	Fatal Injury
Left Turning Vehicle (1/0)	0.999	0.001	-0.037	-0.166	0.012	0.075	0.114
Pedestrian Alcohol impairment (1/0)	0.913	0.000	-0.033	-0.151	0.011	0.068	0.104
Motorist not yielding to pedestrian (1/0)	1.954	0.000	-0.072	-0.324	0.024	0.147	0.223

Foggy Weather (1/0)	0.591	0.048	-0.022	-0.098	0.007	0.044	0.067
Pedestrian at Designated Crossing (1/0)	-0.438	0.024	0.016	0.073	-0.005	-0.033	-0.050
Pedestrians aged above 60 years (1/0)	1.121	0.003	-0.041	-0.186	0.014	0.084	0.128
Speed limit 50-55 mph (1/0)	0.733	0.000	-0.027	-0.121	0.009	0.055	0.083
Presence of Traffic Signs (1/0)	-0.617	0.035	0.022	0.102	-0.007	-0.046	-0.070
Summary Statistics							
N			794				
LL at zero			-1128.39				
LL at convergence			-900.34				
Pseudo-R^2			0.2021				
χ^2 (8)			456.10				
Prob > χ^2			0.000				
AIC			1816.68				
BIC			1854.09				

Note: LL = Log-likelihood, AIC = Akaike Information Criteria, BIC = Bayesian Information Criteria

Table 8. Results of Ordered Logit Model for Nighttime Pedestrian Crashes at Non-Intersections (N=1535)

Variables	**Parameter Estimate**	**p-value**	**Marginal Effects**				
			No Injury	**Possible Injury**	**Minor Injury**	**Incapacitating Injury**	**Fatal Injury**
Pedestrian crossing at non-crosswalk (1/0)	0.728	0.000	-0.026	-0.110	-0.002	0.050	0.088
Local Street (1/0)	0.676	0.010	-0.024	-0.102	-0.001	0.046	0.081
Pedestrian Alcohol impairment (1/0)	0.670	0.000	-0.024	-0.101	-0.001	0.046	0.081
Walking along Roadway (1/0)	1.437	0.000	-0.051	-0.217	-0.003	0.098	0.173
Hit and Run Crash (1/0)	1.211	0.000	-0.043	-0.183	-0.002	0.083	0.146
Stop and Go Signal (1/0)	-0.300	0.031	0.011	0.045	0.001	-0.021	-0.036

Speed limit 60-75 mph (1/0)	0.953	0.000	-0.034	-0.144	-0.002	0.065	0.115
Roadway without lights (1/0)	0.558	0.000	-0.020	-0.084	-0.001	0.038	0.067
Multilane Road	0.435	0.000	-0.015	-0.066	-0.001	0.030	0.052
Rural Locality	0.265	0.045	-0.009	-0.040	-0.001	0.018	0.032
Pedestrian Dash & Dart	0.227	0.049	-0.008	-0.034	-0.001	0.015	0.027
Male Driver	0.251	0.011	-0.009	-0.038	-0.001	0.017	0.030
Summary Statistics							
N			1535				
LL at zero			-2178.184				
LL at convergence			-1734.92				
Pseudo R^2			0.2035				
LR χ^2 (12)			886.53				
Prob > χ^2			0.000				
AIC			3493.84				
BIC			3557.87				

In addition to the traditional frequentist approach, Random Forest is estimated to classify the outcomes of the pedestrian injury severity in pedestrian crashes at intersections and non-intersections using the predictions from multiple decision trees. The dataset for intersection crashes contains 794 observations and 90 features, including driver and pedestrian demographic information, vehicle characteristics, intersection geometric characteristics, crash characteristics, etc. The random forest model was trained on 70% of the data and tested on the remaining 30%. A grid search was performed to determine the optimal hyperparameters of the model. The optimal hyperparameters obtained through a grid search consist of 100 trees, 3 variables tried for splitting the node, a tree depth of 5, and a sample fraction of 0.8. The confusion matrices for the training and test datasets are presented in Tables 9 and 10. The model results in a prediction accuracy of 84.81% for the test dataset. The performance metrics indicate that the model performs exceedingly well on the predictions, with a balanced accuracy of more than 90% in predicting each of the classes of the dependent variable. The feature importance analysis indicates the individual contribution of the predictors in the model accuracy. Figure 10 presents the ten most influential predictors in the model with their relative importance. A similar random forest model was employed to classify pedestrian injury outcomes in pedestrian crashes at non-intersection locations.

Overall, the random forest analysis yields better predictive performance than the conventional frequentist methods and provides valuable insights into the determinants of nighttime pedestrian crashes at intersections and non-intersections. By employing random forest for predicting pedestrian crashes at intersections, AI-powered systems can assist in identifying high-risk areas, understanding contributing factors, and developing targeted interventions to enhance pedestrian safety.

TABLE 9. Confusion Matrix for Training Dataset (Intersection Crashes N_{train} = 557)

Injury Class	Fatal Injury	Incapacitating Injury	Non-incapacitating Injury	Possible Injury	No injury
Fatal Injury	59	1	0	0	1
Incapacitating Injury	0	52	0	0	0
Non-incapacitating Injury	14	21	211	12	16
Possible Injury	3	9	1	150	6
No injury	0	0	0	0	1
Accuracy			0.8492		

TABLE 10. Confusion Matrix for Test Dataset (Intersection Crashes N_{test} = 237)

Injury Class	Fatal Injury	Incapacitating Injury	Non-incapacitating Injury	Possible Injury	No injury
Fatal Injury	27	1	0	0	0
Incapacitating Injury	0	24	0	0	0
Non-incapacitating Injury	8	8	77	5	5
Possible Injury	2	6	0	72	1
No injury	0	0	0	0	1
Accuracy			0.8481		

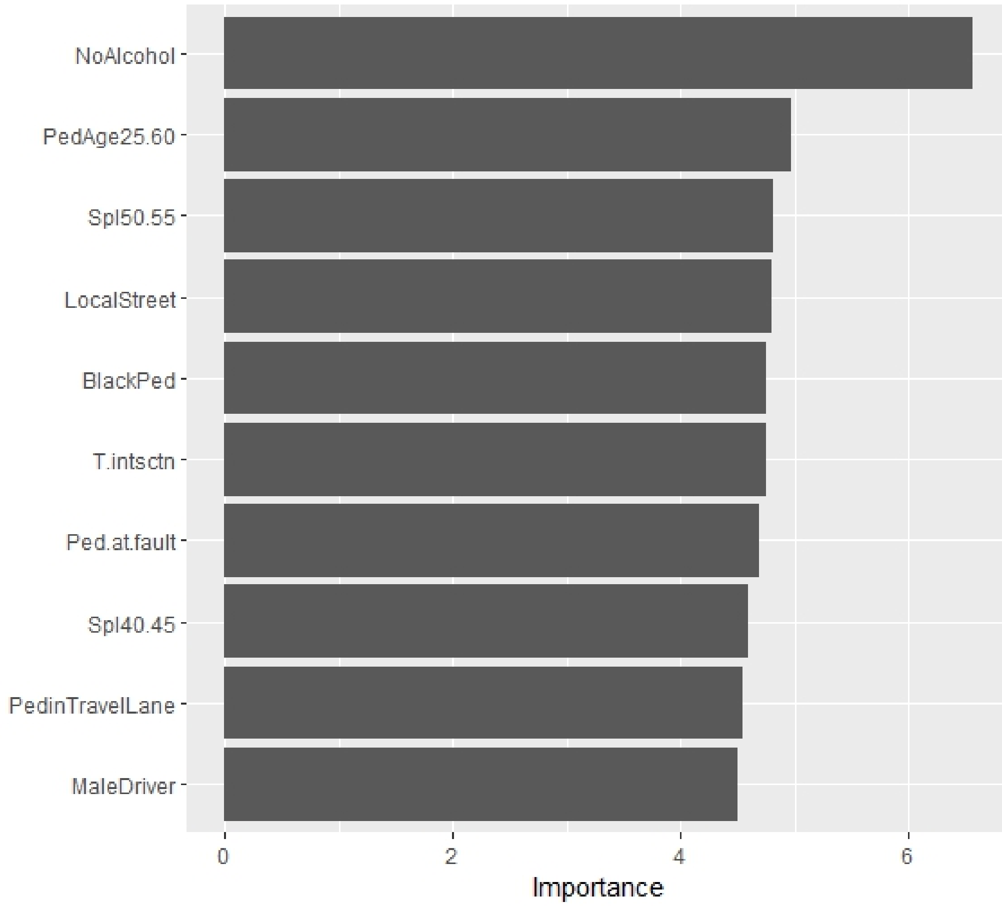

Fig. 10: Variable Importance Plot – Pedestrian Crashes on Intersections

4.6 Conclusion

This study explores the correlates of nighttime pedestrian crash injury severity in vehicle-pedestrian crashes at intersections and non-intersections. The study provided valuable insights into the vehicle's behavioral, infrastructural, and regulatory aspects to pedestrian interactions at intersections and non-intersection locations. The key factors associated with severe pedestrian injuries in intersections include pedestrian alcohol impairments, left-turning vehicles, drivers not yielding to pedestrians, and intersection approaches with high-speed limits. At road segments and non-intersections, pedestrian crossing at non-crosswalk, dash-and-dart behavior, walking along the road, multilane roads with high-speed limits, and roadways without proper lights were found to be associated with fatal and severe pedestrian injuries in crashes. By estimating a random forest model for predicting pedestrian crashes, AI-powered systems can assist in identifying high-risk areas, understanding contributing factors, and developing targeted interventions to enhance pedestrian safety. These predictions can inform policy decisions, urban planning strategies, infrastructure improvements, and the allocation of resources to mitigate the risk of pedestrian crashes and create safer environments for all road users. Based on the study results, pedestrian injury severity can be mitigated at both intersections and non-intersections by applying pedestrian safety countermeasures such as adequate nighttime lighting, traffic calming measures (e.g., speed humps, narrowed lanes, chicanes, etc.), elevated pedestrian crossings, exclusive-protected pedestrian signal phase, and pedestrian warning signs for drivers and sidewalks on both sides of roads. The study findings are expected to assist transportation safety planners in implementing roadway-specific pedestrian safety countermeasures to mitigate pedestrian crash injury severity.

References

Berres, A.S., Laclair, T.J., Wang, C., Xu, H., Ravulaparthy, S., Todd, A., Tennille, S.A., Sanyal, J., 2021. Multiscale and multivariate transportation system visualization for shopping district traffic and regional traffic. Transportation Research Record 2675 (6), 23-37.

Cai, Q., Lee, J., Eluru, N., Abdel-Aty, M., 2016. Macro-level pedestrian and bicycle crash analysis: Incorporating spatial spillover effects in dual state count models. Accident Analysis & Prevention 93, 14-22.

Fars, 2019. Fatality analysis reporting system. National highway traffic safety administration (nhtsa).

Fars, 2020. Fatality analysis reporting system. United States Department of Transportation, National Highway Traffic Safety Administration.

Hcm, 2000. Highway capacity manual. Washington, DC 2 (1).

Iihs, 2021. Fatality facts 2021, pedestrians. Insurance Institute for Highway Safety.

Kalisvaart, S., Svanberg, E., Barnard, Y., Innamaa, S., Sanz, L., Bou, J., Koskinen, S., 2021. Proceedings of workshop on edge cases. Aligning research & innovation for connected and automated driving in europe.

Mahdinia, I., Khattak, A.J., Haque, A.M., 2022. How effective are pedestrian crash prevention systems in improving pedestrian safety? Harnessing large-scale experimental data. Accident Analysis & Prevention 171, 106669.

Mongkolluksamee, S., Visoottiviseth, V., Fukuda, K., Year. Enhancing the performance of mobile traffic identification with communication patterns. In: Proceedings of the 2015 IEEE 39Th annual computer software and applications conference, pp. 336-345.

Mutcd, 2009. Manual on uniform traffic control devices. US Department of Transportation, Federal Highway Administation.

Nhtsa, 2023. Early estimates of motor vehicle traffic fatalities and fatality rate by sub-categories in 2021.

Nsc, 2021. Pedestrians and car crashes - injury facts. National Safety Council.

Ntsb, 2019. Collision between vehicle controlled by developmental automated driving system and pedestrian. National Transportation Safety Board (NTSB), Washington, DC.

Sze, N., Su, J., Bai, L., 2019. Exposure to pedestrian crash based on household survey data: Effect of trip purpose. Accident Analysis & Prevention 128, 17-24.

Usdot, 2021. Lessons learned from development of vision zero action plans. U.S. Department of Transportation.

Uttley, J., Fotios, S., 2017. The effect of ambient light condition on road traffic collisions involving pedestrians on pedestrian crossings. Accident Analysis & Prevention 108, 189-200.

Collaborative Sciences Center for ROAD SAFETY

730 Martin Luther King Jr. Blvd.
Suite 300
Chapel Hill, NC 27599-3430
info@roadsafety.unc.edu

www.roadsafety.unc.edu