Examining the Impact of Vehicle Automation Levels on Road Safety in Rural Areas

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

FINAL REPORT

Principal Investigator:
Emmanuel Kidando, Ph.D., P.E.,
Assistant Professor
Department of Civil & Environmental Engineering
Cleveland State University
Washkewicz College of Engineering
2121 Euclid Ave, FH 122.,
Cleveland, OH 44115-2214, USA
Phone: +1(216) 687-2533
E-mail: e.kidando@csuohio.edu

Co-Principal Investigator:
Josiah S Owusu-Danquah, Ph.D.
Assistant Professor
Department of Civil & Environmental Engineering
Cleveland State University
Washkewicz College of Engineering
2121 Euclid Ave, FH 122.,
Cleveland, OH 44115-2214, USA
E-mail: j.owusudanquah@csuohio.edu

Research Assistant:
Abdul S Ngereza,
PhD Student
Department of Civil & Environmental Engineering
Cleveland State University
Washkewicz College of Engineering
2121 Euclid Ave, FH 122.,
Cleveland, OH 44115-2214, USA
E-mail: a.ngereza@vikes.csuohio.edu

February 2025

DISCLAIMER

METRIC CONVERSION CHART

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

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Examine the Impact of Vehicle Automation Levels on Road Safety in Rural Areas		5. Report Date 02/28/2025 6. Performing Organization Code 59-0977035
7. Author(s) Emmanuel Kidando, Josiah S Owusu-Danquah, Abdul S Ngereza		8. Performing Organization Report No.
9. Performing Organization Name and Address Washkewicz College of Engineering, Cleveland State University 2121 Euclid Ave, FH 122., Cleveland, OH 44115-2214, USA		10. Work Unit No. (TRAIS) 11. Contract or Grant No. 69A3552348321
12. Sponsoring Agency Name and Address Rural Safe Efficient Advanced Transportation Center 2525 Pottsdamer Street Tallahassee, FL 32310		13. Type of Report and Period Covered Final Report Period Covered: 03/01/2024 – 02/28/2025 14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

Motor vehicle crashes are a prominent and distressing cause of fatalities in the United States and globally. Addressing this issue, the integration of Partially Automated in-vehicle technologies, notably Advanced Driver Assistance Systems (ADAS), emerged as a promising avenue for enhancing safety on highways. These systems become even more critical to older adult drivers, who face increased risks of fatality and crashes due to age-related declines in physical, health, and cognitive abilities. ADAS has the potential to decrease the sensory cognitive load of the driving task, and many automated safety features can decrease crash severity. The ADAS vary widely in complexity and scope, which can mainly be classified into three major groups: collision warning, collision intervention, and driving control assistance. Several researchers have investigated these in-vehicle technologies to learn older drivers' perceptions of safety and interaction with the ADAS. However, little is known about the role of these technologies and their impact on crash injuries. It will be beneficial to the community to understand the role of ADAS technologies in the safe mobility of drivers in rural areas.

17. Key Words Advanced Driver Assistance Systems (ADAS), rural areas, rear-end collisions, sideswipe collisions, vehicle identification number (VIN)	18. Distribution Statement No restrictions		
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 70	22. Price

ACKNOWLEDGMENTS

This project was sponsored by the Rural Safe Efficient Advanced Transportation (R-SEAT) Center and the United States Department of Transportation (USDOT). The Principal Investigators would like to thank the representatives of the R-SEAT Center for their valuable feedback throughout the project activities.

EXECUTIVE SUMMARY

Rural areas experience a higher fatality rate per distance traveled compared to urban areas. Despite only 19% of the American population residing in rural areas, these regions encompass over 70% of the roadways and exhibit a higher fatality rate than urban areas. Major types of crashes in rural crashes constitute sideswipe, rear-end, and pedestrian-related crashes that are attributed to driver errors. Advanced Driver Assistance Systems (ADAS) such as crash imminent braking (CIB), forward collision warning (FCW), pedestrian automated emergency braking system (PAEB), Blind Spot Warnings (BSW), Lane Departure Warnings (LDW), and Lane Keeping Assistance (LKA) can help mitigate these types of crashes. Although these technologies are becoming more widely available, their adoption in rural areas remains notably low. This limited penetration has resulted in a scarcity of research examining the potential of ADAS to enhance road safety in rural settings.

This research project contributes to existing studies by evaluating the impact of ADAS on reducing crash severity, focusing on Rural Ohio as a case study. Using a comparative approach, this project analyzes the differential impact of ADAS-equipped vehicles versus those without such technologies. The study utilized Latent Dirichlet Allocation (LDA) Topic Modelling and Bayesian Networks in the analysis of crash data collected from 49 rural counties in Ohio between 2017 and 2023. The analysis revealed several compelling insights into the factors driving elevated fatality rates in rural regions. Also, it highlights the potential role of ADAS in mitigating road safety challenges specific to these areas. Key findings from the study are briefly discussed below.

Crash statistics indicate a high likelihood for drivers aged between 25 and 64 to be involved in rear-end or sideswipe crashes. The analysis further indicates that vehicles equipped with ADAS are less likely to be involved in fatal or severe injury crashes, particularly under adverse weather conditions and during speeding events. The findings highlight the positive impact of traffic control systems in reducing rear-end collisions, especially on highway access roads. However, it also notes that the presence of drugs or alcohol significantly increases the risk of severe rear-end and sideswipe crashes, regardless of the vehicle's technology. Additionally, the analysis revealed that vehicles classified as Level 0 automation are more prone to sideswipe and rear-end crashes compared to those equipped with higher levels of automation. Furthermore, pedestrians also face an elevated likelihood of experiencing fatal or serious injuries when involved in vehicle-related crashes, primarily due to their unprotected and exposed position in the traffic environment. Although the findings from this project demonstrate that vehicles equipped with ADAS are generally less likely to be involved in crashes, their effectiveness in protecting pedestrians, particularly for vehicles equipped with PAEB, can be compromised. Key limiting factors include driver intoxication, distracted driving, and the system's reduced ability to detect pedestrians at long range, especially under adverse weather conditions.

Conclusively, this study highlights the potential of ADAS technologies to improve road safety in rural areas by reducing crash incidence and severity. Key findings show that mid-aged drivers are more prone to rear-end and sideswipe collisions, and that vehicles with higher levels of automation are less likely to be involved in severe crashes. While traffic control systems help mitigate rear-end crashes, factors like intoxication and distraction still pose significant risks. Pedestrians remain highly vulnerable, and although PAEB systems offer safety benefits, their effectiveness is limited by drivers' behavior, environmental conditions, and detection challenges. Overall, the research emphasizes the need for integrating these technologically improved systems and traditional strategies to enhance rural traffic safety.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

Vehicle automation presents a transformative shift in the transportation landscape, with significant implications for road safety, particularly in rural areas. This report delves into these aspects by analyzing the role of automation technologies such as Advanced Driver Assistance Systems (ADAS) in reducing crash risks and protecting vulnerable road users. The introduction section provides an overview of road safety in rural areas and the role of ADAS in crash prevention. This section will also discuss challenges associated with adapting to ADAS vehicles in rural areas. Furthermore, discussing the main and specific objectives of the research project, and focusing on the relevance of this research work to the Rural Safe Efficient Advanced Transportation (R-SEAT) center, considering the themes and the United States Department of Transportation (USDOT) Strategic Plan. Finally, providing the structure of this technical report.

1.1 Road Safety in Rural Areas

Road safety in rural areas of the United States presents unique challenges distinct from urban settings. While rural roads account for a smaller portion of the nation's traffic volume, they disproportionately contribute to traffic fatalities. According to data from the National Highway Traffic Safety Administration (NHTSA) 2024 fact sheet on rural/urban fatalities, show that rural areas have constantly had a higher fatality rate per every 100 million vehicle miles traveled (VMT) compared to urban areas, as shown in Figure 1. These statistics indicate the presence of traffic safety disparities that require targeted interventions and policies that consider the specific characteristics of rural roadways and communities.

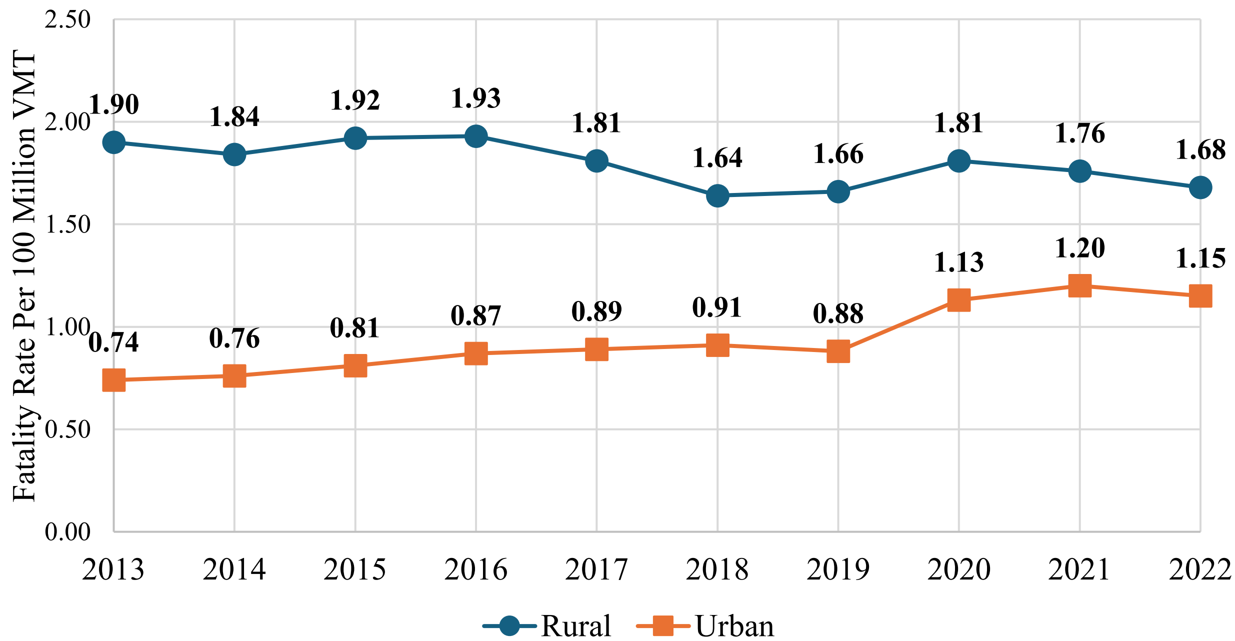

Figure 1: Fatality Rates per 100 Million VMT in Traffic Crashes by Land Use (Source: FARS 2013-2021 Final File, 2022 ARF; VMT – FHWA)

Rural roads exhibit distinct characteristics compared to urban roads. For example, features such as narrow lanes, the absence of shoulders, and poorly maintained surfaces are more prevalent in rural areas. Additionally, many rural roads consist of two-lane highways with limited access points and minimal signage, creating a unique travel experience. However, these geometric differences alone do not fully explain the factors contributing to higher fatality rates, nor do they address how vulnerable road users interact with rural roads, or the traditional strategies implemented to enhance road safety in these areas.

1.1.1 Factors Associated with an Increase in Fatality Rate

Several factors contribute to the higher fatality rates observed in rural areas. One notable factor is the higher speed limits on rural roads, combined with drivers' tendency to speed due to the perception of open and empty roadways, which significantly increases the likelihood of fatal crashes. According to statistics from NHTSA (2024), a substantial proportion of rural crashes involve alcohol impairment. Over the past decade, the fatality rate per 100 million vehicle miles traveled (VMT) in rural areas consistently surpassed that of urban areas, as illustrated in Figure 2. Additionally, the long distances between destinations and the limited availability of public transportation in rural regions contribute to drunk driving and elevating the risk of fatigue-related crashes.

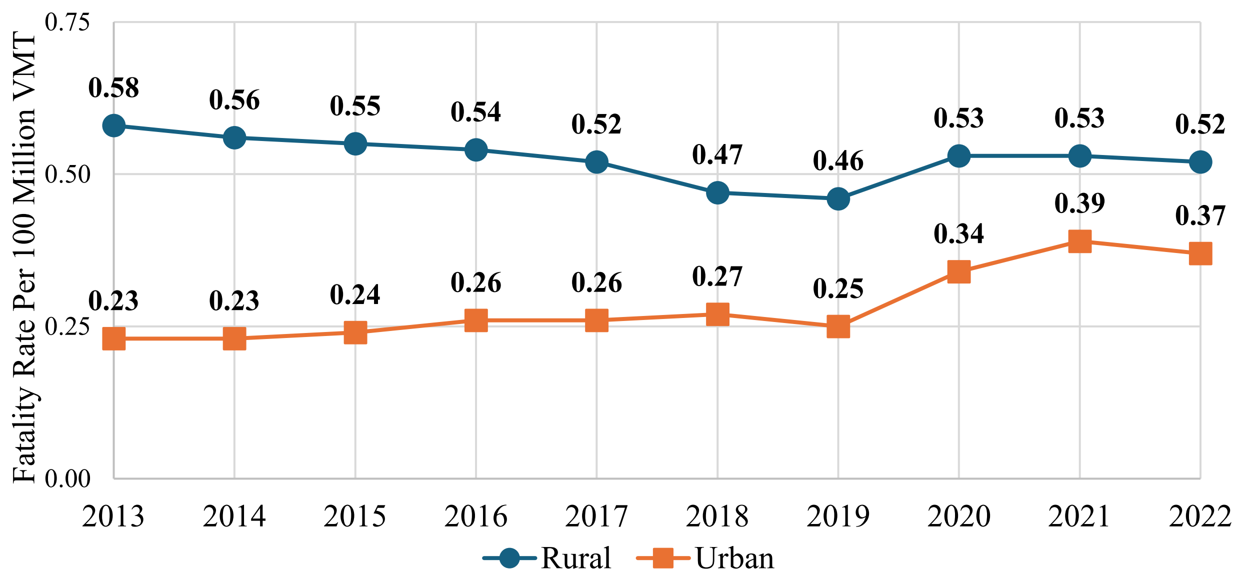

Figure 2: Alcohol-Impaired-Driving Fatality Rate per 100 million VMT in Traffic Crashes, by Rural/Urban Classification, 2013–2022 (Source: FARS 2013-2021 Final File, 2022 ARF; VMT – FHWA)

According to existing literature, additional contributors to fatal crash risk include seat belt usage, which tends to be significantly lower in rural areas than in urban environments (Mohamed et al., 2017; Uddin & Huynh, 2020; Zou et al., 2023). From the literature, the following are identified. Rural roads are more prone to animal-vehicle collisions, especially in areas near forests and farmland. Uniquely, the presence of a high number of special attention and vulnerable road users in rural areas faces increased crash risks. For instance, older drivers are more vulnerable to severe injuries in crashes and may struggle with navigating poorly designed rural roads. Limited pedestrian infrastructure, such as sidewalks and crosswalks, increases the risk of crashes involving non-motorized road users. The presence of slow-moving farm equipment on roads creates additional hazards. These factors, combined with the unique characteristics of rural roadways, underscore the need for targeted interventions to improve road safety in these areas.

1.1.2 Strategies for Improving Road Safety

Over the years, various traditional strategies have been implemented to enhance road safety in rural areas, combining engineering, enforcement, education, and emergency response improvements. These strategies include widening shoulders, adding rumble strips to mitigate run-off-road incidents, improving road signage and lighting for better visibility, and installing barriers and median separations on high-speed routes. Additionally, increasing police presence to monitor speeding and impaired driving, promoting seat belt usage, and educating drivers about the dangers of speeding and drunk driving through local campaigns have been key initiatives. Strengthening coordination between rural communities and emergency services, expanding telemedicine capabilities to assist first responders in remote areas, and implementing automated enforcement technologies such as speed cameras have also contributed to road safety efforts. Furthermore, utilizing technologically advanced vehicles equipped with advanced driver assistance systems (ADAS) holds significant potential in reducing crashes. Improving road safety in rural areas of the USA remains a critical public health and infrastructure challenge. By addressing the unique characteristics of rural roadways and adopting a comprehensive approach, the high rate of traffic fatalities and injuries in these areas can be significantly reduced. However, some strategies, such as the adoption of ADAS-equipped vehicles, remain underestimated despite their potential to substantially decrease the number of crashes in rural settings.

1.2 Role of ADAS in Rural Crash Prevention

In the United States, over 90 percent of vehicle crashes can be attributed to driver error (NHTSA, 2015), with rural areas consistently experiencing a higher rate of vehicle fatalities per distance traveled versus urban areas (Clark & Cushing, 2004). To mitigate crashes, newer vehicles are increasingly equipped with technological features such as warnings for forward collision, lane departure, and blind spot, automatic emergency braking, lane-keeping assistance, and adaptive cruise control, with these and similar technologies being collectively known as advanced driver assistance systems (ADAS). However, in rural areas, vehicles are likely to be less technologically advanced, thus having fewer or less advanced ADAS (Lowell et al., 2020). The systems will often face suboptimal roadway surface and pavement marking conditions, hence causing challenges or total failure of ADAS technology equipped in a vehicle especially in adverse weather conditions (Mahlberg et al., 2021; Pike et al., 2018; Rahman et al., 2023; Roh et al., 2020). Additionally, the demographics of rural areas, which feature large populations of older and elderly adults, influence driving behavior and the perception and use of ADAS. Given the unique conditions of the rural environment, it provides an interesting context for understanding the full interaction between ADAS equipment and engagement, the environmental and exposure conditions, and demographics, particularly age.

The purpose of ADAS is to reduce the severity of crashes involving driver error by alerting the driver to dangerous maneuvers and taking control of the vehicle when necessary. Research studies on the effectiveness of ADAS have consulted driving simulators, showing safety benefits during mandatory lane-changing maneuvers (Ali et al., 2020) and reductions in the occurrence of lane departure, speeding, and events of excessive acceleration and braking (Birrell & Young, 2011; Gouribhatla & Pulugurtha, 2022). However, the ADAS technologies have faced setbacks in rural areas where the adoption of these technologies has become a major challenge due to various reasons that are explored in this project.

1.3 Challenges in Adoption of ADAS in Rural Areas

The adaptation and implementation of ADAS vehicles in rural areas of the United States present unique challenges. These challenges are shaped by the distinct characteristics of rural regions, including infrastructure, demographics, and driver behavior. Some of these challenges are explained below.

- ADAS technologies often rely on high-quality infrastructure, such as well-maintained roads, visible lane markings, and clear signage, for optimal functionality. Rural areas frequently lack these features due to inadequate funding for road maintenance. Additionally, many ADAS vehicles depend on GPS and cellular networks for real-time updates and navigation. Rural areas, which often have limited connectivity, pose significant challenges for these systems. Poor communication networks can disrupt the functioning of features such as traffic sign recognition and navigation-based adaptive systems.
- Rural areas are home to older populations who may be less familiar with and more resistant to adopting new technologies. The perception that ADAS is unnecessary or overly complex further hinders adaptation among rural populations. Moreover, the primary users in rural areas often include farmers, truck drivers, and other professionals who rely on large vehicles for their livelihood. Adapting ADAS features to these specific vehicle types and user needs presents an additional technological and educational challenge.
- Rural residents generally have lower median incomes compared to urban populations, limiting their ability to purchase newer vehicles equipped with ADAS features. This financial divide contributes to slower adoption rates, leaving rural drivers with older vehicles that lack these safety enhancements.
- Rural areas often have unique driving conditions, including unpaved roads, sharp curves, and limited visibility. These conditions challenge the effectiveness of ADAS features, many of which are optimized for urban environments. Systems such as automatic emergency braking may struggle to detect obstacles like wildlife on rural roads.
- Another critical challenge is the lack of awareness and understanding of ADAS technologies among rural populations. Many drivers are unaware of the potential safety benefits or how to use ADAS features effectively.
- The maintenance and repair of ADAS vehicles require specialized equipment and trained technicians, which are often unavailable in rural areas. As a result, even minor issues with ADAS systems can lead to extended downtime for vehicles or drivers opting not to repair these systems.

1.4 Objective of the Research Project

The primary objective of this study is to evaluate the influence of Advanced Driver Assistance Systems (ADAS) on road safety outcomes in rural areas, with stratification by age group. The specific objectives of the research were to assess the influence of ADAS in crash prevention within rural areas and to assess the influence of ADAS in protecting Vulnerable Road Users in rural areas.

1.5 Relevance of the Research Project to the R-SEAT Center

This project is consistent with the US DOT priorities and goals on highway safety. The findings from this research will shed light on the effective ADAS technologies that significantly reduce crashes and injuries of different road users and age groups in rural areas. This project will contribute to a safe system, particularly in safe vehicle components. Anticipated output from this project will offer comprehensive insights into the most effective ADAS technologies that ensure safety based on age groups and other socio-economic factors in rural areas. Analyses will focus on the major types of crashes prominent in the rural areas. The research team will also provide recommendations based on the study findings, which will benefit policymakers, engineers, and stakeholders in making decisions that can ultimately enhance road safety for a vulnerable demographic while bolstering transportation technology's trajectory. Furthermore, the proposed project is expected to assist with meeting some of the major goals outlined in the USDOT 2022-2026 strategic plan, including improving the safety of transportation systems and their users and establishing new policies and procedures (mainly focusing on emergency evacuation planning) to satisfy the critical needs of communities.

1.6 Structure of the Technical Report

This report is organized to guide the readers through the major activities associated with examining the impacts of vehicle automation levels on road safety in rural areas. More specifically, the main sections of the present report were organized as follows. Section 1 sets the project background on road safety in rural areas, stating the measures that have traditionally been used to improve road safety in rural areas and the problem statement by showing the roles and challenges of implementing technological advancement in the rural transportation system. Section 2 reviews the previous efforts related to the theme of this project. The reviews provide insight into different safety practices, types of crashes, and different approaches and efforts, showing how technological advancement in vehicles (specifically assessing ADAS) has been used to prevent crashes. In section 3, the steps followed to acquire and prepare the data are described. Furthermore, this section shows the study area and the types of data used for this project. Section 4 covers the methodology and the materials used to perform the analysis. Section 5 shows the results and the discussion that tends to provide insight into the response to the two specific objectives of the project. Section 6 provides the main concluding remarks and summarizes the main outcomes of this project.

2 LITERATURE REVIEW

Rural areas, despite having a smaller population, account for a substantial portion of roadways and crash fatalities. Although only 19% of the population lives in rural areas, they account for more than 70% of the 4 million miles of roadways in the United States. According to the National Highway Traffic Safety Administration (NHTSA) (NHTSA, 2023), the fatality rate in rural areas is 1.5 times higher than in urban areas. In Ohio, the fatality rate per 100 million vehicle miles traveled (VMT) is 1.53 in rural areas compared to 1.04 in urban areas. Different kinds of traditional safety measures have been implemented to improve safety on rural roads with relatively minimal significant changes. However, technological improvements in vehicles, such as equipping the vehicle with ADAS, have helped to improve road safety, especially in urban areas. Various traditional safety measures have been implemented to enhance safety on rural roads with minimal significant changes. However, advancements in vehicle technology, such as equipping vehicles with Advanced Driver Assistance Systems (ADAS), have significantly improved road safety, particularly in urban areas. Evaluating the impact of these technologies in rural areas is challenging due to their lower penetration rates. Nevertheless, the limited available data on vehicle automation levels in rural regions presents an opportunity to assess how these technologies are contributing to safety improvements. To gain a deeper understanding of vehicle automation in rural areas, it is essential to first examine existing literature on the most common types of crashes and collision patterns in these regions. Additionally, reviewing previous studies on the effectiveness of various vehicle technologies in preventing these crashes is crucial.

2.1 Prominent types of crashes in rural areas

Rural areas feature unique crash characteristics, with a higher likelihood of a fatal crash involving a light or heavy truck, intoxication, occupant ejection, or a non-collision crash (such as a mechanical failure) than a fatal crash in an urban context (Muelleman & Mueller, 1996). Single-vehicle crashes, including rollovers and roadway departures, as well as head-on collisions, rear-end collisions, and sideswipe collisions, are common rural crash types, caused by factors including roadway curvature and grade, speeding, darkness, land and shoulder width, and roadside hazards, such as utility poles and ditches (H. Y. Chen et al., 2009; Lord et al., 2011). There is a marked influence of driver demographics on base driving behavior, with a large influence being exercised by driver age. Older drivers are less capable of handling distractions, possess poorer memory, and struggle in complex driving situations (Mather, 2007). However, rear-end and sideswipe collisions were found to be more prominent types of crashes contributing significantly to an increase in fatality rate in rural areas. The use of ADAS has been observed to continuously decrease and prevent these types of crashes, as elaborated below.

2.2 Prevention of crashes using ADAS

Real-world crash data has shown results indicating crash mitigation, but also unsafe changes in driving behavior induced by ADAS. An analysis of over three hundred thousand Toyota and Lexus vehicle crashes between 2015 and 2019 showed vehicles equipped with automatic emergency braking to be 43% less likely to be the striking vehicle in front-to-rear collisions, as well as finding vehicles equipped with lane-keeping assistance to be 9% less likely to experience a roadway departure event (Spicer et al., 2021). However, this study did not determine whether the relevant ADAS system was triggered or active during the crash and did not consider demographic factors. A study comparing rear-end crash incidence between ADAS and automated driving system (ADS) equipped vehicles found that ADAS-involved crashes were more likely to occur on highways and rural roads, with a plausible explanation being driver over-reliance on ADAS until the moment before collision, leading to unexpected hard braking and a higher likelihood of rear-end collision (Huang et al., 2024). ADAS has also been shown to increase the time that drivers spend glancing away from the road (Bärgman & Victor, 2020).

Perception and use of ADAS are also variably correlated with age and other demographic factors. A Korean experimental study utilizing an aftermarket ADAS system found that males were more accepting of front collision warnings and received more lane departure warnings, while females experienced a significant increase in both warning types and a large decrease in headway when compared to the control group operating a non-ADAS vehicle (Son et al., 2015). Older drivers were more accepting lane departure warnings and had a generally more positive attitude towards ADAS. A German survey of elderly drivers' attitudes toward ADAS found barriers to perceived usefulness, functional limitation, system cost, and lack of system trust (Trübswetter & Bengler, 2013). However, the case can be different when evaluating a specific type of crash, such as a rearend or sideswipe collision. Rear-end collisions constitute approximately one-third of all traffic accidents in the United States, with over 2.5 million incidents occurring annually. These crashes are a leading cause of injuries and fatalities worldwide (Mohamed et al., 2017). The introduction of Advanced Driver Assistance Systems (ADAS) has significantly improved road safety and reduced accident rates. ADAS features such as forward collision warning (FCW), rear-end collision warning, crash imminent braking (CIB), and pilot assistance aid drivers in minimizing preventable rear-end collisions (Hang et al., 2022; Perumal et al., 2021).

Crash Imminent Braking (CIB) is designed to automatically engage a vehicle's brakes to prevent or lessen the severity of a collision. By utilizing radar sensors and video cameras (Ackermann et al., 2014), CIB enhances safety when interacting with pedestrians (Abdel-Aty et al., 2022; Broggi et al., 2009; Cicchino, 2022; Coelingh et al., 2010; Keller et al., 2011) and helps mitigate rear-end collisions involving other vehicles (Cicchino, 2019; Elsasser et al., 2019; Guo et al., 2022; Hang et al., 2022; Pipkorn & Bianchi Piccinini, 2020) as well as two-wheelers (Giovannini et al., 2013; Huertas-Leyva et al., 2023; Lucci et al., 2021; Sui et al., 2021). Research by Tan et al., (2021) suggests that CIB, particularly when integrated with active steering, exhibits greater crash avoidance capabilities compared to other warning systems. In low-severity collisions, vehicles equipped with CIB have been shown to reduce occupant injuries, providing protection not only for passengers but also for pedestrians, especially at intersections where rear-end crashes frequently occur (Abdel-Aty et al., 2022; Broggi et al., 2009; Cicchino, 2022). Another system recognized as a leading solution for reducing rear-end collisions is Forward Collision Warning (FCW). This technology helps drivers maintain shorter headway and improves their reaction time when the lead vehicle accelerates or when there is a significant speed difference between the lead and the following vehicle. However, FCW frequently generates a high number of alerts, some of which have low or no relevance, potentially impacting driver responsiveness and satisfaction (Seaman et al., 2022). While FCW enhances safety for all drivers, aggressive drivers particularly benefit from adaptive FCW systems, as they find them less frustrating and stressful (Jamson et al., 2008).

FCW has been shown to significantly reduce rear-end crash rates and related injuries, with the combination of FCW and Crash Imminent Braking (CIB) proving to be the most effective. Estimates suggest that if all vehicles in the U.S. had been equipped with these technologies in 2014, nearly one million rear-end crashes and over 400,000 associated injuries could have been prevented (Cicchino, 2017). However, ADAS systems alone do not ensure occupant safety, as the severity of injuries remains high in the absence of protective features such as airbags and seatbelts

(F. Chen et al., 2019). Research highlights the crucial role of ADAS technologies, including FCW and CIB, in crash reduction, particularly in urban areas. However, rear-end collisions are also a major cause of fatalities in rural regions of the U.S., emphasizing the need for further assessment of how these technologies contribute to crash prevention in rural environments.

Sideswipe collisions are among the most common types of crashes, second only to rear-end collisions (Ning et al., 2022). Several factors contribute to these accidents, including driver behavior, speed, and road design. Of these, driver behavior is the most significant, accounting for approximately 88% of all vehicle collisions (Ning et al., 2022). According to crash data from the Ohio Department of Public Safety (ODPS) covering rural crashes from 2017 to 2023, sideswipe collisions make up around 10% of all accidents. This high occurrence is largely attributed to hazardous road conditions such as poorly designed roads, blind spots, narrow lanes, inadequate signage, insufficient lighting, and roadside obstacles, all of which heighten the risk of severe crashes in rural areas (ODPS, 2020). The integration of advanced driver assistance systems (ADAS) in modern vehicles has helped mitigate crash severity by alerting drivers to dangerous maneuvers and, in some cases, taking corrective action. However, older vehicles, which are more prevalent in rural areas, often lack updated ADAS technology, making them more susceptible to crashes (Lowell et al., 2020). Additionally, rural road conditions—such as faded pavement markings and uneven surfaces—can hinder ADAS functionality, leading to system failures, particularly in adverse weather conditions (Mahlberg et al., 2021; Pike et al., 2018; Roh et al., 2020)

Key ADAS technologies, including lane departure warnings (LDW), lane-keeping assistance (LKA), and blind spot warnings (BSW), play a crucial role in preventing sideswipe collisions. LDW systems use cameras and optical recognition to detect when a vehicle drifts toward the lane edge or center line, alerting the driver through sound or vibration. A study of single-vehicle, sideswipe, and head-on crashes across 25 U.S. states found that vehicles equipped with LDW were 11% less likely to be involved in sideswipe collisions and 21% less likely to be involved in crashes resulting in injuries (Cicchino, 2018). Simulation studies further highlight LDW's effectiveness in reducing crash likelihood (Kusano & Gabler, 2012; Sternlund et al., 2017).

However, concerns remain regarding ADAS reliability, particularly in rural settings. A study conducted in Italy revealed two significant flaws in LDW systems on passenger vehicles: they issued alerts closer to the edge line when drifting right than when drifting left and, more critically, failed to detect road edges in the absence of signs or pavement markings (Re et al., 2021) These issues are especially concerning in rural areas, where narrow lanes and steep drop-offs make accurate and reliable LDW systems essential for driver safety. Like LDW, LKA relies on cameras to monitor lane positioning and provides steering input to prevent a vehicle from crossing the lane edge or center line. Research indicates that combining LDW and LKA can reduce certain crash types, including sideswipe, head-on, and single-vehicle accidents, by 12% (Leslie et al., 2021). Additionally, vehicles equipped with LKA are 9% less likely to experience roadway departures (Spicer et al., 2021). However, LKA's effectiveness is diminished by factors such as poor pavement markings, adverse weather conditions (e.g., heavy rain, snow, darkness, or glare), and inadequate lighting, all of which can lead to system errors (Jumaa et al., 2019). Simulation studies suggest that clearer lane markings and wider shoulders enhance the performance of LKA and LDW, reducing the likelihood of roadway departures and serious driver injuries. This implies that these systems may be less reliable in suboptimal driving conditions.

Blind Spot Warning (BSW) systems help drivers detect vehicles in their blind spots, particularly in adjacent lanes to the side and rear. Research on BSW has primarily focused on its application in large commercial vehicles, such as buses and trucks, and its potential to prevent crashes involving vulnerable road users (Jansen & Varotto, 2022; Pyykönen et al., 2015; Schaudt et al., 2014). In General Motors passenger vehicles, the side blind zone alert has been found to reduce lane-change crashes by 9% (Leslie et al., 2021). This suggests that BSW, similar to LKA and LDW, plays a crucial role in preventing collisions (Tan et al., 2021). Assessing the impact of these ADAS technologies in reducing severe crashes is particularly important in rural areas, where fewer drivers may have access to these safety features. However, many other studies show how the implementation of the ADAS technologies has helped to improve safety, as shown in Table 1. Different findings and objectives have shown how ADAS can significantly assist in lowering the risk of crashes

Table 1: Summary of literature review on ADAS technologies

Author	Objective/Focus	Data	Findings
Mason et al., (2023)	• Examine the understanding of advanced vehicle technologies among drivers and other road user populations.	• An online survey was conducted to collect data from a representative sample of more than 2500 respondents.	• Findings suggest that road users with a strong understanding of ADAS are younger. • Young road users preferred relying on videos and the internet to find educational material. • Results also underscore the importance of targeted education about vehicle technology.
Mcdonald et al., (2017)	• Provide insight on how learning about ADAS technologies from an owner's manual or through a ride-along demonstration drive impacts a driver's knowledge and understanding of the technology.	• Study procedures included a Pre-Visit Survey, a site visit (including an Intake Survey), completion of a randomly assigned learning protocol (either reading an owner's manual, participating in a ride-along demonstration drive, or a combination of	• Regardless of the learning protocol, participants gained knowledge about the ADAS technologies. • Learning protocol had an overall effect on participants' knowledge of the ADAS technologies.

Author	Objective/Focus	Data	Findings
		the two), and a Post-Visit Survey.	
Nees et al., (2020)	• Explore mental models of ADAS (ACC, LKA, and level 2 systems).	• The study used qualitative, semi-structured interviews to explore mental models of ADAS.	• There are shortcomings in the driver's understanding of the hardware, software, and limitations of these systems. • Mental models will affect behavior while using automation.
Bato & Boyle,(2011)	• Evaluate the perceived use and safety of Adaptive Cruise Control (ACC).	• A survey was distributed to drivers to gather specific opinions from drivers about the ACC.	• The less-dense roadways of Iowa might lead this group of drivers to feel that ACC is effective in detecting vehicles and allowing drivers to avoid crashes.
Utriainen et al., (2020)	• Focus on LKA systems and their potential safety effects by analyzing real-world crash data and LKA's possibilities to prevent fatal passenger car crashes.	• The study utilized 364 fatal head-on and single-vehicle crashes. • Data provided by the Finnish Crash Data Institute in Finland.	• Based on the analysis, LKA could potentially have prevented 27% of 364 fatal crashes and 28% of 415 fatalities. • In these crashes, which LKA was assessed to potentially prevent, lane markings were fully visible, and weather and driver's input were favorable for the operation of LKA.
Sternlund et al., (2017)	• Estimate the safety benefits of in-vehicle LDW/LKA systems in reducing head-on and single-vehicle passenger car crashes.	• The study was based on police-reported crashes. • Crashes were extracted from the Swedish Traffic	• The analysis showed a positive effect of the LDW/LKA systems in reducing lane departure crashes.

Author	Objective/Focus	Data	Findings
		Crash Data Acquisition database (STRADA).	• 53% reduction in head-on and single-vehicle crashes.
Masello et al., (2022)	• Quantify the expected impact of ADAS on crash reduction across a combination of road types, lighting, and weather conditions.	• Utilized road safety reports from the UK Department of Transportation.	• Deployment of the 6 most common ADAS would reduce crash frequency in the UK by 23.8%. • AEB is the most impactful technology.
Cicchino, (2017)	• Examine the effectiveness of FCW in preventing rear-end crashes.	• Police-reported crashes from various agencies in the US.	• FCW alone, low-speed AEB, and FCW with AEB reduced rear-end striking crash involvement rates by 27%, 43%, and 50%, respectively.
Fildes et al., (2015)	• Evaluate the effectiveness of low-speed autonomous emergency braking (AEB) technology.	• Used the national (police-reported) crash database for rear-end crashes from 2009.	• Findings show a 38 percent overall reduction in rear-end crashes for vehicles fitted with AEB compared to a comparison sample of similar vehicles.

2.3 Influence of ADAS on Vulnerable Road Users' Safety

Pedestrians are among the most vulnerable road user groups, and their crashes have become increasingly prevalent in recent years. In the United States, traffic crashes claimed the lives of over 7,500 pedestrians in 2022, marking an 11 percent increase in pedestrian injuries in comparison to the previous year (NHTSA, 2024). The nationwide disparity is evident as rural communities accounted for 15% of pedestrian fatalities in 2022 (IIHS, 2022), even though 8% of walking trips occurred in rural communities that same year (Jones et al., 2024). In 2022, Ohio recorded a 1.61 fatality rate per 100 million VMT in rural areas compared to urban areas, 0.94 (NHTSA, 2024). These statistics underscore the efforts needed to improve pedestrian safety in rural areas to lower the number of pedestrian fatalities.

Traditional safety measures such as traffic lights, stop signs, and pedestrian crossings have long played a crucial role in ensuring road safety. However, despite their benefits, these measures have proven insufficient to fully address the escalating risks to pedestrians (Bella et al., 2017).

Without disregarding the advantages of these traditional safety measures, advances in vehicle technology offer promising solutions that enhance pedestrian safety. A widely adopted example of vehicle technology is the ADAS (Sangve et al., 2024). Within the ADAS, a key system specifically aimed at preventing pedestrian crashes is the Pedestrian Automatic Emergency Braking (PAEB) system, which has become increasingly prevalent in modern vehicles. The PAEB utilizes a combination of camera and radar sensors to detect pedestrians along the predicted vehicle path (Haus et al., 2019). This technology aims to minimize the impact of a collision with a pedestrian by preventing fatalities or injuries. The PAEB system assists by either avoiding the crash altogether or reducing the vehicle's speed before the impact (Haus et al., 2019; Kullgren et al., 2023; Nasution & Dirgantara, 2023). Lowering the vehicle's velocity decreases the crash's severity, significantly reducing the likelihood of serious injury to the pedestrian. However, the potential of PAEB in rural areas remains underexplored. Lower income levels and underdeveloped transportation infrastructure contribute to technological inequities, such as lower penetration rates of ADAS-equipped vehicles (Dianin et al., 2021; Fatima et al., 2024).

Despite the promising benefits of PAEB, existing studies have identified critical limitations in its effectiveness. Previous research has shown that PAEB has two major limitations: the range of pedestrian detection and the varying appearance of the pedestrian (Bella et al., 2017; Nasution & Dirgantara, 2023; Tang et al., 2015). These limitations are particularly significant in rural settings, where crashes often occur under challenging conditions such as poor lighting, higher speeds, and fewer pedestrian infrastructure. Efforts like improving machine learning models to cater to the varying appearance of pedestrians are important improvements (Tang et al., 2015). The significance of these improvements can be underlined by addressing the gap in knowledge regarding PAEB's effectiveness in rural pedestrian crashes, focusing on the real-world performance of PAEB-equipped vehicles compared to non-equipped vehicles in reducing pedestrian injury severity.

The increased interest in PAEB-equipped vehicles underscores the importance of assessing the efficiency in reducing pedestrian fatalities. This is particularly crucial in rural settings where fatality rates remain disproportionately high. A growing body of literature depicts the methodologies used to assess the effectiveness of ADAS technologies. Logistic regression has been widely used in estimating the probability of crash occurrence given a dataset of independent variables/factors. It has been employed to identify significant variables directly related to crash risks associated with various medical disorders (Ridella et al., 2015), as well as crash severity and factors influencing lane-change crashes, including driver characteristics, road features, and environmental conditions (Shawky, 2020). Torkashvand et al., (2022) used binomial logistic regression mixed with high-order ordinary differential equations to examine the risk probability of time to collision threshold for rear-end collisions on two-lane roads. On a similar note, Reagan & McCartt, (2016) assessed the extent to which total mileage, vehicle model, and dealership had significance on whether a vehicle would be observed with lane-departure warning turned on. Chi-square tests and t-tests were employed to compare the observed results with the expected results of the studies through the means of two groups of data sets. A relationship between the presence of advanced driver assistance equipment and crash outcomes such as injury severity could be established (Schoner et al., 2023). The difference between two subsets of cars with and without automated emergency braking was established to evaluate the crash mitigation effect of low-speed automated emergency braking systems (Isaksson-Hellman & Lindman, 2016). Despite extensive research on determining the effectiveness of ADAS technologies, a specific gap exists in the performance of PAEB systems, particularly in rural areas.

3 DATA PREPARATION AND PREPROCESSING

3.1 Study Area

The research project focused on the state of Ohio, where 49 rural counties were considered for the research. The criteria used to identify the rural counties were based on the population. The details of these rural counties were obtained from the Census Bureau repository. Figure 3 shows the distribution of the rural counties across Ohio. The research team identified these counties because the data utilized in this project were centered around these counties.

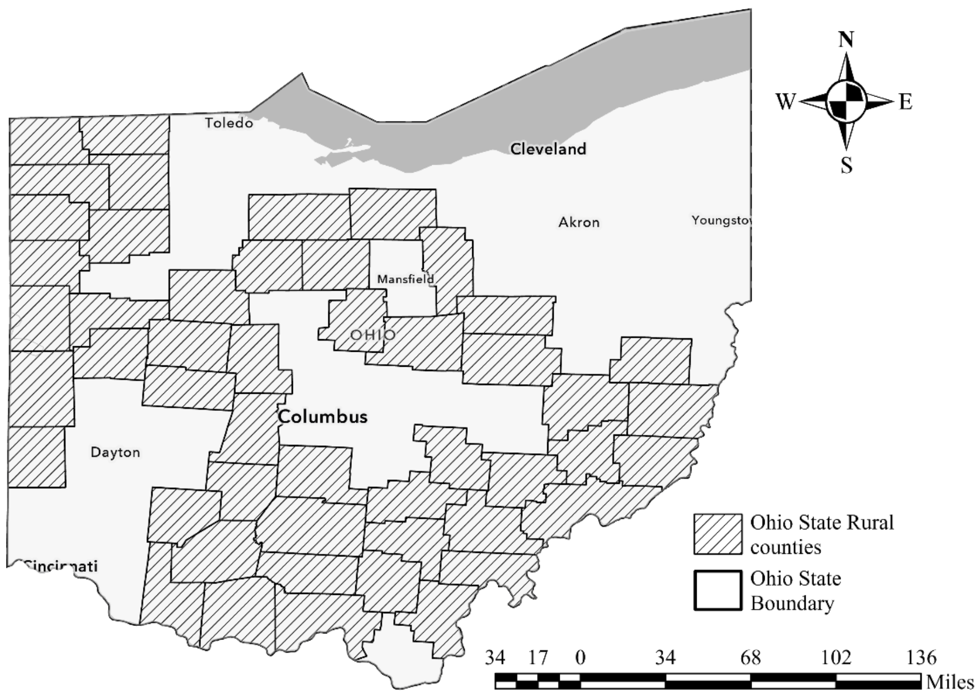

Figure 3: Rural counties in Ohio

3.2 Types of Data

The research team analyzed crash data in Ohio from 2017 to 2023, obtained from the Ohio Department of Public Safety (ODPS). The data is divided into three key repositories: crash statistics, unit statistics, and person statistics, each representing a dataset with unique details about the crashes. Crash statistics provided information such as crash severity, weather, posted speed limit, and impact location. Unit statistics included details about the vehicles involved, such as vehicle identification number (VIN) and vehicle model and make. Person statistics contained information about the vehicle's occupants, such as age, gender, and person type. These three datasets are connected through unique identifiers (document numbers) to merge the data. The research team used the VIN to obtain automation information about the vehicle from the NHTSA website through web scraping. ADAS technology data obtained from the website indicated only what type of technologies a particular vehicle is equipped with, based on the parsed VIN.

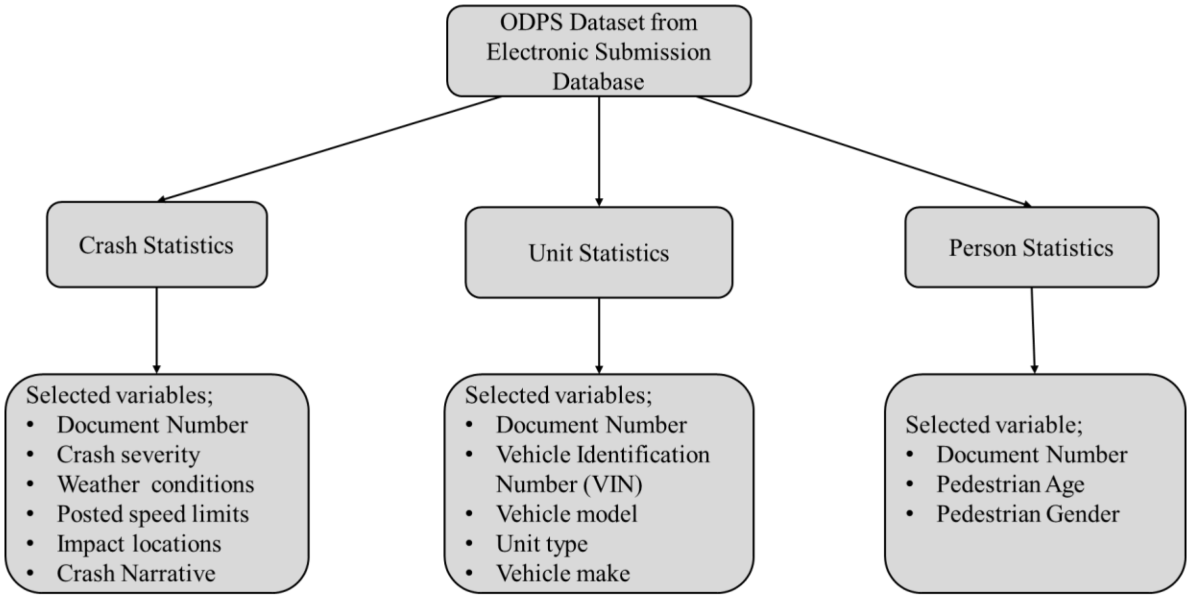

Figure 4: Distribution of the crash dataset

3.3 Data Preprocessing

The research project focused on three major types of crashes that were highlighted in the literature review to significantly affect rural areas. These types of crashes include rear-end collisions, sideswipe collisions, and pedestrian crashes. Crash data that involved this type of scenario were collected and preprocessed, and the following elaboration explains how the crash data were preprocessed and also shows the data summary.

In this research project, crashes were analyzed by categorizing the crash data based on the type of collision for evaluation. The datasets, which included information on the vehicle's ADAS technology, were merged, and the necessary variables for analysis were selected. The primary focus of the study was to determine the impact of ADAS-equipped vehicles on reducing crash severity, specifically assessing CIB and FCW technologies in rear-end crashes, LKA, LDW, and BSW in sideswipe crashes, and PAEB in pedestrian crashes. Additionally, the ADAS operating mode and automation level were considered when selecting data for the study, which are reflected in the unit statistics. Each vehicle involved in the crash was identified alongside its automation status and the ADAS technologies equipped. However, in these rural area crashes, there was a high proportion of conventional vehicles (those not equipped with ADAS), leading to a data imbalance. To address this, the crashes were mapped using the ArcGIS Pro application, and based on the literature review, a 50-feet buffer was established around the crash location of each ADAS-equipped vehicle (Chengula et al., 2024; Kutela et al., 2020; Md Shakir Mahmud et al., 2024). All conventional vehicles within the buffer zone were extracted, and each ADAS-equipped vehicle was associated with one to five surrounding conventional vehicles. We were able to obtain a well-balanced amount of datasets that were used for the analysis.

The data description in **Table 2** contains both the rear-end crash data. It should be noted that the data presented is essential unit-level data, where the crash data is described for every vehicle involved in the crash. According to the data description in **Table 2**, crashes that led to property damage only (PDO) were more frequent in Ohio rural areas than possible injury, minor injury, serious injury, and fatal (KABC) crashes. About 65.41% of all rear-end crashes had a PDO outcome, while all the severe outcomes of a crash were combined to form 34.59% of the crash dataset for the analysis. Drivers aged between 25 – 64 years old were in most of the crashes, where 63.01% of all drivers were involved in rear-end crashes.

Table 2: Data Description Summary for Rear-end Crashes

Variable	Category	Rear End Crashes (n=11238) Count	Percent
Crash Severity			
crash_severity	PDO	7351	65.41%
	KABC	3887	34.59%
Age Group			
age_group	Under 25	2874	25.57%
	25 - 64	7081	63.01%
	65+	1283	11.42%
Gender			
gender	Female	4911	43.70%
	Male	6327	56.30%
Unit Type			
unit_Type	Non-passenger cars	6383	56.80%
	Passenger cars	4855	43.20%
ADAS In Error			
ADASinError	No	9697	86.29%
	Yes	1541	13.71%
ADAS Operating			
ADAS_operating	No	11085	98.64%
	Yes	153	1.36%
Automation Level			
automation_level	Level 0	10981	97.71%
	Level 1+	257	2.29%
Posted Speed Limit			
posted_speed	< 35 mph	1789	15.92%
	35 - 45 mph	3043	27.08%
	> 45 mph	6406	57.00%
Traffic Control			
traffic_control	No	7203	64.10%
	Yes (includes stop sign, yield sign, or signalized control)	4035	35.90%
Thrulanes			
thrulanes	Not two thrulanes	2524	22.46%
	Two thrulanes	8714	77.54%
Intersection Related			
intersectionrelated	No	7046	62.70%
	Yes	4192	37.30%
Impact Location			
impact_location	On roadway	10886	96.87%
	Off roadway	352	3.13%
Weather			
weather	Clear	7037	62.62%
	Adverse condition	4201	37.38%
Road Condition			

Variable	Category	Rear End Crashes (n=11238)	
		Count	Percent
road_condition	Dry	9136	81.30%
	Wet/Snow/Icy	2102	18.70%
Light Condition			
lght_condition	Daylight	9276	82.54%
	Dark	1962	17.46%
Speed Related			
speed_related	No	10275	91.43%
	Yes	963	8.57%
Under Influence			
UnderInfluence	No	10922	97.19%
	Yes	316	2.81%
Vehicle Technology			
VehicleTechnology	No ADAS system	6462	57.50%
	1+ ADAS system	4776	42.50%

Most drivers involved in the rear-end crashes were male drivers (56.30%) compared to female drivers (43.70%). The data show that 56.8% of vehicles involved in rear-end crashes were not passenger cars. Along the same line, only 2.29% of the vehicles involved in rear-end crashes had automation levels greater than one, whereas 1.36% of all the vehicles in rear-end crashes had the ADAS in operation. The data indicate that 86.29% of the vehicles found in error were not ADAS-equipped vehicles. Furthermore, the data shows 57.50% of vehicles in rear-end crashes were not equipped with ADAS, and 42.50% of vehicles were equipped with ADAS for the vehicles.

Data suggest that most rear-end (57.00%) crashes occur on the road with a posted speed limit greater than 45 mph. 64.10% of all vehicles involved in rear-end crashes were using road sections without traffic control. The data indicates that most rear-end crashes (77.54%) occur on roads with two through lanes. About 62.70% of rear-end crashes occur in areas that are not intersection-related, and this is shown by the impact areas mainly on the roadway, where more than 95% of rear-end crashes occur. Finally, some of the exposure conditions incorporated in the study as variables show that most of the rear-end crashes occurred during clear weather, implying during the daytime when there are dry road conditions. Also, most drivers involved in these crashes were not speeding or under the influence of drugs or alcohol.

Table 3 describes sideswipe crash data, focusing on unit-level details for each vehicle involved in crashes. Notably, crashes resulting in property damage only (PDO) were predominant in Ohio's rural areas, accounting for 83.82% of all sideswipe crashes. Additionally, drivers aged between 25 and 64 were involved in most of these incidents, with 65.75% of all sideswipe crash participants falling within this age group.

Table 3: Data Description Summary for Sideswipe Crashes

Variable	Category	Sideswipe Crashes (n = 1971)	
		Count	Percent
Crash Severity			
crash_severity	PDO	1652	83.82%
	KABC	319	16.18%

Variable	Category	Sideswipe Crashes (n = 1971)	
		Count	Percent
Age Group			
age_group	Under 25	313	15.88%
	25 - 64	1296	65.75%
	65+	362	18.37%
Gender			
gender	Female	810	41.10%
	Male	1161	58.90%
Unit Type			
unit_type	Non-passenger cars	1164	59.06%
	Passenger cars	807	40.94%
ADAS In Error			
ADASinerror	No	1635	82.95%
	Yes	336	17.05%
ADAS Operating			
ADAS_operating	No	1906	96.70%
	Yes	65	3.30%
Automation Level			
automation_level	Level 0	1878	95.28%
	Level 1+	93	4.72%
Posted Speed Limit			
posted_speed	< 35 mph	335	17.00%
	35 - 45 mph	391	19.84%
	> 45 mph	1245	63.17%
Traffic Control			
traffic_control	No	1612	81.79%
	Yes	359	18.21%
Thrulanes			
thrulanes	Not Two thrulanes	531	26.94%
	Two thrulanes	1440	73.06%
Intersection Related			
intersectionrelated	No	1577	80.01%
	Yes	394	19.99%
Impact Location			
impct_location	On roadway	1913	97.06%
	Off roadway	58	2.94%
Weather			
weather	Clear	1219	61.85%
	Adverse condition	752	38.15%
Road Condition			
road_condition	Dry	1627	82.55%
	Wet/Snow/Ice	344	17.45%
Light Condition			
lght_condition	Daylight	1606	81.48%

Variable	Category	Sideswipe Crashes (n = 1971)	
		Count	Percent
	Dark	365	18.52%
Speed Related			
speed_related	No	1609	81.63%
	Yes	362	18.37%
Under Influence			
UnderInfluence	No	1902	96.50%
	Yes	69	3.50%
Vehicle Technology			
VehicleTechnology	No ADAS system	1075	54.54%
	1+ ADAS system	896	45.46%

Most drivers involved in sideswipe crashes were male (58.90%) compared to female drivers (41.10%). Additionally, 59.06% of the vehicles involved in these crashes were not passenger cars. Only 4.72% of the vehicles had higher automation levels than one, and just 3.3% had ADAS operating during the crash. The data indicate that 82.95% of the vehicles found at fault in sideswipe crashes were not equipped with ADAS, suggesting that ADAS-equipped vehicles were less likely to be at fault. After data processing, the study showed that 54.54% of the vehicles were not equipped with ADAS, while 45.46% were equipped with ADAS.

Furthermore, the data suggest that most sideswipe crashes (63.17%) occur on roads with a posted speed limit greater than 45 mph, and most of these crashes happen in areas without traffic control. Specifically, 81.79% of drivers involved in sideswipe crashes were on road sections lacking traffic control. The data also indicate that 73.06% of sideswipe crashes occur on roads with two through lanes. Additionally, 80.01% of these crashes happen in non-intersection areas, with over 95% of sideswipe crashes occurring on the roadway. The study also incorporated exposure conditions as variables, revealing that most sideswipe crashes occurred during clear weather, typically in the daytime with dry road conditions. Furthermore, most drivers involved in these crashes were neither speeding nor under the influence of drugs or alcohol.

Table 4 presents a summary of the crash data, focusing on injury-level details sustained by pedestrians. Pedestrians were significantly more likely to suffer incapacitating injuries in crashes occurring in rural areas, accounting for 447 incidents, which represents 41.97% of all pedestrian crashes. Additionally, pedestrians aged between 25 and 64 were involved in most of these incidents, with 51.45% of all incapacitating injuries sustained by this age group, 53.44% of all non-incapacitating injuries falling within this age group, and 51.11% of all no injury crashes involved an individual within this age group.

Table 4: Description of Pedestrian Crashes

Variables	Incapacitating Injury (N=447)		Non-Incapacitating Injury (N=393)		No Injury (N=225)	
	Count	percent	Count	percent	Count	percent
Age						
25-64	230	51.45%	210	53.44%	115	51.11%
65+	116	25.95%	56	14.25%	23	10.22%
Under 25	101	22.60%	127	32.32%	87	38.67%
Gender						
Female	144	32.21%	145	36.90%	87	38.67%

Variables	Incapacitating Injury (N=447)		Non-Incapacitating Injury (N=393)		No Injury (N=225)	
	Count	percent	Count	percent	Count	percent
Male	303	67.79%	248	63.10%	138	61.33%
Unit Type						
Non-Passenger Vehicle	239	53.47%	183	46.56%	97	43.11%
Passenger Vehicle	208	46.53%	210	53.44%	128	56.89%
Posted Speed Limit						
35-45 mph	61	13.65%	75	19.08%	28	12.44%
< 35 mph	125	27.96%	195	49.62%	149	66.22%
> 45 mph	261	58.39%	123	31.30%	48	21.33%
Traffic Control						
Controlled	46	10.29%	135	34.35%	91	40.44%
No Control	401	89.71%	258	65.65%	134	59.56%
Weather						
Clear	316	70.69%	262	66.67%	146	64.89%
Not Clear	131	29.31%	131	33.33%	79	35.11%
Road Condition						
Dry	382	85.46%	313	79.64%	176	78.22%
Not Dry	65	14.54%	80	20.36%	49	21.78%
Lighting Conditions						
Dark	231	51.68%	164	41.73%	84	37.33%
Daylight	216	48.32%	229	58.27%	141	62.67%
Under Influence						
False	373	83.45%	363	92.37%	215	95.56%
True	74	16.55%	30	7.63%	10	4.44%
Speed Related						
False	378	84.56%	363	92.37%	220	97.78%
True	69	15.44%	30	7.63%	5	2.22%
PAEB System						
Equipped	167	37.36%	210	53.44%	117	52.00%
Not Equipped	280	62.64%	183	46.56%	108	48.00%

Most pedestrians involved in crashes were male and sustained incapacitating injuries (67.79 % of all incapacitating injuries) compared to female drivers, who were 32.21% of all incapacitating injuries. Additionally, non-passenger vehicles caused more incapacitating injuries, amounting to 53.47% of all incapacitating injuries, while crashes involving passenger cars resulted in pedestrians sustaining non-incapacitating injuries and no injury (53.44% and 56.89% of all the injuries, respectively). Furthermore, the data indicates that 58.39% of all the incapacitating injuries occurred in the roadway that had a posted speed limit greater than 45 mph, while 49.62% of all the non-incapacitating injuries and 66.22% of all the no injury vehicle-pedestrian crashes occurred in the roadway with a posted speed limit less than 35 mph.

Most of the crash incidents are observed to occur in areas with no traffic control, whereas incapacitating injuries (89.71%) were the predominant type of injuries that pedestrians sustained. The data indicates most vehicle-pedestrian crashes occurred during clear weather conditions and dry road surfaces suggesting that either few numbers of people or none walked during these adverse weather conditions The data also indicate that lighting conditions had a role in the occurrence of the crashes with incapacitating injuries outcome since 51.68% of all the incapacitating injuries occurred during dark light while 58.27% and 62.67% of all the non-incapacitating and no injuries respectively occurred during daylight times. The data clearly shows that the majority of the vehicle-pedestrian crashes involved drivers who were neither speeding nor under the influence of alcohol or drugs. The data validates that vehicles that were not equipped with the PAEB technology caused 62.64% of all the incapacitating injury crashes, while the vehicles equipped with the PAEB technology were involved in crashes that had non-incapacitating and no injury crashes (53.44% and 52.00% respectively).

4 METHODS AND MATERIALS

The research project implemented mainly two methodologies, which were latent Dirichlet allocation (LDA) topic modeling and Bayesian network. These two methodologies were selected because of the nature of the data, which were mainly categorical data and unstructured text data. The two methodologies, considering their respective capabilities, can accurately analyze the mentioned types of data to provide accurate inferences about the road safety conditions that prevail in the case study. This section shows the mathematical formulation of both methodologies and the assumptions that were considered during the analysis to make the inference.

Latent Dirichlet Allocation (LDA) Topic Modeling

LDA topic modeling is a generative probabilistic model that discloses the hidden meaning or semantic structures in a collection of discrete data from text corpora. The LDA topic modeling follows a series of data processing and analysis to obtain the results, as shown in **Figure 5**. Most of the data processing involves cleaning the unstructured text to obtain a bag of words that can be manipulated through topic modeling.

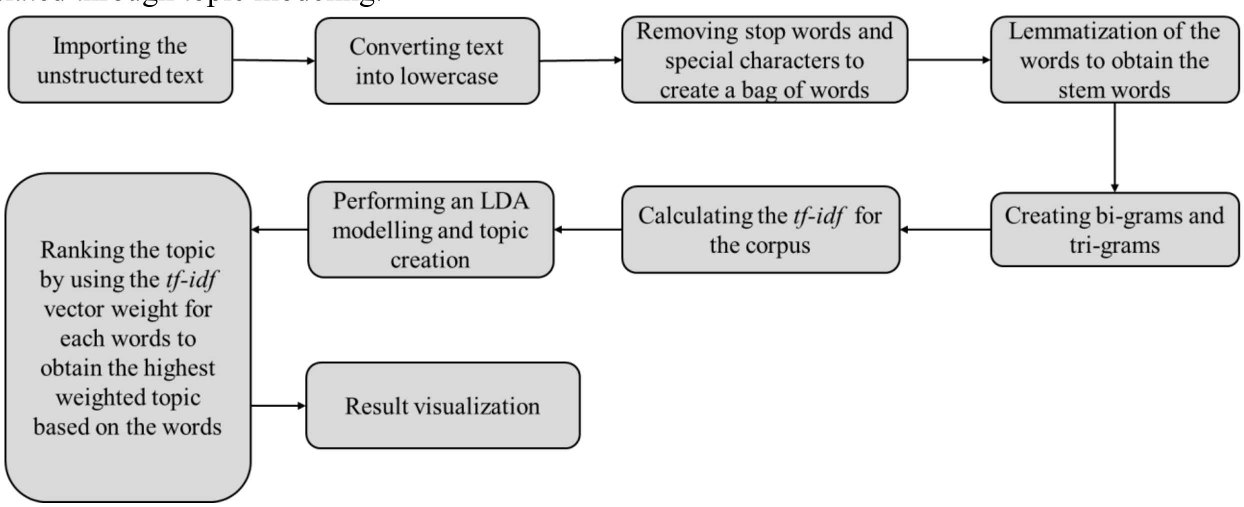

Figure 5: Data processing and analysis with LDA topic modeling

LDA is a three-level hierarchical Bayesian model, whereas each document (text corpora) contains a mixture of latent topics wherein each topic is characterized by a distribution over the words, and the relative importance of the topics captured in the form of different weights varies from document to document. The underlying generative process of LDA topic modeling is shown in **Figure 6**. For instance, given the parameters α and β, consider the dimensional Dirichlet random variables of topic mixture θ, a set of N topics z, and a set of N words w and K being the number of topics generated.

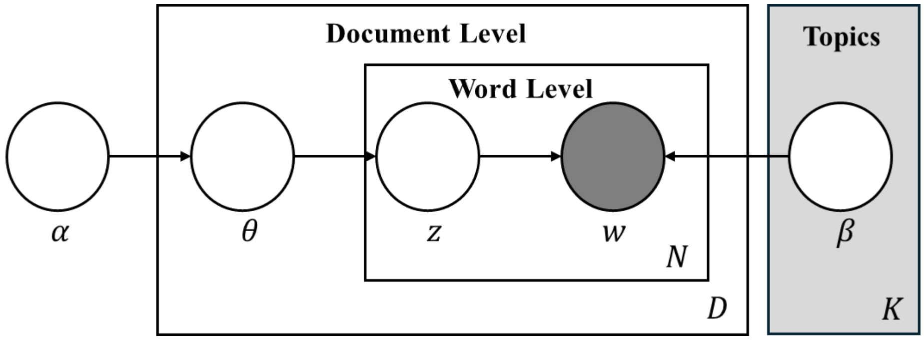

Figure 6: Three-level LDA topic modeling

Considering the illustration in **Figure 6**, where the linking arrow lines show conditional interdependency. The probability of generating a topic β given the corpora of text generated from the document and word level is given by;

$$\boldsymbol{p(\theta, z, w|\alpha, \beta) = p(\theta|\alpha) \prod_{n=1}^{N} P(Z_n|\theta) p(w_n|z_n, \beta)} \quad \textbf{(1)}$$

Figure 6 and Equation 1 shows clearly the three levels of hierarchy represented by the LDA model. The parameters α and β are corpus-level parameters, assumed to be sampled once in the process of generating a corpus. The parameter θ are document-level variables, sampled once per document. Finally, the variables $Z_n$and w_n are word-level variables and are sampled once for each word in each document. Inferencing the output of the model is a crucial aspect since we are required to generate relevant and salient words on a topic. The words generated are grouped into topics and ranked based on relevance and salience. Relevance is defined by combining the weight of the probability of a term w to appear in topic K denoted by $\boldsymbol{\emptyset_{kw}}$ and lift (ratio of the probability of the appearance on its topic ($\boldsymbol{\emptyset_{kw}}$) to the probability of the term to appear in the overall corpus of words (p_w))

$$\boldsymbol{r(w, k|\delta) = \delta \log(\emptyset_{kw}) + (1 - \delta) \log\left(\frac{\emptyset_{kw}}{p_w}\right)} \quad \textbf{(2)}$$

Equation 2 defines the relevance of term w to topic k given a weight parameter δ (where $0 \leq \delta \leq 1$) as the δ determines the weight given to the probability of the term w under topic k relative to its lift (measured both on the log scale). For the term to be relevant, the weighing parameter δ should be optimal since when $\delta = 1$, the term will be ranked based on the topic-specific probability, and when $\delta = 0$, the ranking of the term will be solely based on the lift. Therefore, based on the literature and studies, the optimal value for the weight parameter was found to be 0.67 and was adopted for this study. Furthermore, the ranking terms considered salient terms in corpora where the salient term was defined as the product of the probability of the term w being selected for a topic and the distinctiveness of the term w. Whereas the distinctiveness of term w was defined as the Kullback-Leibler divergence between $p(k|w)$ and marginal probability $p(k)$.

$$\boldsymbol{distinctiveness(w) = \sum_T p(k|w) \times \log\left(\frac{p(k|w)}{p(k)}\right)} \quad \textbf{(3)}$$

Whereas k represents the topic and w represents the words. The LDA topic modeling was implemented in Python, and the LDAvis module was used to visualize the LDA analysis results.

Bayesian Networks

The study utilized Bayesian Network (BN) algorithms to explore the influence of the ADAS technology on crash severity for vehicles involved in rear-end crashes. This algorithm was selected because it is a powerful tool that can accommodate multiple variables and produce better results when modeled, providing an upper hand compared to the models (Janssens et al., 2004; Kutela et al., 2022). The BN algorithm offers a distinguishing statistical modeling approach that interrelates variables using nodes, arcs, and conditional probability theory. The nodes represent the random variables, and arcs indicate the conventional relationship between these variables, where arcs are arrows in nature. The node found at the origin of the arc is known as the parent node, while the node at the tail head of the arc is known as the child node. The connection between nodes can be described using the joint probability distribution (Korb & Nicholson, 2010) represented by **Equation 4** below.

$$\boldsymbol{P(X_1 \ldots\ldots . X_n) = \prod_{i=1}^{n} P(X_i|\Pi_{Xi})} \qquad \textbf{(4)}$$

where X_i represent a random variable, and Π_{Xi} represents a set of parent nodes.

The BN involves two significant steps: structure learning and parameter learning. Structure learning is the step that consists of comprehending the conditional interdependencies that exist among the variables. This process can be performed through three analysis methods: the analytical approach, expert knowledge, and a combination of analytical and expert knowledge to form a hybrid approach (Demiroluk & Ozbay, 2014). The data set consists of uncertainty, so utilizing that analytical approach is advisable. Additionally, the data set incorporates expert knowledge in familiar matters (Rizzo & Blackburn, 2018). This study utilizes a hybrid approach, which allows the analytical approach to formulate the dependencies and the expert knowledge to make reasonable variable connections, hence striking a balance that is aligned with the study's objective. A greedy hill algorithm was employed to form the best network, and multiple scoring functions were used to determine the optimal network (Kutela et al., 2022). These scoring functions include the Akaike Information Criterion (AIC), K2 score, Bayesian Information Criterion (BIC), and Bayesian Dirichlet equivalent uniform (Bdeu) score. The expression for each of the scoring functions is shown in the equation below.

$$\mathbf{AIC = 2 * LL + 2 * n} \qquad \textbf{(5)}$$

$$\mathbf{k2_{score}(X_i, S_s, D) = \log(S_s, D) + \sum_{i=j}^{n}(\sum_{j=1}^{q_i}(\log\left(\frac{(r_i-1)!}{(N_{ij}+r_i-1)!}\right) + \sum_{k=1}^{r_i}\log(N_{ijk}!))} \qquad \textbf{(6)}$$

$$\mathbf{BIC = \ln(N) * n - 2 * LL} \qquad \textbf{(7)}$$

$$\mathbf{BDeu\,(S,X) = \log\big(P(X)\big) + \sum_{i=1}^{n} \left(\sum_{j=1}^{q_i}(\log\left(\frac{\Gamma\left(\frac{N'}{q_i}\right)}{\Gamma\left(N_{ij}+\frac{N'}{q_i}\right)}\right) + \sum_{k=1}^{r_i}\log(\frac{\Gamma\left(N_{ijk}+\frac{N'}{r_iq_i}\right)}{\Gamma\left(\frac{N'}{r_iq_i}\right)} \right)} \qquad \textbf{(8)}$$

Where LL represents the log-likelihood; n represents the number of instances of parameters in a Bayesian Network, Individual sensitivity analysis. S_s represents the BN structure; N' represents the sample size; N_{ij} represents the number of instances in data D; r_i represents the number of states of the finite random variable X_i, where the value X_i represent the possible configuration of the parent set.

The optimal structure that results from the scoring function is determined using structure learning, and parameter learning proceeds to estimate the variables' Conditional Probability Distribution (CPD). Two methods for determining CPD are maximum likelihood estimation (MLE) and comprehensive simulations known as Markov Chain Monte Carlo. This study utilizes the MLE method for parameter learning (Koller & Friedman, 2009). This method estimates the parameters of a specific distribution by using observed data to maximize the likelihood function, considering a set of observations, for example, $x_1, x_2, x_3, x_4, \dots\dots, x_n$. Therefore, the optimization function is represented as shown in **Equation 9**.

$$\boldsymbol{f(x_1, x_2, x_3, x_4, \dots\dots, x_n|\emptyset)} \tag{9}$$

The MLE is defined as a logarithmic probability of the observation given the parameters (Scutari, 2009), denoted by **Equation 10**.

$$\boldsymbol{LL\left(\frac{S}{D}\right) = \sum_i^n \sum_j^N log\, P\left(\frac{D_{ij}}{PA_{ij}}\right) LL\left(\frac{S}{D}\right) = \sum_i^n \sum_j^N log\, P\left(\frac{D_{ij}}{PA_{ij}}\right) LL\left(\frac{S}{D}\right) = \sum_i^n \sum_j^N log\, P\left(\frac{D_{ij}}{PA_{ij}}\right)} \tag{10}$$

where D_{ij} represents the counts of the observations for the variable x_i in dataset D_j, while PA_{ij} represents the count of occurrences of x_iParent variables in D_j. S represents BN's structure, D is the data, n represents the total number of distinct variables in the BN structure, and ∅ represents the projected parameters. To determine the influence of an ADAS-equipped vehicle on a rear-end crash, a value of 1.0 (equivalent to 100%) was assigned to the category of parent variable, and its influence on the category of child variable was assessed as denoted in **Equation 11**. This type of analysis is known as sensitivity analysis, where the model provides an evaluation of the impact of a given variable. Thus, the sensitivity analysis provides an estimated change in the predicted probability for the given sets of variables.

$$\boldsymbol{P(crash\ severity = i|Evidence_x = 1)} \tag{11}$$

Where i is the probability of whether the respondent will incur a severe rear-end crash, provided that evidence x represents a hypothesis variable, such as ADAS operation mode usage. The BN was performed on the R 4.3.2 environment. Multiple packages, including Rgraphviz and bnlearn, were utilized to perform this analysis (R Core Team, 2024).

5 RESULTS AND DISCUSSION

Based on the analysis conducted, the results and discussions were presented in two sections. The first section shows the influence of ADAS on crash prevention, where the research team discusses the results from analyzing the rear-end collision and sideswipe collision. In the second section, the research team discusses the influence of the ADAS systems in the protection of the vulnerable road users (VRUs), specifically pedestrians. The following are the results discussions of the analysis.

5.1 Influence of ADAS on Crash Prevention

Consider the following BNs for the trained and optimal network, which aim to identify the variation in the severity level for vehicles involved in rear-end crashes based on the ADAS technology equipped in the vehicle.

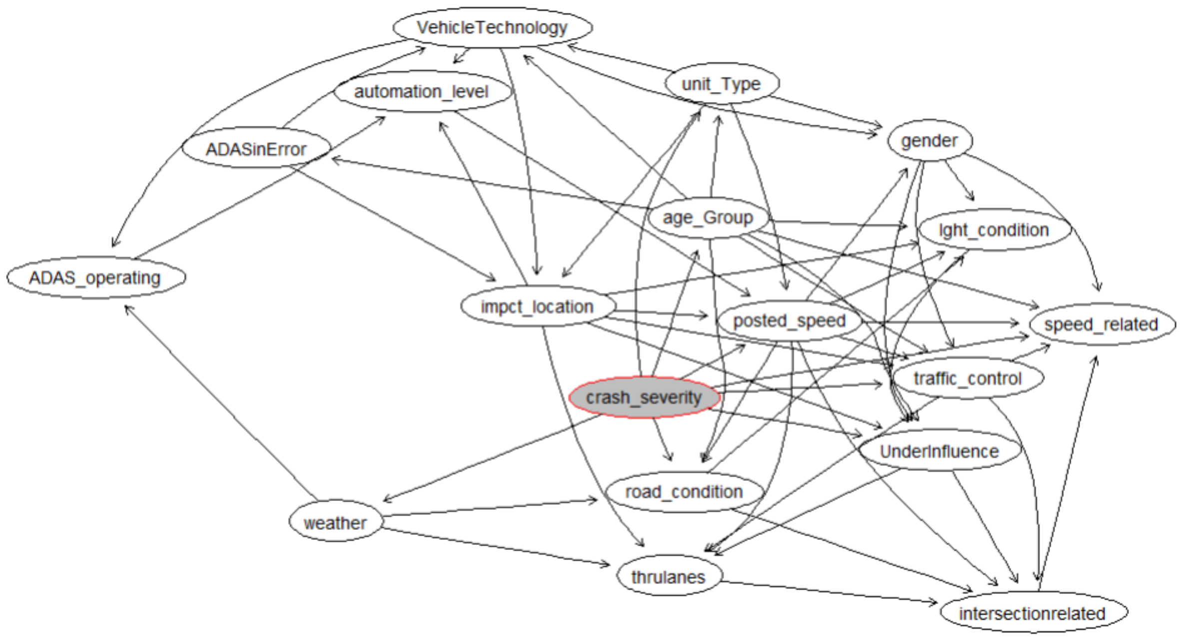

Figure 7: Initial trained network from either the rear-end crashes

The response variable is the crash severity, which has two categories: PDO and KABC. The BN structures selected as the initially trained network for either manner of collision assessed in this study were characterized by having the lowest value of the score function. Thus, the initially trained network for rear-end crashes, as shown in **Figure 7**, is obtained from the AIC scoring function. The interconnection shown by the arcs in **Figure 7** between the variables (both explanatory and response variables) shows the influence of one variable on another. Nevertheless, when there is no connection between the variables, there is an implication that there is insufficient information within the data to initiate or define the interdependency between these variables. However, it should be considered that the scoring algorithm initiated the interdependency observed in **Figure 7** and does not reflect the actual scenarios. Therefore, expert knowledge and the findings from previous studies are used to redefine the interconnection between the variables to obtain an optimal BN structure that has logical connections aligned with the study objective and can be formed, as shown in **Figure 8**.

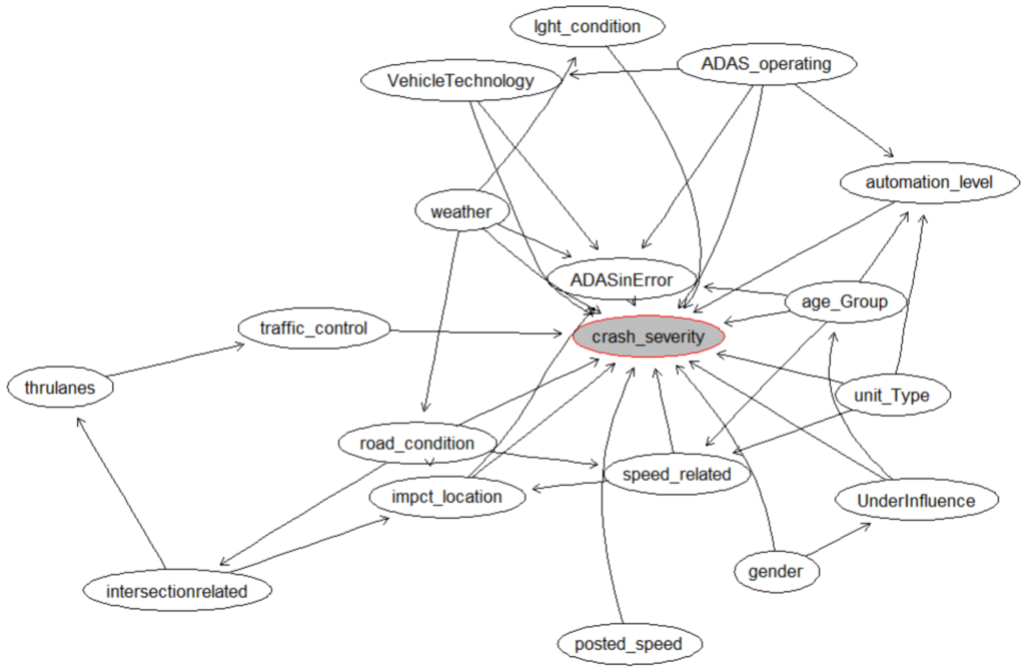

Figure 8: Optimal network used for rear-end crashes

Connections shown in **Figure 8** are constructed by reversing, setting, and deleting the initial arc relations established from the initial BN structure, respectively, for either of the two types of manner of collision analyzed. The optimal network shows that the response variable, which is crash severity, is a child variable for 15 explanatory variables, which are weather, lighting conditions, vehicle technology equipped, automation level, ADAS operating mode, unit in error (if it is ADAS equipped), the age group for the driver, vehicle type, driving under the influence, gender, speeding related, posted speed limit, road conditions, location of the collision, and lastly traffic control involved. Although some explanatory variables did not have a direct connection response variable, these variables were parented to some of the hypothesis variables and thus influenced these explanatory variables. For instance, intersection-related and number of thrulanes were attributed to the location of the collision and the traffic control, respectively. Furthermore, the direct and indirect interdependencies shown in **Figure 8** were evaluated to obtain the predicted probabilities of the hypothesis variables, which were the estimation of the effects of individual evidence on the likelihood of severe crashes that caused injury or fatal outcomes. A sensitivity analysis involving all the hypothesis variables was conducted along the same lines.

The study includes both individual evidence and combined evidence analysis. Individual evidence analysis focuses on the likelihood of the crash with an injury or fatal outcome using individual variable evidence. Also, the study conducted a combination analysis to examine the likelihood of a vehicle equipped with one or more ADAS technologies being involved in a crash with an injury or fatal outcome.

Individual Evidence Analysis

The results of the individual evidence analysis are presented in **Table 5** for rear-end crashes. Crash severity is used as the targeted variable for prediction purposes. Interpretation performed for this model is based on the predicted probability and the sensitivity analysis results. The analysis and interpretation focused on responding to the research question: what is the likelihood of the vehicle equipped with ADAS being involved rear-end crash with a severity outcome of injury or fatal injury? The reference category used in **Table 5** was selected based on the criteria that it has the least likelihood of occurring or leading to less severe crash outcomes.

Table 5: Predictions and Sensitivity Scores for Individual Evidence

Variable/Category	Predict Probability	Overall Sensitivity Score
Age Group		
Under 25	30.06%	
25 - 64	35.34%	5.28%
65+	35.69%	5.64%
Gender		
Female	33.72%	
Male	34.47%	0.75%
Unit Type		
Non-passenger cars	34.54%	
Passenger cars	33.58%	-0.95%
ADAS In Error		
No	34.03%	
Yes	35.07%	1.04%
ADAS Operating		
No	33.96%	
Yes	43.45%	9.49%
Automation Level		
Level 0	34.04%	
Level 1+	42.51%	8.47%
Posted Speed Limit		
< 35 mph	18.17%	
35 - 45 mph	28.86%	10.69%
> 45 mph	40.25%	22.08%
Traffic Control		
No	38.15%	
Yes	26.45%	-11.70%
Thrulanes		
Not Two thrulanes	32.32%	
Two thrulanes	34.71%	2.39%
Intersection Related		
No	34.18%	
Yes	34.22%	0.05%
Impact Location		
On roadway	34.17%	
Off Roadway	32.60%	-1.58%
Weather		
Clear	34.91%	
Adverse condition	32.33%	-2.58%
Road Condition		

Variable/Category	Predict Probability	Overall Sensitivity Score
Dry	35.00%	
Wet/Snow/Ice	29.68%	-5.32%
Light Condition		
Daylight	33.46%	
Dark	36.89%	3.43%
Speed Related		
No	32.90%	
Yes	52.93%	20.03%
Under Influence		
No	34.01%	
Yes	48.95%	14.93%
Vehicle Technology		
No ADAS system	34.76%	
1+ ADAS system	33.26%	-1.49%

The findings of the study indicate that the probability of severe rear-end crashes is increased by 5.28% for a driver aged between 25 to 64 years old, whereas the probability increases by 5.64% for the senior drivers with an age of more than 65 years old. This finding substantiates the fact that as people age, the perception of reaction time increases; thus, the capability of instantly applying brakes before colliding with the front vehicle decreases, especially for senior drivers (F. Chen et al., 2019; Hell et al., 2002; Zou et al., 2023). The results show that male drivers have a 0.75% probability higher probability of being involved in crashes with severe outcomes than female drivers. The findings are highly associated with the vehicle's speeding since male drivers are found to be mostly speeding and hence fail to stop on short notice when required (Li et al., 2016). Hang et al., (2022) indicate that male drivers are more aggressive compared to females.

The results indicate a 33.58% probability of passenger cars being involved in rear-end crashes with a severe outcome, which was 0.95% lower than the probability of other non-passenger cars (34.54%). The findings complement the advancement in technology that has been made in the passenger car, such as equipping the passenger car with an effective braking system and equipping it with ADAS technology, such as CIB and FCW. Counterintuitively, the results indicate that the probability of the rear-end having a severe outcome increases by 1.04% when an ADAS-equipped vehicle in an error, and the magnitude of the likelihood increases by 9.49% when the vehicle involved was operating in ADAS mode (Masello et al., 2022), and capping all the results indicates the probability of the rear-end to have a severe outcome increases by 8.47% when the vehicle has with automation level greater than one. These counterintuitive results complement the observation in the data description in **Table 2** that most rear-end crashes in Ohio rural areas involve conventional vehicles that are not equipped with ADAS. Few ADAS-equipped vehicles were found in error, and the one ADAS operating when involved in rear-end crashes with severe outcomes, driver behavior, and action had a high contribution since most of these vehicles are not fully automated.

Furthermore, the probability of rear-end crashes having severe outcomes increases with an increase in the posted speed limit, where there was a 28.86% probability of this crash occurring on the road with a speed limit ranging from 35 mph to 45 mph. There is a 10.69% increase compared to the road, with a speed limit of less than 35mph. There was a 40.25% probability of this crash occurring on the road with a posted limit greater than 45 mph, which indicated a 22.08% increase compared to the road with a posted speed limit of less than 35 mph. This finding suggests that rear-end crashes with severe outcomes mainly occur on highways and arterial roads (Dabbour et al., 2020). Using traffic control systems on the road section tends to decrease the probability of rear-end crashes with severe outcomes by 11.7%. This finding indicates that traffic control is helping Ohio rural areas to control congestion, which is the primary cause of rear-end crashes in rural areas. The probability of severe rear-end crashes decreases by 2.58% under adverse weather conditions and decreases by 5.32% when the road surface condition is wet, snowy, or icy. The decrease in probability is caused by concentration, alertness, and relatively lower travel speed by drivers traversing these harsh conditions.

Rear-end crashes are 3.43% more likely to occur during dark times than daytime when the surroundings are visible and the sight distance is long enough to spot a stopped vehicle from a distance, alerting the driver (Dabbour et al., 2020). Intuitively, speeding vehicles are 20.03% more likely to be involved in rear-end crashes that have severe outcomes because the vehicle fails to stop on time; hence, a hard rear-end collision has a high probability of occurring. Similarly, drivers driving under the influence of drugs or alcohol have a 14.93% higher likelihood of being involved in a rear-end crash with severe outcomes. The finding suggests that drivers who are influenced by alcohol or drugs are not mentally well enough to make decisions on the road, hence causing collisions (Masello et al., 2022). However, the probability of a vehicle equipped with one or more ADAS technologies is decreased by 1.49%. Therefore, this finding indicates that equipping more vehicles with ADAS or influencing the people in Ohio's rural areas to use technologically improved vehicles will decrease the probability of rear-end crashes with severe outcomes.

Combined Evidence Analysis Results

Table 6 presents the predicted probabilities and associated sensitivity scores for the various combinations of variables. The main goal of performing the combined evidence analysis was to explore the additional benefits for vehicles involved in severe rear-end crashes when equipped with ADAS technology.

Table 6: Predictions and Sensitivity Scores for the Combined Evidence Analysis

Variable	Category	Predict Probability	Sensitivity Scores	
			No ADAS Equipped	ADAS Equipped
Age Group				
	Under 25	31.07%		
No ADAS Equipped	25 - 64	36.21%	5.14%	
	65+	34.80%	3.74%	
	Under 25	28.91%		
1+ ADAS Equipped	25 - 64	33.88%		4.98%
	65+	38.05%		9.15%
Gender				
No ADAS Equipped	Female	33.87%		
	Male	35.73%	1.86%	
1+ ADAS Equipped	Female	32.57%		
	Male	33.48%		0.90%
Unit Type				
No ADAS Equipped	Non-passenger cars	34.83%		

Variable	Category	Predict Probability	Sensitivity Scores	
			No ADAS Equipped	ADAS Equipped
	Passenger cars	34.80%	-0.04%	
1+ ADAS Equipped	Non-passenger cars	33.84%		
	Passenger cars	31.62%		-2.22%
ADAS In Error				
No ADAS Equipped	No	34.90%		
	Yes	0.00%	-34.90%	
1+ ADAS Equipped	No	32.13%		
	Yes	35.18%		3.05%
ADAS Operating				
No ADAS Equipped	No	34.76%		
	Yes	58.19%	23.43%	
1+ ADAS Equipped	No	32.80%		
	Yes	42.33%		9.53%
Automation Level				
No ADAS Equipped	Level 0	34.76%		
	Level 1+	45.81%	11.05%	
1+ ADAS Equipped	Level 0	33.02%		
	Level 1+	39.39%		6.36%
Posted Speed Limit				
	< 35 mph	19.14%		
No ADAS Equipped	35 - 45 mph	29.72%	10.59%	
	> 45 mph	41.13%	21.99%	
	< 35 mph	16.61%		
1+ ADAS Equipped	35 - 45 mph	28.11%		11.50%
	> 45 mph	39.37%		22.75%
Traffic Control				
No ADAS Equipped	No	38.67%		
	Yes	26.97%	-11.70%	
1+ ADAS Equipped	No	37.29%		
	Yes	25.45%		-11.85%
Thrulanes				
No ADAS Equipped	Not Two thrulanes	32.90%		
	Two thrulanes	35.36%	2.46%	
1+ ADAS Equipped	Not Two thrulanes	31.04%		
	Two thrulanes	33.67%		2.63%
Intersection Related				
No ADAS Equipped	No	34.85%		
	Yes	34.84%	-0.01%	
1+ ADAS Equipped	No	32.92%		
	Yes	33.06%		0.14%
Impact Location				
No ADAS Equipped	On roadway	34.69%		
	Off roadway	38.13%	3.44%	
1+ ADAS Equipped	On roadway	33.02%		
	Off roadway	24.01%		-9.01%
Weather				

Variable	Category	Predict Probability	Sensitivity Scores	
			No ADAS Equipped	ADAS Equipped
No ADAS Equipped	Clear	35.08%		
	Adverse condition	34.25%	-0.83%	
1+ ADAS Equipped	Clear	34.67%		
	Adverse condition	29.49%		-5.17%
Road Condition				
No ADAS Equipped	Dry	35.58%		
	Wet/Snow/Ice	31.71%	-3.87%	
1+ ADAS Equipped	Dry	34.18%		
	Wet/Snow/Ice	26.77%		-7.41%
Light Condition				
No ADAS Equipped	Daylight	34.54%		
	Dark	36.06%	1.52%	
1+ ADAS Equipped	Daylight	32.44%		
	Dark	37.70%		5.26%
Speed Related				
No ADAS Equipped	No	33.32%		
	Yes	53.96%	20.63%	
1+ ADAS Equipped	No	32.18%		
	Yes	51.28%		19.09%
Under Influence				
No ADAS Equipped	No	34.61%		
	Yes	47.13%	12.52%	
1+ ADAS Equipped	No	32.49%		
	Yes	51.07%		18.58%

Based on the results, each hypothesis displayed a trend when vehicle technology was kept as evidence for the combination analysis. The discussion in **Table 7** shows a clear understanding of the trend for different explanatory variables used in the study.

Table 7: Findings of the combination analysis of the rear-end crashes

Variable	Discussion
Age Group	There was an increase in the probability of vehicles being involved in a severe rear-end crash as the driver's age increased for both vehicles equipped and not equipped with ADAS technology. However, the magnitude of the probability changes for the drivers aged between 25 to 64 years old who were using vehicles equipped with one or more ADAS technology (4.98%) is observed to be lower than drivers of similar age but using a vehicle with no ADAS technology (5.14%). Implies that a significant number of adult drivers are likely to be involved in crashes when using vehicles equipped with one or more ADAS technologies (Hell et al., 2002). However, the opposite becomes valid in the case of senior drivers since there is a rise in the magnitude of the probability change for the senior drivers utilizing vehicles equipped with ADAS.
Gender	Male drivers are found to have an increased probability of being involved in severe rear-end crashes. The likelihood of male drivers being involved in severe rear-end crashes is increased by 1.86% when using a vehicle not equipped with ADAS. In comparison, the probability is increased by 0.9% when using a vehicle equipped

Variable	Discussion
	with ADAS. However, the magnitude of the probability changes decreases when the male driver is using the ADAS-equipped vehicle, implying that when a vehicle is equipped with either CIB or FCW or both, the male driver is less likely to be involved in a severe rear-end crash (Md Shakir Mahmud et al., 2024).
Unit Type	Passenger cars were less likely to be involved in severe rear-end crashes, and the probability of passenger cars not being equipped with ADAS decreased by 0.04%, while those equipped with ADAS decreased by 2.22%. The findings indicate that passenger cars equipped with ADAS are less likely to be involved in severe rear-end crashes than vehicles not equipped with ADAS technologies (F. Chen et al., 2019).
ADAS In Error	The results also indicate that when a vehicle equipped with one or more ADAS technologies was found to be in error, the probability of rear-end collisions with severe outcomes increased by 3.05%.
ADAS Operating	Furthermore, the probability of change for the vehicles equipped with one or more ADAS and during the crash had their ADAS technology operating (9.53%) was less than those not equipped with ADAS (23.43%).
Automation Level	vehicle that was equipped with ADAS and the automation level of the vehicle was higher than that of a typical conventional vehicle, the probability of this vehicle being involved in a severe crash was lower (6.36%) compared to the vehicle that was not equipped with ADAS technology, which had a probability change of 11.05%. The study's findings indicate that when the vehicle is equipped with ADAS and has a higher automation level, the probability of being involved in a severe rear crash is lowered significantly, improving safety.
Posted Speed Limit	Regarding the influence of speed, the findings indicate that the higher the posted speed limit along the road section, the higher the probability of severe rear-end crashes for vehicles equipped with ADAS and those not equipped with ADAS. This finding validates that vehicles traversing highways and other high-speed roads cannot stop on short notice or in time to prevent rear-end collisions.
Traffic Control	Traffic control along the road decreases the probability of both vehicles that are equipped and vehicles that are not equipped with ADAS technology. The finding shows that traffic control signs and systems, such as stop signs, yield signs, and traffic signals, help reduce preventable rear-end collisions that are prominent in Ohio's rural areas (Dabbour et al., 2020; Zou et al., 2023).
Impact Location	Vehicles not equipped with ADAS were found to be more likely to be involved in off-roadway rear-end crashes, where the probability of these vehicles being involved increased by 3.44%. In contrast, the probability of vehicles equipped with ADAS being involved in an off-roadway severe rear-end crash was decreased by 9.01%. The findings show that vehicles with ADAS technology could detect and alert the driver, preventing crashes.
Weather	During adverse weather conditions, visibility is obscured, preventing drivers from having to extend long-sighted distances. The adverse weather conditions affect the road, causing the road to be wet and slippery due to rain or snow. However, the study results show that when the vehicle is equipped with one or more ADAS technologies, the probability of the crash is decreased by 5.17% during adverse weather conditions, and the probability is decreased by 7.41% when there are poor road conditions. The finding shows that ADAS-equipped vehicles are much safer to use for travel during adverse weather conditions because drivers will be alerted to

Variable	Discussion
	stopped vehicles or reduce the speed of the leading vehicle, hence stopping at much safer distances.
Light Condition	The probability of a vehicle equipped with ADAS technology and a vehicle not equipped with ADAS technology increased by 5.26% and 1.52%, respectively, during nighttime when the light condition is dark. Therefore, vehicles equipped with ADAS technology do not help reduce severe rear-end crashes during the night for vehicles in rural areas in Ohio. However, poor lighting conditions affect the efficiency of the sensors (Ma & Yan, 2014; Zou et al., 2023).
Speed Related	The study's findings indicate that the probability of a vehicle equipped with ADAS technology and a vehicle not equipped with ADAS technology increased by 19.09% and 20.63%, respectively, when the vehicle is speeding. Therefore, vehicles equipped with ADAS technology do not help prevent rear-end crashes for vehicles speeding in Ohio's rural areas. However, equipping the vehicle with ADAS technology decreased the number of speeding vehicles.
Under Influence	The findings also indicated that the probability of both a vehicle equipped with ADAS technology and a vehicle that is not equipped with ADAS technology having a severe outcome in a crash was increased by 18.58% and 12.52%, respectively, when the driver is under the influence of either drugs or alcohol. Therefore, vehicles equipped with ADAS technology do not have the assurance to prevent severe rear-end crashes by intoxicated drivers.

Consider the following Bayesian Networks for the trained and optimal network, which aim to identify the variation in the severity level for vehicles involved in sideswipe crashes based on the ADAS technologies equipped in these vehicles. The response variable is the crash severity, which has two categories: PDO and KABC (severity level includes minor injury, injury suspected, serious injury, and fatal crash). The BN structure selected as the initially trained network assessed in this study was characterized by having the lowest value of the score function. Thus, the initially trained network of the sideswipe crashes, as shown in **Figure 9,** is obtained from the K2 search algorithm scoring function. The interconnection shown by the arcs in **Figure 9** between the variables (both explanatory and response variables) shows the influence of one variable on another. Nevertheless, when there is no connection between the variables, there is an implication that there is insufficient information within the data to initiate or define the interdependency between these variables. However, it should be considered that the scoring algorithm initiated the interdependency observed in **Figure 9** and does not reflect the actual scenarios. Therefore, expert knowledge and the findings from previous studies are used to redefine the interconnection between the variables to obtain an optimal BN structure that has logical connections aligned with the study objective. The refined network is shown in Figure 10.

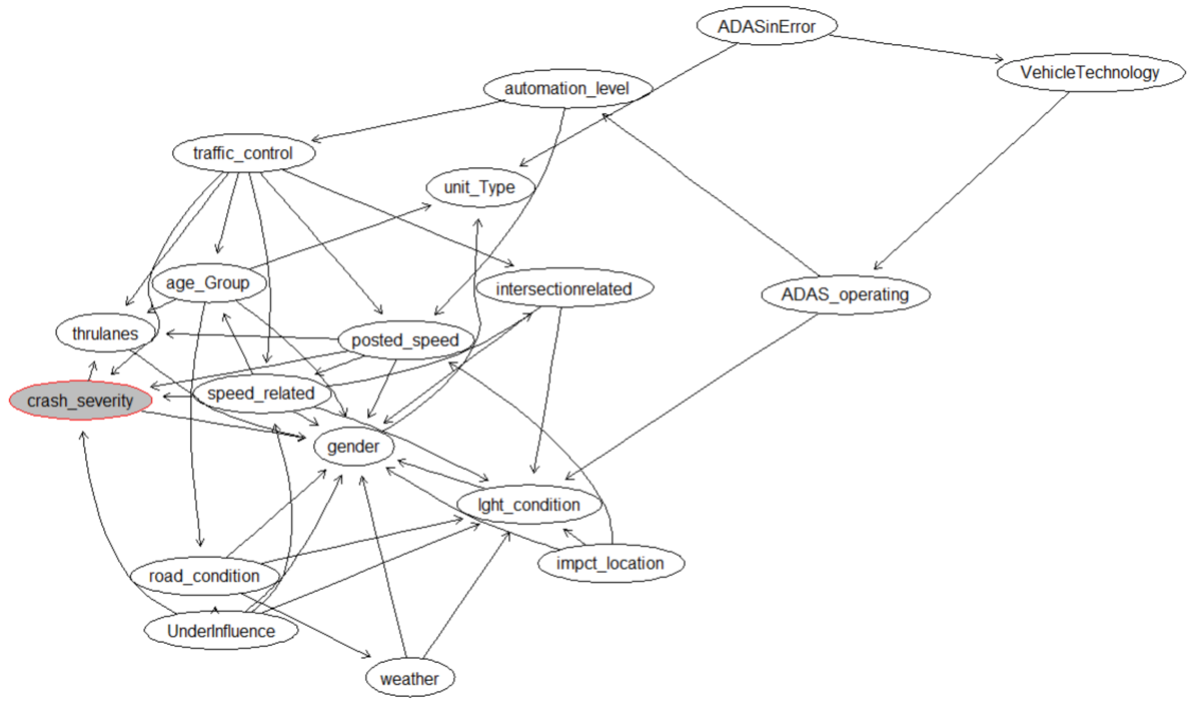

Figure 9: Initial trained network from sideswipe crashes.

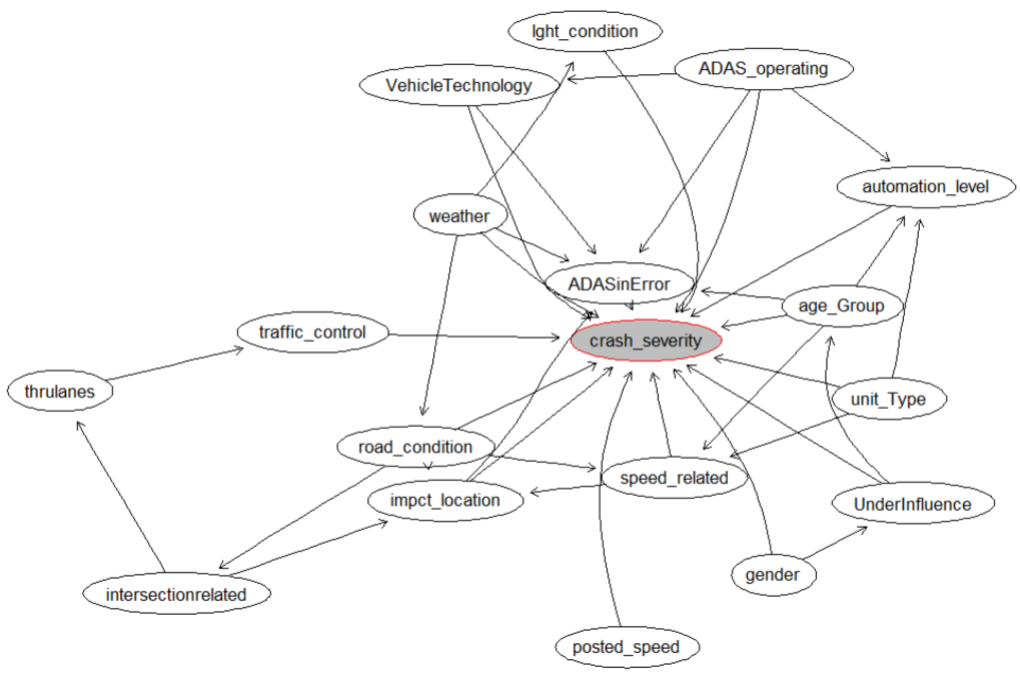

Figure 10: Optimal network used for sideswipe crashes

The connections shown in **Figure 8** are constructed by reversing, setting, and deleting the initial arc relations established from the initial BN structure, respectively, for either of the two types of manner of collision analyzed. The optimal network shows that the response variable, which is crash severity, is a child variable for 15 explanatory variables, which are weather, lighting conditions, vehicle technology equipped, automation level, ADAS operating mode, unit in error (if it is ADAS equipped), the age group for the driver, vehicle type, driving under the influence, gender, speeding related, posted speed limit, road conditions, location of the collision, and lastly traffic control involved. Although some explanatory variables did not have a direct connection response variable, these variables were parented to some of the hypothesis variables and thus influenced these explanatory variables. For instance, intersection-related and number of thru lanes were attributed to the location of the collision and the traffic control, respectively. Furthermore, the direct and indirect interdependencies shown in **Figure 8** were evaluated to obtain the predicted probabilities of the hypothesis variables, which were the estimation of the effects of individual evidence on the likelihood of severe crashes that caused injury or fatal outcomes. A sensitivity analysis involving all the hypothesis variables was conducted along the same lines.

The study includes both individual evidence and combined evidence analysis. An individual evidence analysis analyzed the likelihood of the crash with injury or fatal outcome using individual variable evidence. Also, the study conducted a combination analysis to examine the likelihood of a vehicle equipped with one or more ADAS technologies to be involved in a crash with an injury or fatal outcome concerning the hypothesis variables. The results of the individual evidence analysis are shown in Table 8. Also, the results of the combination analysis are presented in Table 9.

Individual Evidence Analysis for Hypothesis Variables

Model results presented in Table 8 are obtained by considering crash severity as the targeted variable for the prediction. Interpretation performed for this model is based on the predicted probability and the sensitivity analysis results. The analysis and interpretation focused on responding to the research question: *What is the likelihood of the vehicle equipped with ADAS being involved in a sideswipe crash resulting in a severe injury outcome (KABC)?* The reference category used in Table 8 was selected based on the criteria that has the least likelihood of occurring or leading to less severe injury outcomes.

Table 8: Predicted Probability and Sensitivity Analysis Scores

Variable/Category	Predict Probability	Overall Sensitivity Score
Age Group		
Under 25	12.62%	
25 - 64	15.65%	3.02%
65+	11.17%	-1.46%
Gender		
Female	16.83%	
Male	13.00%	-3.83%
Unit Type		
Non-passenger cars	14.72%	
Passenger cars	14.46%	-0.26%
ADAS In Error		
No	14.39%	
Yes	15.33%	0.94%
ADAS Operating		
No	14.64%	
Yes	8.79%	-5.86%
Automation Level		
Level 0	14.61%	
Level 1+	13.18%	-1.43%
Posted Speed Limit		

Variable/Category	Predict Probability	Overall Sensitivity Score
< 35 mph	3.83%	
35 - 45 mph	9.09%	5.26%
> 45 mph	17.57%	13.73%
Traffic Control		
No	15.16%	
Yes	10.48%	-4.68%
Thrulanes		
Not Two thrulanes	14.36%	
Two thrulanes	14.47%	0.11%
Intersection Related		
No	14.52%	
Yes	14.55%	0.03%
Impact Location		
On roadway	14.65%	
Off roadway	9.98%	-4.66%
Weather		
Clear	14.10%	
Adverse condition	15.07%	0.96%
Road Condition		
Dry	14.48%	
Wet/Snow/Ice	14.93%	0.45%
Light Condition		
Daylight	14.20%	
Dark	16.83%	2.63%
Speed Related		
No	13.76%	
Yes	19.68%	5.92%
Under Influence		
No	14.35%	
Yes	38.73%	24.38%
Vehicle Technology		
No ADAS system	14.29%	
1+ ADAS system	14.84%	0.55%

The findings of individual evidence analysis are based on analyzing the sideswipe crashes dataset. There was a 0.26% decrease in the probability of passenger cars being involved in sideswipe crashes with severe outcomes. The likelihood of ADAS vehicles being in error in sideswipe crashes with severe outcomes was increased by 0.94%. Roads with a posted speed limit of more than 35 mph have a higher probability of severe sideswipe crashes. For instance, the likelihood of a vehicle being involved in a sideswipe crash that has a severe outcome increases by 5.26% while traversing roads with posted speed limits ranging between 35mph and 45mph. Furthermore, the probability increased by 13.73% while crossing a road with a posted speed limit greater than 45 mph. However, for roads with traffic control, the probability of a vehicle being involved in a sideswipe crash with a severe outcome is decreased by 4.68%.

In the same line, the results indicate a 4.66% decrease in the probability of severe sideswipe crashes off the roadway, thus indicating that most severe sideswipe crashes in Ohio rural areas occur between vehicles traveling in adjacent lanes. The results suggest that the probability of severe sideswipe crashes increases by 2.63% during dark conditions, whereas Jumaa et al. (Jumaa et al., 2019) suggest that the darkness hinders the ADAS system from detecting the road markings. The probability increases by 5.92% when the vehicle is speeding, which is similar to various studies (Fildes et al., 1991; Fleiter et al., 2010). Also, the results indicate that the probability of a sideswipe crash with a severe outcome is increased by 24.38% when the driver is under the influence of alcohol or drugs; thus, it is difficult to maintain road stability (Alonso et al., 2015).

The probability of drivers aged between 25 and 64 years old being involved in a severe sideswipe crash is increased by 3.02%. In comparison, the likelihood of senior drivers aged 65 years and above being involved in similar crashes decreased by 1.46%. This finding validates that the adult group of drivers is often distracted and aggressive when driving, hence increasing the chance of moving out of the lane or not seeing vehicles that are in the blind spot of the vehicle, which are typical causes of sideswipe collisions. However, the senior drivers were most likely experienced, aware of their surroundings while driving, and concentrated on staying in their travel lane. The probability of male drivers being involved in severe sideswipe crashes decreases by 3.83% compared to female drivers. The findings indicate that most females have a higher chance of moving out of their travel lane and colliding with other vehicles than male drivers.

Furthermore, the results indicated that for vehicles with ADAS systems operating at the time of the crash and with automation levels greater than one, their probability of being involved in a severe sideswipe crash decreased by 5.83% and 1.43%, respectively. The findings are intuitively valid because systems like LKA, which offer a degree of automation, have been found to reduce the occurrence of certain types of crashes (Leslie et al., 2021). The findings imply that the ADAS technology lowers the likelihood of vehicles being involved in severe sideswipe crashes. However, when considering the influence of weather implying the presence of adverse weather conditions that directly led to having wet, snowy, or icy road conditions, the probability of a vehicle to involved in a severe sideswipe crash was increased by 0.96% during adverse weather and 0.45% when the road section was wet, snowy, or icy. This finding implied that drivers' chances of moving out of the lane or being unable to see the vehicle in the blind spot increased during adverse weather and road conditions caused by a loss of traction or poor visibility. Finally, the probability of a vehicle equipped with ADAS technology being involved in a severe sideswipe crash increased by 0.55%. The probability increase observed indicates that vehicles involved in the crashes were equipped with these technologies. Still, only a few of the vehicles had the technology operating during the crash.

Combination Analysis for the Hypothesis Variables

Table 9 presents the predicted probabilities and associated sensitivity scores for the various combinations of variables. Based on the results in **Table 9**, each hypothesis displayed a trend when vehicle technology was kept as evidence for the combination analysis. The results of the combination analysis show a decrease in the probability of vehicles being involved in severe sideswipe crashes as the driver's age increased for both vehicles equipped and not equipped with ADAS technology. However, the magnitude of the probability changes for drivers aged between 25 to 64 years old who were using vehicles equipped with one or more ADAS technology (0.17%) is observed to be lower than drivers of similar age but using a vehicle with no ADAS technology (4.34%). This implies that the number of adult drivers likely to be involved in crashes when using vehicles equipped with one or more ADAS technologies is decreasing. Concurrently, a similar case was observed on senior drivers, where the probability of the senior drivers utilizing vehicles equipped with ADAS decreased by 2.56% compared to senior drivers driving vehicles not equipped with ADAS. The findings align with previous studies indicating that ADAS has significantly reduced the sideswipe crashes in rural areas. Overall, male drivers were found to have an increased probability of being involved in severe sideswipe crashes. In contrast, the likelihood of male drivers being involved in severe sideswipe crashes decreased by 2.97% when using a vehicle not equipped with ADAS. In comparison, the likelihood decreased by 4.28% when using a vehicle equipped with ADAS. The magnitude of the probability change decreased further below when the male driver was using the ADAS-equipped vehicle, implying that when the vehicle is equipped with either BSW, LKA, or LDW, all led to the male driver being less likely to be involved in a severe sideswipe crash.

Passenger cars were found to be less likely to be involved in severe sideswipe crashes, where the probability of passenger cars not equipped with ADAS increased by 1.90% while the number of ones equipped with ADAS decreased by 3.98%. The findings indicate that passenger cars that are equipped with ADAS are less likely to be involved in severe sideswipe crashes compared to vehicles that are not equipped with ADAS technologies since these drivers are alerted as soon as they start moving out of their lanes or when there was the vehicle on their blind spot hence significantly reduces the likelihood of causing or involved in these types of crashes. The result indicates that when the vehicle with one or more ADAS technologies was in error, the probability of sideswipe collisions having severe outcomes increased by 0.98%. This is because of the adaptive behavior of the drivers, which is caused by dependencies on the ADAS technology (Vertlib et al., 2023).

Table 9: Predicted Probabilities and Sensitivity Score for the Combined Evidence Analysis

Variable	Category	Predict Probability	Sensitivity Scores	
			No ADAS Equipped	ADAS Equipped
Age Group				
No ADAS Equipped	Under 25	11.45%		
	25 - 64	15.79%	4.34%	
	65+	10.51%	-0.94%	
1+ ADAS Equipped	Under 25	15.06%		
	25 - 64	15.23%		0.17%
	65+	12.50%		-2.56%
Gender				
No ADAS Equipped	Female	16.11%		
	Male	13.13%	-2.97%	
1+ ADAS Equipped	Female	17.50%		
	Male	13.21%		-4.28%
Unit Type				
No ADAS Equipped	Non-passenger cars	13.55%		
	Passenger cars	15.45%	1.90%	
1+ ADAS Equipped	Non-passenger cars	16.26%		
	Passenger cars	12.37%		-3.89%
ADAS In Error				
No ADAS Equipped	No	14.11%		
	Yes	0.00%	-14.11%	
1+ ADAS Equipped	No	14.53%		
	Yes	15.51%		0.98%
ADAS Operating				
No ADAS Equipped	No	14.31%		
	Yes	1.06%	-13.25%	
1+ ADAS Equipped	No	14.97%		

Variable	Category	Predict Probability	Sensitivity Scores	
			No ADAS Equipped	ADAS Equipped
	Yes	9.00%		-5.97%
Automation Level				
No ADAS Equipped	Level 0	14.40%		
	Level 1+	12.65%	-1.75%	
1+ ADAS Equipped	Level 0	14.75%		
	Level 1+	13.11%		-1.65%
Posted Speed Limit				
No ADAS Equipped	< 35 mph	3.63%		
	35 - 45 mph	10.18%	6.55%	
	> 45 mph	17.54%	13.91%	
1+ ADAS Equipped	< 35 mph	4.50%		
	35 - 45 mph	7.33%		2.82%
	> 45 mph	18.54%		14.03%
Traffic Control				
No ADAS Equipped	No	14.83%		
	Yes	10.77%	-4.06%	
1+ ADAS Equipped	No	15.53%		
	Yes	10.09%		-5.44%
Thrulanes				
No ADAS Equipped	Not Two thrulanes	13.85%		
	Two thrulanes	14.26%	0.41%	
1+ ADAS Equipped	Not Two thrulanes	14.34%		
	Two thrulanes	14.99%		0.65%
Intersection Related				
No ADAS Equipped	No	14.12%		
	Yes	14.22%	0.11%	
1+ ADAS Equipped	No	14.84%		
	Yes	14.72%		-0.12%
Impact Location				
No ADAS Equipped	On roadway	14.49%		
	Off Roadway	9.05%	-5.44%	
1+ ADAS Equipped	On roadway	14.77%		
	Off Roadway	11.96%		-2.81%
Weather				
No ADAS Equipped	Clear	13.36%		
	Adverse condition	16.22%	2.86%	
1+ ADAS Equipped	Clear	15.29%		
	Adverse condition	13.72%		-1.57%
Road Condition				
No ADAS Equipped	Dry	13.91%		
	Wet/Snow/Ice	17.11%	3.19%	
1+ ADAS Equipped	Dry	15.31%		
	Wet/Snow/Ice	12.02%		-3.29%
Light Condition				
No ADAS Equipped	Daylight	14.49%		
	Dark	13.11%	-1.38%	
1+ ADAS Equipped	Daylight	13.87%		
	Dark	22.77%		8.90%

Variable	Category	Predict Probability	Sensitivity Scores	
			No ADAS Equipped	ADAS Equipped
Speed Related				
No ADAS Equipped	No	13.37%		
	Yes	19.58%	6.21%	
1+ ADAS Equipped	No	14.36%		
	Yes	18.89%		4.53%
Under Influence				
No ADAS Equipped	No	14.03%		
	Yes	39.06%	25.03%	
1+ ADAS Equipped	No	14.77%		
	Yes	29.78%		15.02%

The results indicated that the probability of change for vehicles equipped with one or more ADAS and had their ADAS technology operating decreased by 5.97% during the crash. Similarly, the vehicle that was equipped with ADAS and the automation level of the vehicle was higher than regular conventional vehicles, the probability of the vehicle being involved in a severe crash decrease by 1.65% compared to the cars that were not equipped with ADAS technology, which had a reduced probability change of 1.75%. The study's findings indicate that when the vehicle is equipped with ADAS and has a higher automation level, the probability of being involved in a severe sideswipe crash is lowered significantly, hence improving the safety of the occupants (Cicchino, 2018; Jumaa et al., 2019). The finding is valid because ADAS, like LKA, offers a degree of automation and has been found to reduce the occurrence of certain types of crashes (Leslie et al., 2021).

The study's findings indicate that the higher the posted speed limit along the road section, the higher the probability of severe sideswipe crashes occurring for vehicles equipped with ADAS and those not equipped with ADAS. The finding validates that vehicles traversing highways and other high-speed roads are generally unstable in one lane, and a slight tilt on the steering wheel can lead to a severe sideswipe crash. The findings indicated that traffic control along the road decreases the probability of both vehicles that are equipped and vehicles that are not equipped with ADAS technology. The finding suggests that traffic control signs and systems, such as stop signs, yield signs, and traffic signals, help reduce preventable sideswipe collisions that are likely to occur in Ohio's rural areas.

Vehicles not equipped with ADAS were found to be less likely to be involved in off-roadway sideswipe crashes, where the probability of these vehicles being involved in these crashes decrease by 5.44%. At the same time, the likelihood of the vehicle equipped with ADAS being engaged in an off-roadway severe sideswipe crash was decreased by 2.01%. The findings show that both vehicles equipped with ADAS technology and those that are not equipped are less likely to be involved in roadway sideswiping since crashes at off-roadway, for instance, merging and diverging ramp areas depend on the driver's attentiveness to the surroundings by knowing where other vehicles are located before making a maneuver action thus the severity of this crash is not affected by the presence of the technology. During adverse weather conditions, visibility is obscured, preventing drivers from maintaining traction on the tire, and they can slip to the next lane or off the road without notice. The adverse weather conditions affect the road, causing the road to be wet and slippery due to rain or snow. However, the study results show that when the vehicle is equipped with one or more ADAS technologies, the probability of a crash is decreased by 1.57% during adverse weather conditions. In contrast, the likelihood of vehicles not being equipped with ADAS technology increased by 2.86%. Similarly, the probability of a vehicle equipped with ADAS technology being involved in a sideswipe crash with a severe outcome was decreased by 3.29% when there were poor road conditions.

In comparison, the probability of a vehicle not equipped with ADAS technology was increased by 3.19%. The finding shows that ADAS-equipped vehicles are much safer to use for travel during adverse weather conditions because drivers would be alerted that the vehicle is moving out of the lane; thus, drivers can reduce their speed and gain control of the vehicle, hence maneuvering quickly and safely without causing or being involved in a sideswipe crash (Uddin & Huynh, 2020). The finding is counterintuitive because, according to Jumaa et al., (2019), adverse weather, such as heavy rain and snow, interferes with the effectiveness of LKA, which may increase the probability of crashes. However, this study's findings show this is not the case in rural areas. The study's findings are counterintuitive since they indicate that the probability of a vehicle equipped with ADAS technology being involved in a severe sideswipe crash is increased by 8.9%. Jumaa et al., (2019) support this by validating that poor light conditions compromise the effectiveness of ADAS, causing errors in the system that drivers rely on in these conditions. In comparison, the likelihood of vehicles not being equipped with ADAS technology decreased by 1.38% when the light condition was dark. Therefore, the vehicle has been equipped with ADAS technology, which helps reduce severe sideswipe crashes during the night for vehicles in rural areas in Ohio.

The study's findings indicate that the probability of a vehicle equipped with ADAS technology and a vehicle not equipped with ADAS technology increased by 4.53% and 6.21%, respectively, when the vehicle is speeding. Therefore, vehicles equipped with ADAS technology do not help prevent sideswipe crashes caused by speeding cars in Ohio's rural areas. However, equipping the vehicle with ADAS technology decreases the number of speeding vehicles. The findings of the study indicate that the probability of both a vehicle equipped with ADAS technology and a car that was not equipped with ADAS technology was increased by 15.02% and 25.03%, respectively, when the driver is under the influence of either drugs or alcohol. Therefore, vehicles with ADAS technology do not significantly help prevent severe sideswipe crashes for intoxicated drivers. However, if the level of automation increases, these crashes will likely decrease since the driver is required to meet a minimum percentage.

5.2 Influence of ADAS on VRU Protection

LDA topic modeling results

Crash narratives were divided into two groups (vehicles equipped with PAEB and vehicles not equipped with PAEB). These narratives formed a corpus (bag of words) that was analyzed using the LDA topic modeling to obtain relevant and salient topics and terms. The LDA results are based on the two groups of the crash narratives.

Vehicles equipped with PAEB

The left-hand side of Figure 11 shows the Intertopic Distance Map. The topics in the corpus are well-dispersed, indicating a wide range of independent subjects. However, some topics are closely related, as shown by the short intertopic distances, such as between topic 12 and topic 5, and similarly between topic 8 and topic 1. The right-hand side displays the top 30 most salient terms for the overall corpus, ranked based on their relevance. Words such as *"travel", "strike", "pedestrian", "run", "walk", "crosswalk",* and other words on the charts were ranked high as relevant words in the corpus that explained pedestrian crashes involving vehicles equipped with

PAEB. The words provided a general overview of actions and incident points where a crash between a pedestrian and a PAEB-equipped vehicle occurred. However, to obtain a specific interpretation of these corpora, the topics presented in the left side chart were weighted and ranked by level of significance/importance based on the terms contained in the topic.

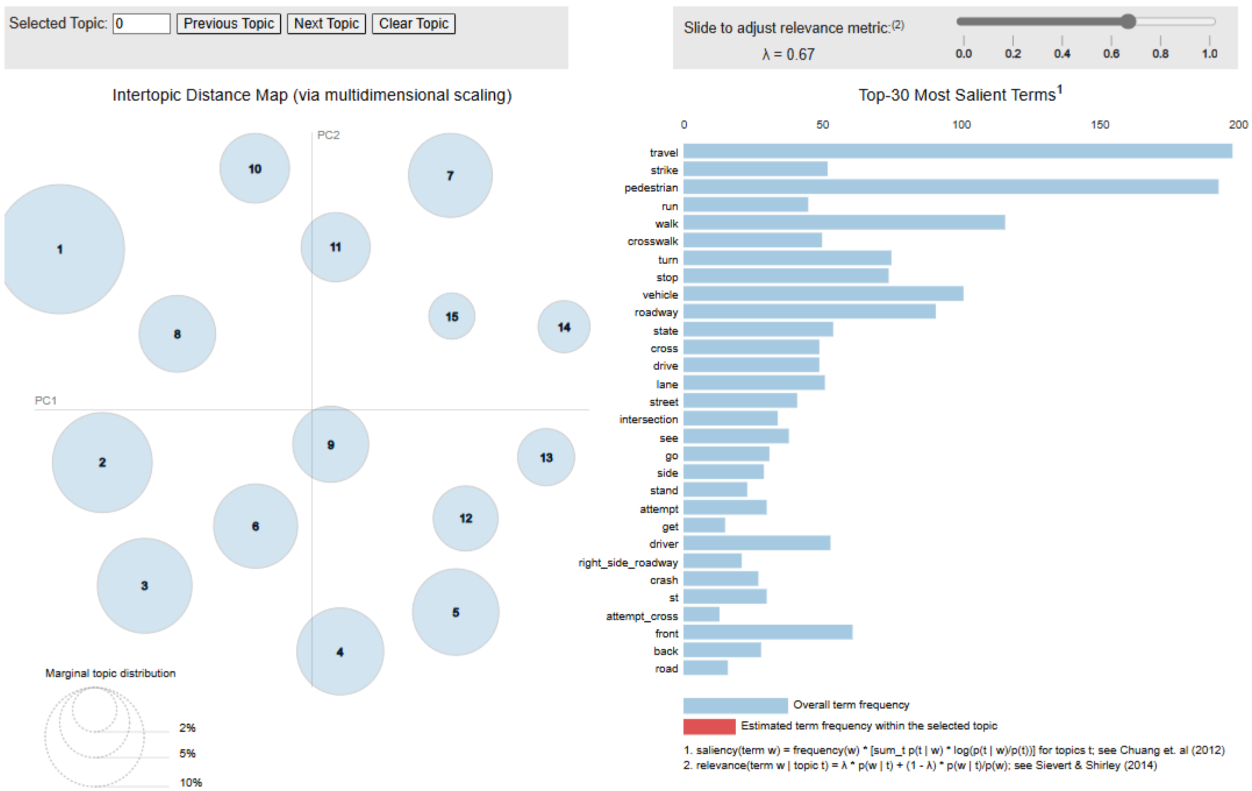

Figure 11: Overall Topics and Relevant Terms for Crashes involving vehicles equipped with PAEB

Words in the topic have different weights in terms of TF-IDF value, causing every topic to carry a unique weight or different value of importance in explaining the corpus of words. Upon analysing the topics that explain the narrative of crashes involving a pedestrian and a vehicle equipped with PAEB. As shown in **Figure 12**, the findings show that topic number 14 carries the highest significance level compared to other topics. Therefore, the words found in this topic can representatively explain the narrative of crashes involving a pedestrian and a vehicle equipped with PAEB.

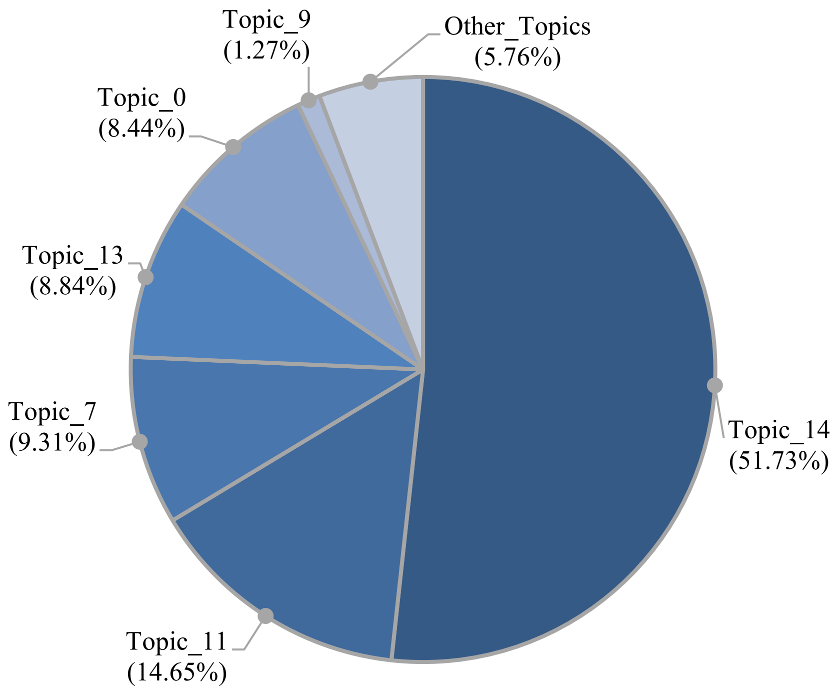

Figure 12: Ranking of the topic's importance

The right-hand side of Figure 13 shows the words contained in topic number 14. Some of the top-ranked relevant words are *"push", "behind", "tree", "leave rear", "ditch", "corner", "drug toxicology",* and other keywords. Most of the top-ranked keywords are observed to be exclusively represented in this topic since the ratio of the estimated term frequency within the selected topic *(represented by the red bar)* to overall term frequency *(represented by the skyblue bar)* is high (*close to 1*). Keywords suggest that most of the crashes involved the action push, and the crashes tend to mostly occur from behind and hit a tree or ditch, and the keywords suggest that victims involved in the crashes undergo drug toxication tests. For instance, one of the crash narratives states *"…Unit 1 drove back onto Township Road 1109 and struck Unit 2 in the rear. Unit 2 was pushed into Unit 3 pedestrian and Unit 4 trailer…",* another narrative states *"…Unit 1 struck Unit 2 rear driver side door; pushing Unit 3 to the ground…"*, from both of these narratives, we observe that the vehicle equipped with the ADAS is parked and then hit by a vehicle in motion initiating motion on the parked vehicle that cause collision (pushing) to the pedestrian standing beside the once parked vehicle. The narrative suggests that the scenario leading to the crash did not activate the PAEB system, as the parked vehicle that struck the pedestrian was not at fault. However, most vehicles are observed to have lost control as suggested in the previous narrative, and the following *"… Unit # 1 traveled onto the right berm and struck unit # 4 and 2 pedestrians standing beside unit # 4. Unit # 1 then lost control; traveled off the right side of the road; and came to final rest…"* and another narrative *"…Unit #2 and Unit #3 were parked on the south berm of eastbound U.S. 30. Unit #4; a pedestrian; was standing on the left side of Unit #2. Unit #1 crossed the solid white edge line of eastbound U.S. 30, sideswiping Unit #2 and striking Unit #4…"*. A driver losing control is an indicator of driving under the influence, causing most of these crashes involving the PAEB vehicle to require a drug toxicology test to confirm whether the driver was influenced by any drug or alcohol.

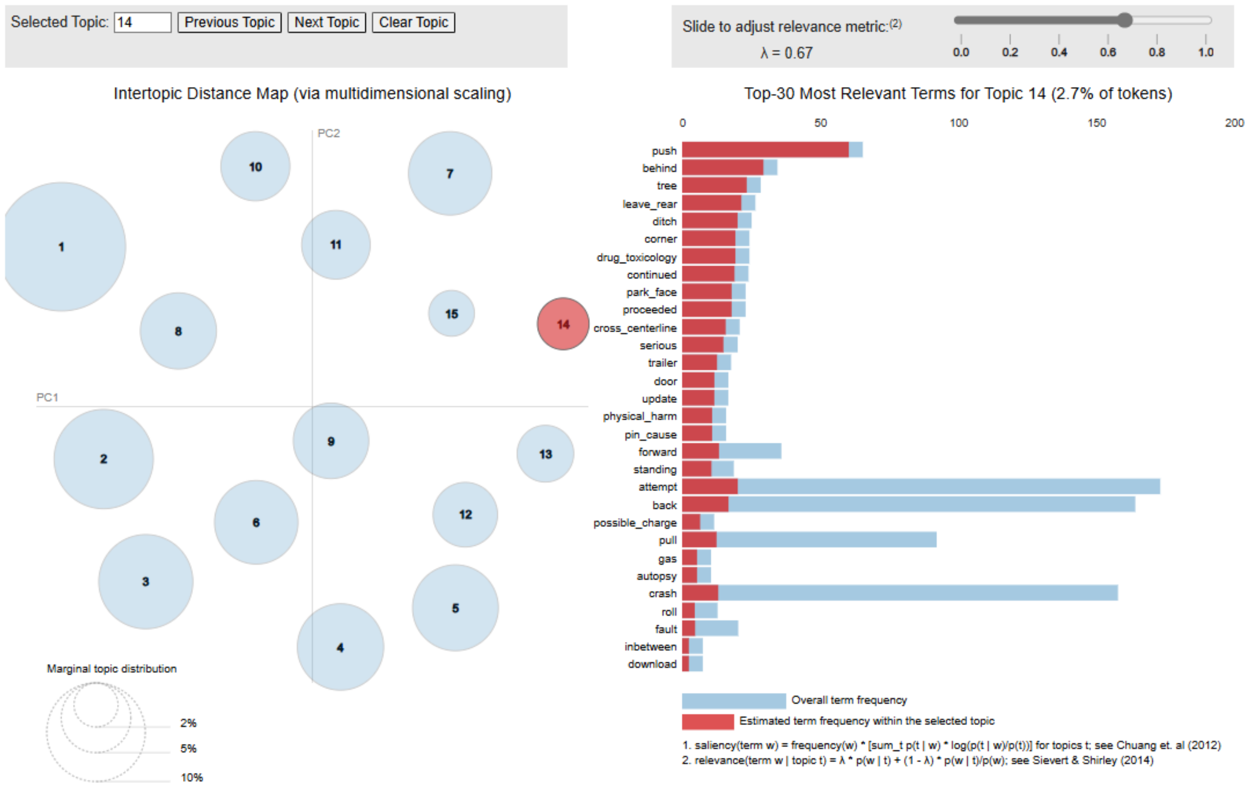

Figure 13: Term frequency and relevant terms for topic_14

The outcomes of these crashes are observed to cause minor injury, or no injury sustained by the pedestrian as suggested by the following narratives *"…unit 1 was assessed by medics and checked fine. Unit 1 was strongly advised to be more careful…"* and another narrative *"…Unit 1 struck the pedestrian causing minor damage to the front of Unit 1 and minor injury to the pedestrian…"*. The finding suggests that more use of the ADAS-equipped vehicle (specifically the PAEB system) can help in the reduction of the crash injury severity sustained by pedestrians in rural areas. These findings are consistent with the previous research (Cicchino, 2022). On the other hand, the literature suggests that PAEB has limitations in the recognition of capabilities, as well as the range of recognition of pedestrians (Tang et al., 2016). These limitations are observed not to be prevailing in rural areas, although the technological upgrading focused on improving the PAEB system should continue to increase the efficiency and effectiveness of the PAEB system. These findings highlight that human behavior (especially driver behavior) has continued to diminish the advantages brought by ADAS in improving safety.

Vehicles not equipped with PAEB.

Following the discussion made on pedestrian crashes involving vehicles equipped with PAEB, Figure 14 summarizes the results of LDA topic modeling for pedestrian crashes involving vehicles not equipped with the PAEB system. Similar to the representation observed in the figures presented while explaining vehicles equipped with PAEB. From Figure 14, we observe that topic 1 is closely related to topic 6. Similarly, topic 14 is closely related to topic 15. On the chart on the right side of Figure 14, it is observed that words such as *"travel", "roadway", "strike", "walk", "turn", "pedestrian",* and other words on the charts were ranked high as relevant words in the corpus that explained pedestrian crashes involving vehicles not equipped with PAEB. The words provide a general overview of actions and incident points where a crash between a pedestrian and a vehicle not equipped with PAEB can occur. However, to obtain a specific interpretation of these corpora, the topics presented in the left side chart were weighted and ranked by level of significance/importance based on the terms contained in the topic. Words in the topic have different weights in terms of *tf-idf* value, causing every topic to carry a unique weight or a different value of importance in explaining the corpus of words. Upon analysing the topics that explain the narrative of crashes involving a pedestrian and a vehicle not equipped with PAEB topics were ranked in level of significance.

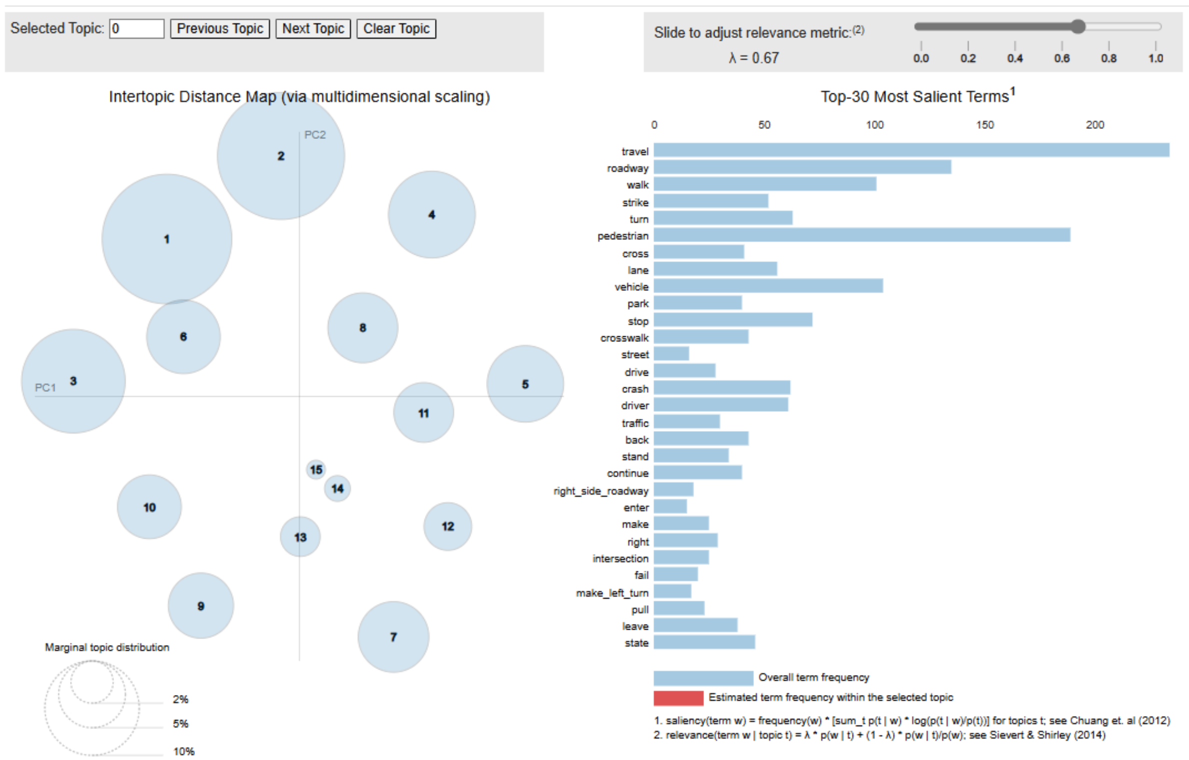

Figure 14: Overall topics and Relevant Terms for Crashes involving vehicles not equipped with PAEB

As shown in Figure 15, the findings show that topic number 9 carries the highest significance level compared to other topics. Therefore, the words found in this topic can representatively explain the narrative of crashes involving a pedestrian and a vehicle not equipped with PAEB.

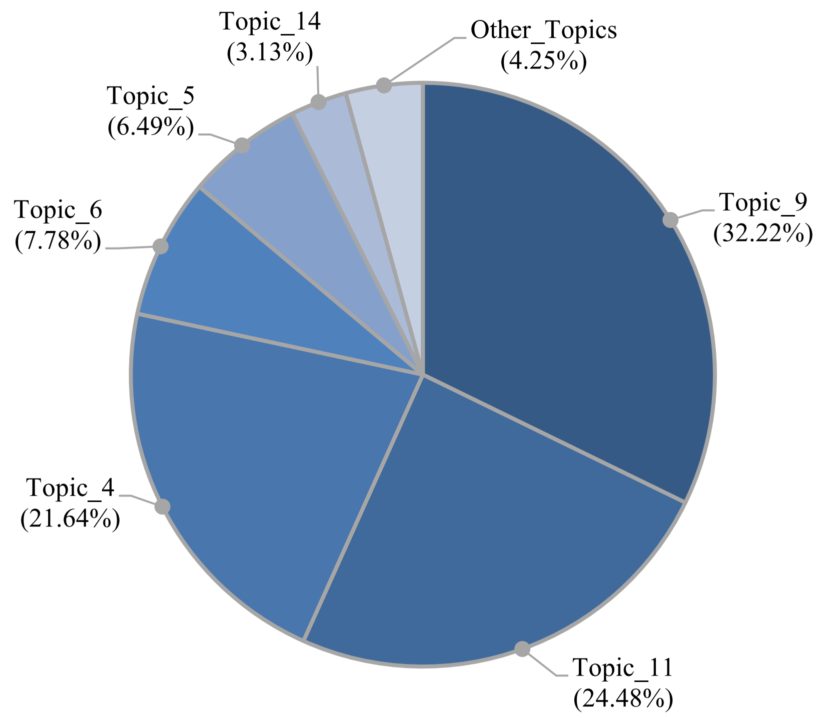

Figure 15: Ranking of the topic's importance

The chart on the right side of Figure 16 shows the words contained in topic number 9. Some of the top-ranked relevant words are *"cross", "enter", "make_left_turn", "begin", "crosswalks", "fail_yield", "crossing",* and other keywords. Most of the top ranked keywords are observed to be exclusively represented in this topic since the ratio of the estimated term frequency within the selected topic *(represented by the red bar)* to overall term frequency *(represented by the skyblue bar)* is high although their top rank words such as *"cross"* and *"crosswalks"* appear to widespread into different topic since the ratio of the estimated term frequency within the selected topic *(represented by the red bar)* to overall term frequency *(represented by the skyblue bar)* is observed to be low. Keywords suggest that most of the crashes involved pedestrian crossing using the crosswalks and the vehicle drivers failing to yield to pedestrians, especially when making turning movements. For instance, one of the crash narratives states *"…Unit 1 made a left turn onto League Street and failed to yield to Units 2 and 3 in the crosswalk; striking both of them.…", "…Unit #2 was found at fault and issued a citation for fail to yield to a pedestrian in a crosswalk…",* another narrative states *"…Unit 2 was traveling west on Walnut Street failing to yield striking the pedestrian. Unit 2 was found at fault in the crash…"*, from these narratives, we observe that the vehicles not equipped with the PAEB system were not capable of detecting from a distance the pedestrian who was interacting with the roadway leading to the vehicle (motorists) failing to yield on time before striking a pedestrian. Another observation shows that most of the pedestrian crashes involving vehicles not equipped with the PAEB system occur mostly in the intersection areas as suggested in the following narrative *"… unit # 2 entered the intersection continuing south across watt st. unit #1 made a right hand turn onto watt st striking unit #2 causing injuries…", "Unit 2 proceeded through the intersection of Dewey Ave and Wheeling Ave; heading eastbound; when struck crossing Unit 1…"* and another narrative *"…As Unit #2 approached the intersection; under a green light; Unit #1 ran into the traffic lane; out of the crosswalk; and was struck by unit #2…"*. The PAEB system helps drivers to brake abruptly when a pedestrian is unexpectedly detected on the roadway. Therefore, vehicles that are not equipped with PAEB were not able to detect and prevent these types of crashes hence resulting in pedestrian crashes.

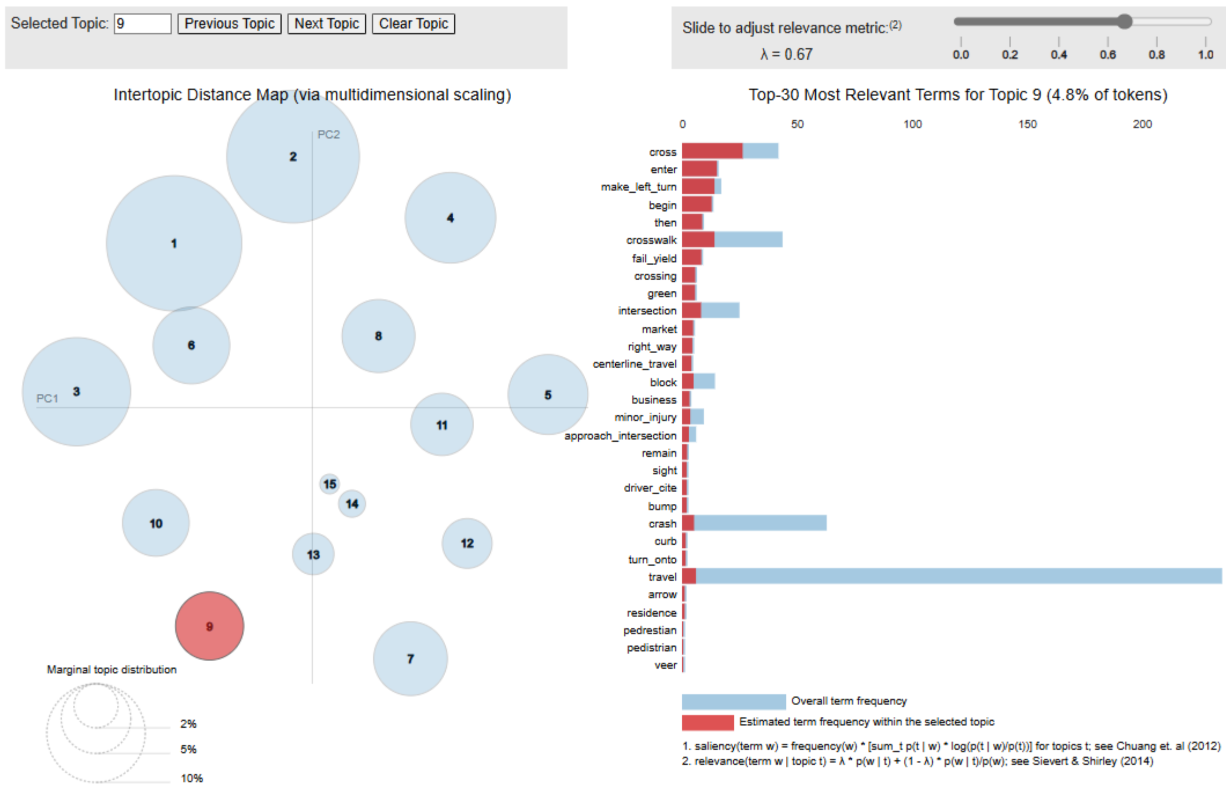

Figure 16: Term frequency and relevant terms for topic_9

The outcomes of these crashes are observed to cause fatal and serious injuries to the pedestrian involved as suggested by the following narratives *"…This is completed to indicate the crash has resulted in fatal injuries to Unit #4.…"*, *"The pedestrian suffered serious injuries as a result of the crash and was transported to the Fisher-Titus Medical Center by North Central EMS and later flown by LifeFlight to University of Toledo Medical Center…"* and another narrative *"…Unit 2 received injuries to her head and leg…"*. The finding suggests that vehicles that are not equipped with the PAEB system increase the vulnerability of pedestrians in the roadway. This is consistent with previous research conducted by Gajera et al., (2023). Although the LDA results have substantiated that vehicles equipped with the PAEB system led to low-severity injuries to the pedestrian. In the next section, we present the results of the Bayesian network analysis to understand variables associated with the probability of incapacitating or non-incapacitating injuries.

Bayesian Network Results

Figure 17 and Figure 18 are Bayesian Networks for the trained and optimal network, respectively, which aim to identify the variation in the injury severity level for pedestrians involved in vehicle-pedestrian crashes. The analysis is focused on the ADAS technology equipped in the vehicle, specifically the PAEB.

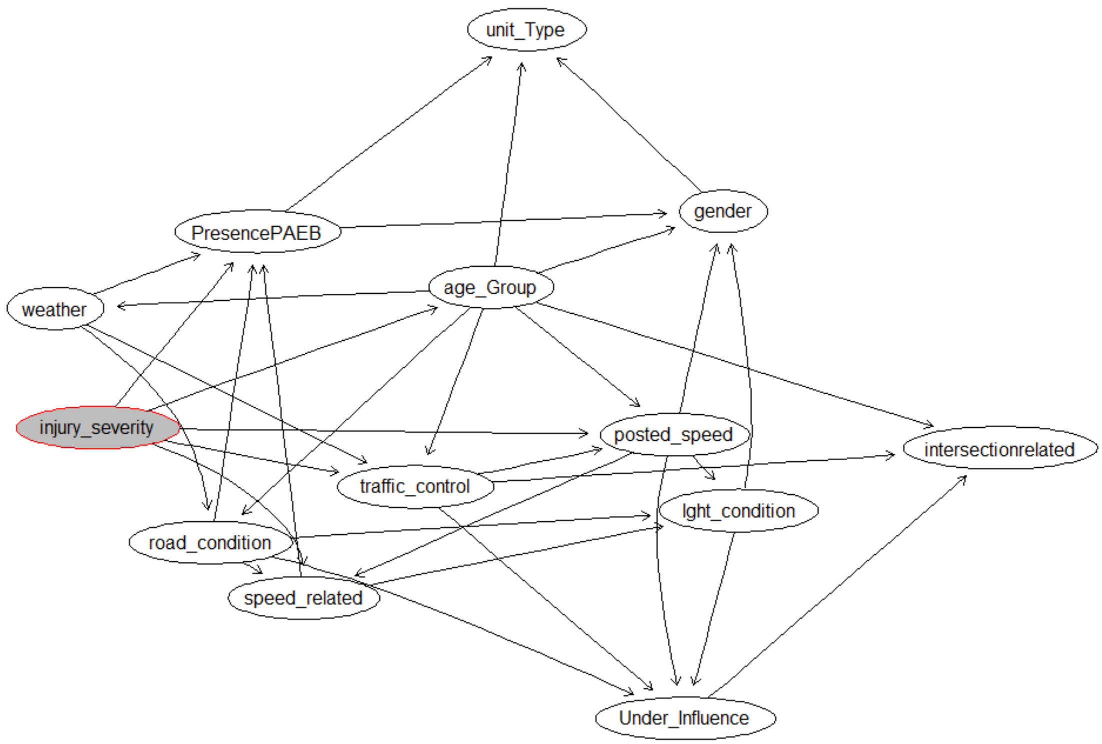

Figure 17: Trained a network for the pedestrian crashes

The response variable is the injury severity, which has three categories: no injury, non-incapacitating injuries, and incapacitating injuries. The BN structure was selected as the trained network (Figure 17) assessed in this study was characterized by having the lowest value of the score function. Thus, the initially trained network of pedestrian crashes, as shown in Figure 17**,** is obtained from the AIC search algorithm scoring function. The interconnection shown by the arcs in Figure 17 between the variables (both explanatory and response variables) shows the influence of one variable on another. Nevertheless, when there is no connection between the variables, there is an implication that there is insufficient information within the data to initiate or define the interdependency between these variables. However, it should be considered that the scoring algorithm initiated by the interdependency observed in Figure 17 reflects the scenarios learned from the data and does not imply the actual scenarios. Therefore, expert knowledge and the findings from previous studies are used to redefine the interconnection between the variables to obtain an optimal BN structure that has logical connections aligned with the study objective and can be formed, as shown in Figure 18.

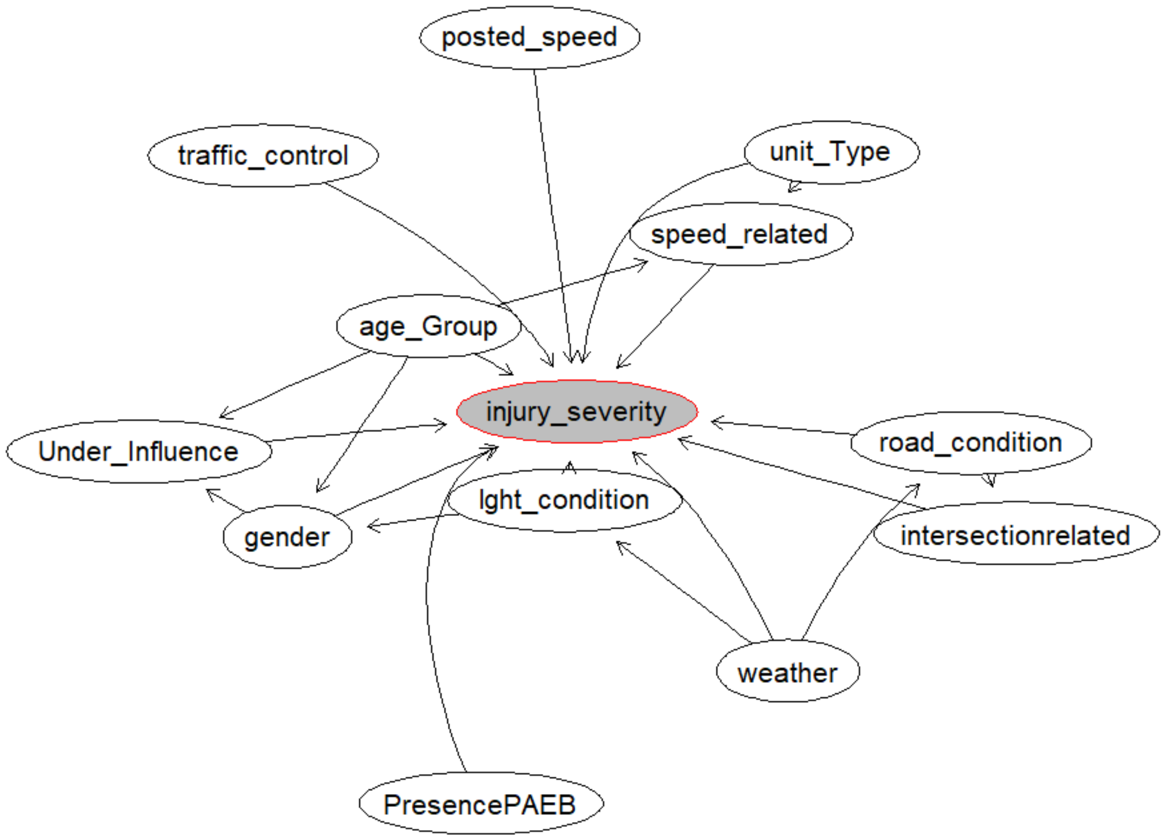

Figure 18: Optimal network for pedestrian crashes

The connections shown in Figure 18 are constructed by reversing, setting, and deleting the arc relations defined through data training. The optimal network shows that the response variable, injury severity is a child variable for 12 explanatory variables, which are weather, lighting conditions, Presence of PAEB in the vehicle, the age group for the driver, vehicle type, driving under the influence, gender, speeding related, posted speed limit, road conditions, location of the collision, and lastly traffic control involved. Figure 18 shows the direct and indirect interdependencies evaluated to obtain the predicted probabilities of the hypothesis variables. These probabilities highlight the estimation of the effects of individual evidence on the likelihood that a pedestrian can either sustain non-incapacitating or incapacitating injuries when involved in a crash with a vehicle. A sensitivity analysis involving all the hypothesis variables was conducted.

The study includes both individual evidence and combined evidence analysis. An individual evidence analysis analyzed the likelihood that a pedestrian can either sustain non-incapacitating or incapacitating injuries using individual variable evidence. Combination analysis examined the likelihood of a vehicle not equipped with PAEB technology being involved in a crash and further assessed the likelihood of the pedestrian either sustaining non-incapacitating or incapacitating injuries concerning the hypothesis variables. The results of the individual evidence analysis are shown in Table 10. Also, the results of the combination analysis are presented in Table 11.

Individual Evidence Analysis for Hypothesis Variables

Model results presented in Table 10 are obtained by considering injury severity as the targeted variable for prediction. Interpretation performed for this model is based on the predicted probability and the sensitivity analysis results. The analysis and interpretation focused on responding to the research question: *what level of injury severity is a pedestrian likely to sustain when involved in a crash with a PAEB-equipped vehicle?* The reference category used in Table 10 was selected based on the criteria that it has the least likelihood of occurring or leading to less severe outcomes.

Table 10: Predicted Probability and Sensitivity Analysis Scores

Variable/Category	Non-Incapacitating Injury		Incapacitating Injury	
	Predict Probability	Overall Sensitivity Score	Predict Probability	Overall Sensitivity Score
Age Group				
Under 25	44.27%		34.27%	
25 - 64	37.32%	-6.95%	40.30%	6.03%
65+	29.30%	-14.97%	57.83%	23.55%
Gender				
Male	37.20%		42.06%	
Female	41.86%	4.66%	36.77%	-5.29%
Unit Type				
Passenger cars	35.70%		44.86%	
Non-passenger cars	40.67%	4.97%	37.25%	-7.61%
Posted Speed Limit				
< 35 mph	44.43%		24.63%	
35 - 45 mph	44.46%	0.04%	42.26%	17.63%
> 45 mph	29.13%	-15.30%	59.45%	34.82%
Traffic Control				
Yes	59.24%		12.00%	
No	35.41%	-23.83%	44.72%	32.73%
Intersection Related				
No	38.35%		41.35%	
Yes	39.38%	1.04%	36.28%	-5.08%
Weather				
Clear	38.44%		41.39%	
Adverse condition	39.13%	0.69%	35.46%	-5.92%
Road Condition				
Dry	38.37%		40.98%	
Wet/Snow/Ice	40.70%	2.33%	35.10%	-5.88%
Light Condition				
Daylight	39.88%		37.89%	
Dark	36.42%	-3.47%	44.31%	6.42%
Speed Related				
No	38.89%		39.65%	
Yes	23.72%	-15.16%	72.34%	32.69%
Under Influence				
No	38.80%		40.19%	

Variable/Category	Non-Incapacitating Injury		Incapacitating Injury	
	Predict Probability	Overall Sensitivity Score	Predict Probability	Overall Sensitivity Score
Yes	29.45%	-9.35%	53.62%	13.43%
Presence PAEB				
Equipped	42.82%		32.03%	
Not Equipped	34.63%	-8.19%	48.38%	16.34%

The findings of individual evidence analysis are based on analyzing the pedestrian crash dataset. As shown in Table 10, there was a 4.97% increase in the probability of the non-passenger car causing non-incapacitating injuries to a pedestrian, while there was a 7.61% decrease in the probability of the same unit type causing incapacitating injuries to pedestrians compared to the passenger cars. On roads with a posted speed limit of more than 35 mph, pedestrians have a higher probability of enduring incapacitating injuries. For instance, the likelihood of a pedestrian sustaining an incapacitating injury is increased by 17.63% when involved in a crash with a vehicle while traversing roads with posted speed limits ranging between 35mph and 45mph. Furthermore, the probability was increased by 34.82% while traversing a road with a posted speed limit greater than 45 mph. Consistently, the likelihood of the pedestrian sustaining an incapacitating injury increased by 32.69% while the likelihood of the pedestrian sustaining a non-incapacitating injury decreased by 15.16% when the vehicle involved was speeding. Furthermore, the likelihood of a pedestrian sustaining an incapacitating injury is increased by 32.73% when a crash occurs on roads without traffic control. However, the result indicates that pedestrians are more likely to sustain a non-incapacitating injury (likelihood is increased by 1.04%) than an incapacitating injury when the crash is intersection-related.

The results suggest that the probability of pedestrians sustaining non-incapacitating injury during dark conditions is decreased by 3.47% but the probability of sustaining incapacitating injuries increases by 6.42% during dark conditions. Jumaa et al., (2019) found that the performance of ADAS technology is hindered by darkness. Also, the results indicate that a pedestrian is more likely to sustain an incapacitating injury (likelihood is increased by 13.43%) than to sustain a non-incapacitating injury (likelihood is decreased by 9.35%) when the driver is under the influence of alcohol or drugs; thus, it is difficult to maintain road stability and concentration during driving (Alonso et al., 2015).

The results indicate that pedestrians aged greater than 25 years are more likely to sustain an incapacitating injury than a non-incapacitating injury when involved in a crash. The results show that the probability of adult pedestrians (aged between 25 and 64 years old) sustaining an incapacitating injury is increased by 6.03% and for senior pedestrians (aged 65 years and older), the likelihood of sustaining an incapacitating injury is increased by 23.55%. In comparison, the likelihood of adults (aged between 25 and 64 years old) and senior pedestrians (aged 65 years) sustaining non-incapacitating injury when involved in vehicle-pedestrian crashes decreased by 6.95% and 14.97% respectively. Furthermore, the result indicates that the probability of female pedestrians sustaining a non-incapacitating injury is increased by 4.66% while the likelihood of the same gender pedestrians sustaining an incapacitating injury is decreased by 5.29% compared to male pedestrians when involved in a vehicle-pedestrian crash. The findings from the analysis indicate that vehicles not equipped with the PAEB technology are more likely to cause incapacitating injuries to a pedestrian (likelihood increased by 16.34%) than to cause non-incapacitating injuries (likelihood is lowered by 8.19%). The results imply that vehicles that are not equipped with PAEB technology are mostly involved in crashes that have fatal or serious injury outcomes for the pedestrian.

However, when considering the influence of weather implying the presence of adverse weather conditions that directly led to having wet, snowy, or ice road conditions, the probability of a pedestrian sustaining an incapacitating injury is decreased by 5.92% while the likelihood of the pedestrian to sustain a non-incapacitating injury is increased by 0.69% during adverse weather conditions compared to the clear weather conditions. This suggests that during adverse weather conditions, there are few pedestrians, and most vehicles travel at low speed, thus causing the outcome of the crashes to be less severe. Finally, the results indicate that a driver under the influence of either drug or alcohol is more likely to be involved in a crash that inflicts incapacitating injuries on a pedestrian (likelihood is increased by 13.43%) than a crash that inflicts non-incapacitating injuries (likelihood is decreased by 9.35%).

Combination Analysis for the Hypothesis Variables

Table 11 presents the predicted probabilities and associated sensitivity scores for the various combinations of variables. Based on the results in **Table 11**, each hypothesis variable displayed a trend when vehicle technology (specifically PAEB technology) was kept as evidence for the combination analysis. The results of the combination analysis show that pedestrians aged 25 years old and older are likely to endure an incapacitating injury when involved in a crash with a vehicle that is not a PAEB-equipped vehicle. The results show that there is an increase of 0.97% likelihood for pedestrians aged between 25 and 64 years old, and there is an increase of 23.76% for pedestrians aged above 65 years old to endure an incapacitating injury when a vehicle.

Table 11: Predicted Probabilities and Sensitivity Score for the Combined Evidence Analysis

Variable	Category	Non-Incapacitating Injury			Incapacitating Injury		
		Predict Probability	Sensitivity Scores PAEB Equipped	Sensitivity Scores No PAEB Equipped	Predict Probability	Sensitivity Scores PAEB Equipped	Sensitivity Scores No PAEB Equipped
Age Group							
PAEB Equipped	Under 25	49.04%			22.03%		
	25 - 64	39.45%	-9.59%		34.06%	12.04%	
	65+	43.59%	-5.45%		44.96%	-4.08%	
No PAEB Equipped	Under 25	40.40%			44.92%		
	25 - 64	35.34%		-5.07%	45.89%		0.97%
	65+	16.59%		-23.81%	68.68%		23.76%
Gender							
PAEB Equipped	Male	41.17%			33.52%		
	Female	47.59%	6.42%		27.27%	-13.90%	
No PAEB Equipped	Male	33.20%			49.79%		
	Female	37.80%		4.61%	44.22%		-5.57%
Unit Type							
PAEB Equipped	PC**	44.48%			32.09%		
	NPC*	41.11%	-3.36%		31.58%	-12.90%	
No PAEB Equipped	PC**	27.86%			56.25%		
	NPC*	39.72%		11.86%	41.72%		-14.53%
Posted Speed Limit							
	< 35 mph	48.64%			16.41%		

Variable	Category	Non-Incapacitating Injury			Incapacitating Injury		
		Predict Probability	Sensitivity Scores		Predict Probability	Sensitivity Scores	
			PAEB Equipped	No PAEB Equipped		PAEB Equipped	No PAEB Equipped
PAEB Equipped	35 - 45 mph	56.67%	8.04%		29.18%	-19.46%	
	> 45 mph	31.19%	-17.45%		53.25%	4.61%	
No PAEB Equipped	< 35 mph	41.19%			32.54%		
	35 - 45 mph	35.04%		-6.15%	53.10%		20.56%
	> 45 mph	27.34%		-13.85%	64.30%		31.76%
Traffic Control							
PAEB Equipped	Yes	61.11%			7.81%		
	No	39.78%	-21.33%		35.94%	-25.17%	
No PAEB Equipped	Yes	57.52%			17.26%		
	No	31.77%		-25.76%	51.89%		34.62%
Intersection Related							
PAEB Equipped	No	43.25%			32.34%		
	Yes	40.36%	-2.89%		23.63%	-19.62%	
No PAEB Equipped	No	33.74%			49.03%		
	Yes	38.18%		4.43%	44.96%		-4.07%
Weather							
PAEB Equipped	Clear	43.75%			31.51%		
	Adverse condition	39.40%	-4.35%		33.44%	-10.31%	
No PAEB Equipped	Clear	33.66%			50.73%		
	Adverse condition	38.37%		4.71%	37.15%		-13.58%
Road Condition							
PAEB Equipped	Dry	42.79%			31.53%		
	Wet/Snow/Ice	44.43%	1.65%		31.67%	-11.11%	
No PAEB Equipped	Dry	33.99%			49.58%		
	Wet/Snow/Ice	39.13%		5.14%	36.60%		-12.98%
Light Condition							
PAEB Equipped	Daylight	44.71%			26.25%		
	Dark	40.32%	-4.39%		39.58%	-5.12%	
No PAEB Equipped	Daylight	35.75%			47.99%		
	Dark	32.61%		-3.14%	48.70%		0.71%
Speed Related							
PAEB Equipped	No	43.39%			30.53%		
	Yes	26.74%	-16.64%		71.08%	27.69%	
No PAEB Equipped	No	34.74%			47.99%		
	Yes	18.67%		-16.07%	76.74%		28.75%
Under Influence							
PAEB Equipped	No	43.08%			31.03%		
	Yes	40.08%	-3.00%		50.85%	7.77%	
No PAEB Equipped	No	35.05%			47.99%		
	Yes	17.53%		-17.52%	54.42%		6.43%
NOTE: * non-passenger cars;**Passenger cars							

The results indicate that vehicles with no PAEB technology are more likely to inflict incapacitating injuries on pedestrians when crashes occur in roadways with a posted speed limit greater than 35 mph. The results indicate that the likelihood of pedestrians sustaining incapacitating injuries when struck by a vehicle that is not equipped with PAEB technology increased by 20.56% and 31.76% for roadways with posted speed limits of 35-45 mph and greater than 45 mph, respectively. On the other hand, the likelihood of pedestrians sustaining incapacitating injuries when struck by a vehicle equipped with PAEB technology is decreased by 19.46% for roadways with posted speed limits ranging between 35 and 45 mph. The findings suggest that pedestrians are more likely to sustain incapacitating injuries (likelihood increased by 34.62%) when struck by a vehicle not equipped with PAEB technology in an area that has no traffic control. However, the likelihood of sustaining incapacitating injuries is lowered (likelihood decreased by 25.17%) when the pedestrian is struck vehicle equipped with PAEB.

The study's findings indicate that regardless of vehicle is equipped or not equipped with PAEB technology, the likelihood of the pedestrian sustaining incapacitating injuries is increased when the vehicle is speeding. The likelihood of pedestrians sustaining incapacitating injuries is increased by 27.69% when struck by a vehicle equipped with PAEB. Furthermore, the likelihood of the pedestrian sustaining incapacitating injuries is increased by 28.75% for vehicles not equipped with PAEB. Similarly to pedestrian crashes that involve a speeding vehicle, the study's findings indicate that regardless of vehicle is equipped or not equipped with PAEB technology, the likelihood of the pedestrian sustaining incapacitating injuries is increased when the driver is under the influence of either drugs or alcohol. The likelihood of pedestrians sustaining incapacitating injuries increased by 7.77% when a driver under the influence (drugs or alcohol) was using a vehicle equipped with PAEB. Furthermore, the likelihood of the pedestrian sustaining incapacitating injuries increased by 6.43% when the driver under the influence (drugs or alcohol) was using a vehicle not equipped with PAEB.

6 CONCLUSION

The research project focused on road safety in rural areas, exploring challenges that contribute to high fatality rates in these areas. The research project employed different state-of-the-art methodologies that assisted in examining pedestrian, rear-end, and sideswipe crashes involving conventional (non-ADAS-equipped) vehicles and those with ADAS technology, utilizing crash data from forty-nine rural counties in Ohio from 2017 to 2023. One of the methodologies implemented was a probabilistic graphical modeling approach that assessed the likelihood of severe crash involvement for ADAS-equipped vehicles, considering factors such as driver demographics, ADAS operation mode, automation level, traffic control, road and weather conditions, speeding, and driving under the influence. The findings offer valuable insights into the role of ADAS in enhancing road safety. For instance, in rear-end crashes, the results indicate that when an ADAS-equipped vehicle is at fault, the probability of a severe crash outcome is lower than with conventional vehicles. Moreover, operating vehicles under ADAS mode significantly reduces the likelihood of rear-end collisions, particularly in adverse weather conditions, where ADAS systems assist drivers by detecting surrounding conditions and activating braking systems to prevent severe crashes. However, ADAS does not mitigate the risk of severe crashes caused by speeding or driving under the influence of highlighting the continued need for strict enforcement of traffic laws. Additionally, the study found that effective traffic control reduces the likelihood of severe rear-end crashes in rural areas, regardless of ADAS engagement.

Similarly, for sideswipe crashes, the analysis revealed that ADAS-equipped vehicles are less likely to be at fault, reinforcing the technology's potential to improve road safety. The data also highlighted a lower prevalence of ADAS-equipped vehicles in rural areas, emphasizing the need for broader adoption of these technologies. Vehicles with operational ADAS systems or automation levels greater than one exhibited a significantly lower probability of severe crash outcomes. However, like in rear-end crashes, ADAS technology did not reduce crash severity when drivers were intoxicated or speeding, further stressing the importance of robust enforcement measures, such as speed regulations and DUI laws. In addition to vehicle-related crashes, this study also explored the effectiveness of PAEB systems in reducing pedestrian fatalities in rural areas. Using Topic Modeling and Bayesian Network Analysis, the findings indicate that vehicles equipped with PAEB were involved in fewer severe crashes, with most resulting in minor or no injuries to pedestrians. In contrast, vehicles lacking PAEB were frequently involved in high-severity crashes, especially at intersections where failure to yield was a common contributing factor. These results highlight the potential of PAEB technology in improving pedestrian safety in rural areas. However, the effectiveness of ADAS can be undermined by poor driver behavior, reinforcing the need for awareness campaigns and policy initiatives to complement technological advancements.

Overall, this study underscores the importance of promoting ADAS-equipped vehicles in rural areas to reduce crash severity and improve road safety. However, a key limitation lies in the assumption that each crash outcome was independent. Additionally, the study lacked detailed information on the specific ADAS technology operating at the time of each crash. Future research should explore crash dynamics involving multiple vehicles and investigate driver behavior in relation to PAEB and other ADAS technologies. Developing predictive models based on these insights could further enhance the strategic deployment of ADAS in high-risk areas, ultimately improving road safety outcomes.

7 REFERENCES

Abdel-Aty, M., Cai, Q., Wu, Y., & Zheng, O. (2022). Evaluation of automated emergency braking system's avoidance of pedestrian crashes at intersections under occluded conditions within a virtual simulator. *Accident Analysis and Prevention*, *176*. https://doi.org/10.1016/j.aap.2022.106797

Ackermann, C., Isermann, R., Min, S., & Kim, C. (2014). *Collision avoidance with automatic braking and swerving*.

Ali, Y., Bliemer, M. C. J., Zheng, Z., & Haque, M. M. (2020). Comparing the usefulness of real-time driving aids in a connected environment during mandatory and discretionary lane-changing manoeuvres. *Transportation Research Part C: Emerging Technologies*, *121*. https://doi.org/10.1016/j.trc.2020.102871

Alonso, F., Pastor, J. C., Montoro, L., & Esteban, C. (2015). Driving under the influence of alcohol: Frequency, reasons, perceived risk and punishment. *Substance Abuse: Treatment, Prevention, and Policy*, *10*(1). https://doi.org/10.1186/s13011-015-0007-4

Bärgman, J., & Victor, T. (2020). Holistic assessment of driver assistance systems: how can systems be assessed with respect to how they impact glance behaviour and collision avoidance? *IET Intelligent Transport Systems*, *14*(9), 1058–1067. https://doi.org/10.1049/iet-its.2018.5550

Bato, J. A., & Boyle, L. N. (2011). Adaptive cruise control: User differences in urban and rural environments. *Proceedings of the Human Factors and Ergonomics Society*, 1943–1947. https://doi.org/10.1177/1071181311551405

Bella, F., Natale, V., & Silvestri, M. (2017). Driver-pedestrian interaction under different road environments. *Transportation Research Procedia*, *27*, 148–155. https://doi.org/10.1016/j.trpro.2017.12.093

Birrell, S. A., & Young, M. S. (2011). The impact of smart driving aids on driving performance and driver distraction. *Transportation Research Part F: Traffic Psychology and Behaviour*, *14*(6), 484–493. https://doi.org/10.1016/j.trf.2011.08.004

Broggi, A., Cerri, P., Ghidoni, S., Grisleri, P., & Jung, H. G. (2009). A new approach to urban pedestrian detection for automatic braking. *IEEE Transactions on Intelligent Transportation Systems*, *10*(4), 594–605. https://doi.org/10.1109/TITS.2009.2032770

Chen, F., Song, M., & Ma, X. (2019). Investigation on the injury severity of drivers in rear-end collisions between cars using a random parameters bivariate ordered probit model. *International Journal of Environmental Research and Public Health*, *16*(14). https://doi.org/10.3390/ijerph16142632

Chen, H. Y., Ivers, R. Q., Martiniuk, A. L. C., Boufous, S., Senserrick, T., Woodward, M., Stevenson, M., Williamson, A., & Norton, R. (2009). Risk and type of crash among young drivers by rurality of residence: Findings from the DRIVE Study. *Accident Analysis and Prevention*, *41*(4), 676–682. https://doi.org/10.1016/j.aap.2009.03.005

Chengula, T. J., Kutela, B., Novat, N., Shita, H., Kinero, A., Tamakloe, R., & Kasomi, S. (2024). Spatial instability of crash prediction models: A case of scooter crashes. *Machine Learning with Applications*, *17*, 100574. https://doi.org/10.1016/j.mlwa.2024.100574

Cicchino, J. B. (2017). Effectiveness of forward collision warning and autonomous emergency braking systems in reducing front-to-rear crash rates. *Accident Analysis and Prevention*, *99*, 142–152. https://doi.org/10.1016/j.aap.2016.11.009

Cicchino, J. B. (2018). Effects of lane departure warning on police-reported crash rates. *Journal of Safety Research*, *66*, 61–70. https://doi.org/10.1016/j.jsr.2018.05.006

Cicchino, J. B. (2019). Real-world effects of rear automatic braking and other backing assistance systems. *Journal of Safety Research*, *68*, 41–47. https://doi.org/10.1016/j.jsr.2018.12.005

Cicchino, J. B. (2022). Effects of automatic emergency braking systems on pedestrian crash risk. *Accident Analysis and Prevention*, *172*. https://doi.org/10.1016/j.aap.2022.106686

Clark, D. E., & Cushing, B. M. (2004). Rural and urban traffic fatalities, vehicle miles, and population density. *Accident Analysis and Prevention*, *36*(6), 967–972. https://doi.org/10.1016/j.aap.2003.10.006

Coelingh, E., Eidehall, A., & Bengtsson, M. (2010). Collision warning with full auto brake and pedestrian detection - A practical example of automatic emergency braking. *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, 155–160. https://doi.org/10.1109/ITSC.2010.5625077

Dabbour, E., Dabbour, O., & Martinez, A. A. (2020). Temporal stability of the factors related to the severity of drivers' injuries in rear-end collisions. *Accident Analysis and Prevention*, *142*. https://doi.org/10.1016/j.aap.2020.105562

Demiroluk, S., & Ozbay, K. (2014). Adaptive Learning in Bayesian Networks for Incident Duration Prediction. *Transportation Research Record: Journal of the Transportation Research Board*, *2460*(1), 77–85. https://doi.org/10.3141/2460-09

Dianin, A., Ravazzoli, E., & Hauger, G. (2021). Implications of autonomous vehicles for accessibility and transport equity: A framework based on literature. In *Sustainability (Switzerland)* (Vol. 13, Issue 8). MDPI. https://doi.org/10.3390/su13084448

Elsasser, D., Kamel Salaani, M., Boday, C., & Research Center, T. (2019). *Test Track Procedures for Heavy-Vehicle Forward Collision Warning and Automatic Emergency Braking Systems*. www.ntis.gov

Fatima, S., Hsiu Lee, C., & Dannenberg, A. L. (2024). Equity issues associated with the widespread implementation of autonomous vehicles. *Oxford Open Infrastructure and Health*, *2*. https://doi.org/10.1093/ooih/ouae002

Fildes, B., Keall, M., Bos, N., Lie, A., Page, Y., Pastor, C., Pennisi, L., Rizzi, M., Thomas, P., & Tingvall, C. (2015). Effectiveness of low speed autonomous emergency braking in real-world rear-end crashes. *Accident Analysis and Prevention*, *81*, 24–29. https://doi.org/10.1016/j.aap.2015.03.029

Fildes, Brian., Rumbold, G., Leening, A., Fildes, B. N., Roads Corporation (Vic.), & Monash University. Accident Research Centre. (1991). *Speed behaviour and drivers' attitude to speeding*. Monash University Accident Research Centre.

Fleiter, J. J., Lennon, A., & Watson, B. (2010). How do other people influence your driving speed? Exploring the "who" and the "how" of social influences on speeding from a qualitative perspective. *Transportation Research Part F: Traffic Psychology and Behaviour*, *13*(1), 49–62. https://doi.org/10.1016/j.trf.2009.10.002

Gajera, H., Pulugurtha, S. S., Mathew, S., & Bhure, C. M. (2023). Synthesizing fatal crashes involving partially automated vehicles and comparing with fatal crashes involving non-automated vehicles. *Transportation Engineering*, *12*. https://doi.org/10.1016/j.treng.2023.100178

Giovannini, F., Savino, G., Pierini, M., & Baldanzini, N. (2013). Analysis of the minimum swerving distance for the development of a motorcycle autonomous braking system. *Accident Analysis and Prevention*, *59*, 170–184. https://doi.org/10.1016/j.aap.2013.05.020

Gouribhatla, R., & Pulugurtha, S. S. (2022). Drivers' behavior when driving vehicles with or without advanced driver assistance systems: A driver simulator-based study. *Transportation Research Interdisciplinary Perspectives*, *13*. https://doi.org/10.1016/j.trip.2022.100545

Guo, J., Wang, Y., Yin, X., Liu, P., Hou, Z., & Zhao, D. (2022). Study on the Control Algorithm of Automatic Emergency Braking System (AEBS) for Commercial Vehicle Based on Identification of Driving Condition. *Machines*, *10*(10). https://doi.org/10.3390/machines10100895

Hang, J., Yan, X., Li, X., & Duan, K. (2022). In-vehicle warnings for work zone and related rear-end collisions: A driving simulator experiment. *Accident Analysis and Prevention*, *174*. https://doi.org/10.1016/j.aap.2022.106768

Haus, S. H., Sherony, R., & Gabler, H. C. (2019). Estimated benefit of automated emergency braking systems for vehicle–pedestrian crashes in the United States. *Traffic Injury Prevention*, *20*.

Hell, W., Schick, S., Langwieder, K., & Zellmer, H. (2002). Biomechanics of cervical spine injuries in rear end car impacts: Influence of car seats and possible evaluation criteria. *Traffic Injury Prevention*, *3*(2), 127–140. https://doi.org/10.1080/15389580212000

Huang, C., Wen, X., & He, D. (2024). Characteristics of Rear-End Collisions: A Comparison between Automated Driving System-Involved Crashes and Advanced Driving Assistance System-Involved Crashes. *Transportation Research Record: Journal of the Transportation Research Board*, *2678*(7), 771–782. https://doi.org/10.1177/03611981231209319

Huertas-Leyva, P., Savino, G., Baldanzini, N., & Pierini, M. (2023). Does ABS ensure good performance in emergency braking for less skilled motorcyclists? *Accident Analysis and Prevention*, *190*. https://doi.org/10.1016/j.aap.2023.107148

IIHS. (2022). *Fatality Facts 2022: Pedestrians*. https://www.iihs.org/topics/fatality-statistics/detail/pedestrians#where-they-died

Isaksson-Hellman, I., & Lindman, M. (2016). Evaluation of the crash mitigation effect of low-speed automated emergency braking systems based on insurance claims data. *Traffic Injury Prevention*, *17*, 42–47. https://doi.org/10.1080/15389588.2016.1186802

Jamson, A. H., Lai, F. C. H., & Carsten, O. M. J. (2008). Potential benefits of an adaptive forward collision warning system. *Transportation Research Part C: Emerging Technologies*, *16*(4), 471–484. https://doi.org/10.1016/j.trc.2007.09.003

Jansen, R. J., & Varotto, S. F. (2022). Caught in the blind spot of a truck: A choice model on driver glance behavior towards cyclists at intersections. *Accident Analysis and Prevention*, *174*. https://doi.org/10.1016/j.aap.2022.106759

Janssens, D., Wets, G., Brijs, T., Vanhoof, K., Arentze, T., & Timmermans, H. (2004). Improving Performance of Multiagent Rule-Based Model for Activity Pattern Decisions with Bayesian Networks. *Transportation Research Record: Journal of the Transportation Research Board*, *1894*(1), 75–83. https://doi.org/10.3141/1894-09

Jones, C. E., Yusuf, N., Ahmed, B., Kassogue, M., Wasley, A., & Kanu, F. A. (2024). *Progress Toward Achieving and Sustaining Maternal and Neonatal Tetanus Elimination-Worldwide, 2000-2022*. https://www.cdc.gov/mmwr/mmwr_continuingEducation.html

Jumaa, B. A., Abdulhassan, A. M., & Abdulhassan, A. M. (2019). Advanced Driver Assistance System (ADAS): A Review of Systems and Technologies. *International Journal OfAdvanced Research in Computer Engineering & Technology (IJARCET)*, *8*(6), 231–234.

Keller, C. G., Dang, T., Fritz, H., Joos, A., Rabe, C., & Gavrila, D. M. (2011). Active pedestrian safety by automatic braking and evasive steering. *IEEE Transactions on Intelligent Transportation Systems*, *12*(4), 1292–1304. https://doi.org/10.1109/TITS.2011.2158424

Koller, D., & Friedman, N. (2009). *Probabilistic Graphical Models: Principles and Techniques*. MIT Press.

Korb, K. B., & Nicholson, A. E. (2010). *Bayesian artificial intelligence*. CRC press.

Kullgren, A., Amin, K., & Tingvall, C. (2023). Effects on crash risk of automatic emergency braking systems for pedestrians and bicyclists. *Traffic Injury Prevention*, *24*(S1), S111–S115. https://doi.org/10.1080/15389588.2022.2131403

Kusano, K. D., & Gabler, H. C. (2012). Safety benefits of forward collision warning, brake assist, and autonomous braking systems in rear-end collisions. *IEEE Transactions on Intelligent Transportation Systems*, *13*(4), 1546–1555. https://doi.org/10.1109/TITS.2012.2191542

Kutela, B., Mbuya, C., Swai, S., Imanishimwe, D., & Langa, N. (2022). Associating stated preferences of emerging mobility options among Gilbert City residents using Bayesian Networks. *Cities*, *131*. https://doi.org/10.1016/j.cities.2022.104064

Kutela, B., Mihayo, M. P., Kidando, E., Chengula, T. J., & Lyimo, S. M. (2020). Spatial insights into micro-mobility safety: establishing optimal buffers for scooter crash predictions. *Digital Transportation and Safety*, *0*(0), 1–8. https://doi.org/10.48130/dts-0024-0016

Leslie, A. J., Kiefer, R. J., Meitzner, M. R., & Flannagan, C. A. (2021). Field effectiveness of general motors advanced driver assistance and headlighting systems. *Accident Analysis and Prevention*, *159*. https://doi.org/10.1016/j.aap.2021.106275

Li, X., Yan, X., Wu, J., Radwan, E., & Zhang, Y. (2016). A rear-end collision risk assessment model based on drivers' collision avoidance process under influences of cell phone use and gender—A driving simulator based study. *Accident Analysis and Prevention*, *97*, 1–18. https://doi.org/10.1016/j.aap.2016.08.021

Lord, D., Brewer, M. A., Fitzpatrick, K., Geedipally, S. R., & Peng, Y. (2011). *Analysis of Roadway Departure Crashes on Two-Lane Rural Roads in Texas*.

Lowell, D., Van Atten, C., Culkin, J., & Langlois, T. (2020). Data Analysis-Examining the Demographics and Motor Vehicle Fleets of Rural Communities. *Union of Concerned Scientists*.

Lucci, C., Marra, M., Huertas-Leyva, P., Baldanzini, N., & Savino, G. (2021). Investigating the feasibility of motorcycle autonomous emergency braking (MAEB): Design criteria for new experiments to field test automatic braking. *MethodsX*, *8*. https://doi.org/10.1016/j.mex.2021.101225

Ma, L., & Yan, X. (2014). Examining the nonparametric effect of drivers' age in rear-end accidents through an additive logistic regression model. *Accident Analysis and Prevention*, *67*, 129–136. https://doi.org/10.1016/j.aap.2014.02.021

Mahlberg, J. A., Sakhare, R. S., Li, H., Mathew, J. K., Bullock, D. M., & Surnilla, G. C. (2021). Prioritizing roadway pavement marking maintenance using lane keep assist sensor data. *Sensors*, *21*(18). https://doi.org/10.3390/s21186014

Masello, L., Castignani, G., Sheehan, B., Murphy, F., & McDonnell, K. (2022). On the road safety benefits of advanced driver assistance systems in different driving contexts. *Transportation Research Interdisciplinary Perspectives*, *15*. https://doi.org/10.1016/j.trip.2022.100670

Mason, J., Carney, C., Gaspar, J. G., Kim, W., Romo, A., & Horrey, W. J. (2023). *Mapping Comprehension of ADAS across Different Road Users*. https://orcid.org/0000-0003-1106-2488

Mather, R. D. (2007). Age and Driving behavior: Contributions from Human Factors. *Journal of Scientific Psychology*.

Mcdonald, A., Reyes, M., Roe, C., & Mcgehee, D. (2017). *Driver Understanding of ADAS and Evolving Consumer Education*.

Md Shakir Mahmud, by, Jashami, H., Usamah Megat Johari, M., Gupta, N., Bamney, A., Gates, T. J., Professor, P., Savolainen, P. T., & MSU Foundation Professor, P. (2024). Effects of Speed Feedback Trailer Positioning and Presence of Law Enforcement on Driver Behavior in Freeway Work Zone Lane Closures. *Journal of the Transportation Research Board*, *2678*(9). https://doi.org/10.1177/03611981241230319

Mohamed, S. A., Mohamed, K., & Al-Harthi, H. A. (2017). Investigating Factors Affecting the Occurrence and Severity of Rear-End Crashes. *Transportation Research Procedia*, *25*, 2098–2107. https://doi.org/10.1016/j.trpro.2017.05.403

Muelleman, R. L., & Mueller, K. (1996). Fatal motor vehicle crashes: variations of crash characteristics within rural regions of different population densities. *Journal of Trauma and Acute Care Surgery*, *41*(2), 315–320.

Nasution, S. M., & Dirgantara, F. M. (2023). Pedestrian Detection System using YOLOv5 for Advanced Driver Assistance System (ADAS). *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi)*, *7*(3), 715–721. https://doi.org/10.29207/resti.v7i3.4884

Nees, M. A., Sharma, N., & Herwig, K. (2020). Some Characteristics of Mental Models of Advanced Driver Assistance Systems: A Semi-structured Interviews Approach. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *64*(1), 1313–1317.

NHTSA. (2015). *Critical Reasons for Crashes Investigated in the National Motor Vehicle Crash Causation Survey*.

NHTSA. (2023). *Summary of Motor Vehicle Crashes: 2021 Data 1 Summary of Motor Vehicle Traffic Crashes Key Findings*.

NHTSA. (2024). *Rural/Urban Comparison of Motor Vehicle Traffic Fatalities: 2021 Data (Revised 2024)*.

Ning, H., Yu, Y., & Bai, L. (2022). Unsafe Behaviors Analysis of Sideswipe Collision on Urban Expressways Based on Bayesian Network. *Sustainability (Switzerland)*, *14*(13). https://doi.org/10.3390/su14138142

ODPS. (2020). *Rural Driving Safety*.

Perumal, P. S., Sujasree, M., Chavhan, S., Gupta, D., Mukthineni, V., Shimgekar, S. R., Khanna, A., & Fortino, G. (2021). An insight into crash avoidance and overtaking advice systems for Autonomous Vehicles: A review, challenges and solutions. In *Engineering Applications of Artificial Intelligence* (Vol. 104). Elsevier Ltd. https://doi.org/10.1016/j.engappai.2021.104406

Pike, A. M., Barrette, T. P., & Carlson, P. J. (2018). *Evaluation of the Effects of Pavements Marking Characteristics on Detectability by ADAS Machine Vision*.

Pipkorn, L., & Bianchi Piccinini, G. (2020). The role of off-path glances: A quantitative analysis of rear-end conflicts involving Chinese professional truck drivers as the striking partners. *Journal of Safety Research*, *72*, 259–266. https://doi.org/10.1016/j.jsr.2019.12.023

Pyykönen, P., Virtanen, A., & Kyytinen, A. (2015). Developing intelligent blind spot detection system for Heavy Goods Vehicles. *2015 IEEE International Conference on Intelligent Computer Communication and Processing (ICCP)*.

R Core Team. (2024). *A Language and Environment for Statistical Computing. R Foundation for Statistical Computing*. Https://Www.r-Project.Org/.

Rahman, T., Liu, A., Cheema, D., Chirila, V., & Charlebois, D. (2023). ADAS Reliability against Weather Conditions: Quantification of Performance Robustness. *27th International Technical Conference on the Enhanced Safety of Vehicles (ESV)*.

Re, F., Kriston, A., Broggi, D., & Minarini, F. (2021). Testing the robustness of commercial lane departure warning systems. In *Transportation Research Record* (Vol. 2675, Issue 12, pp. 385–400). SAGE Publications Ltd. https://doi.org/10.1177/03611981211029646

Reagan, I. J., & McCartt, A. T. (2016). Observed activation status of lane departure warning and forward collision warning of Honda vehicles at dealership service centers. *Traffic Injury Prevention*, *17*(8), 827–832. https://doi.org/10.1080/15389588.2016.1149698

Ridella, S., Kang, J., & Kitazaki, S. (2015). The Potential for Adaptive Safety Through In-Vehicle Biomedical and Biometric Monitoring. *Conference: 24th International Technical Conference on the Enhanced Safety of Vehicles*. https://www.researchgate.net/publication/280234814

Rizzo, D. B., & Blackburn, M. R. (2018). Harnessing expert knowledge: Defining a Bayesian network decision model with limited data–Model structure for the vibration qualification problem. *Systems Engineering*, *21*(4), 285–294. https://doi.org/10.1002/sys.21431

Roh, C. G., Kim, J., & Im, I. J. (2020). Analysis of impact of rain conditions on adas. In *Sensors (Switzerland)* (Vol. 20, Issue 23, pp. 1–14). MDPI AG. https://doi.org/10.3390/s20236720

Sangve, S. M., Kulkarni, M., Chawade, K., Marathe, G., & Pawar, P. (2024). Advanced Driver Assistance System(ADAS). *2024 International Conference on Emerging Smart Computing and Informatics, ESCI 2024*. https://doi.org/10.1109/ESCI59607.2024.10497387

Schaudt, W. A., Bowman, D. S., Hanowski, R. J., Olson, R. L., Marinik, A., Soccolich, S., Joslin, S., Toole, L., & Rice, J. C. (2014). *Federal Motor Carrier Safety Administration's Advanced System Utilizing a Data Acquisition System on Highways (FAST DASH) Safety Technology Evaluation Project #1: Blindspot Warning*.

Schoner, J., Sanders, R., & Goddard, T. (2023). Effects of Advanced Driver Assistance Systems on Impact Velocity and Injury Severity: An Exploration of Data from the Crash Investigation Sampling System. *Transportation Research Record: Journal of the Transportation Research Board*. https://doi.org/10.1177/03611981231189740

Scutari, M. (2009). *Learning Bayesian Networks with the bnlearn R Package*. http://arxiv.org/abs/0908.3817

Seaman, S., Gershon, P., Angell, L., Mehler, B., & Reimer, B. (2022). Evaluating the Associations between Forward Collision Warning Severity and Driving Context. *Safety*, *8*(1). https://doi.org/10.3390/safety8010005

Shawky, M. (2020). Factors affecting lane change crashes. *IATSS Research*, *44*(2), 155–161. https://doi.org/10.1016/j.iatssr.2019.12.002

Son, J., Park, M., & Park, B. B. (2015). The effect of age, gender and roadway environment on the acceptance and effectiveness of Advanced Driver Assistance Systems. *Transportation Research Part F: Traffic Psychology and Behaviour*, *31*, 12–24. https://doi.org/10.1016/j.trf.2015.03.009

Spicer, R., Vahabaghaie, A., Murakhovsky, D., Bahouth, G., Drayer, B., & Lawrence, S. S. (2021). Effectiveness of advanced driver assistance systems in preventing system-relevant crashes. *SAE International Journal of Advances and Current Practices in Mobility*, *3*(2021-01–0869), 1697–1701.

Sternlund, S., Strandroth, J., Rizzi, M., Lie, A., & Tingvall, C. (2017). The effectiveness of lane departure warning systems—A reduction in real-world passenger car injury crashes. *Traffic Injury Prevention*, *18*(2), 225–229. https://doi.org/10.1080/15389588.2016.1230672

Sui, B., Lubbe, N., & Bärgman, J. (2021). Evaluating automated emergency braking performance in simulated car-to-two-wheeler crashes in China: A comparison between C-NCAP tests and in-depth crash data. *Accident Analysis and Prevention*, *159*. https://doi.org/10.1016/j.aap.2021.106229
Tan, H., Zhao, F., Hao, H., & Liu, Z. (2021). Evidence for the crash avoidance effectiveness of intelligent and connected vehicle technologies. In *International Journal of Environmental Research and Public Health* (Vol. 18, Issue 17). MDPI. https://doi.org/10.3390/ijerph18179228
Tang, B., Chien, S., Huang, Z., & Chen, Y. (2016). Pedestrian protection using the integration of V2V and the pedestrian automatic emergency braking system. *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, 2213–2218. https://doi.org/10.1109/ITSC.2016.7795913
Tang, B., Chien, S.-P., Chen, Y., & Li, L. (2015). *Pedestrian Protection Using the Integration of V2V Communication and Pedestrian Automatic Emergency Braking System*.
Torkashvand, M. B., Aghayan, I., Qin, X., & Hadadi, F. (2022). An extended dynamic probabilistic risk approach based on a surrogate safety measure for rear-end collisions on two-lane roads. *Physica A: Statistical Mechanics and Its Applications*, *603*. https://doi.org/10.1016/j.physa.2022.127845
Trübswetter, N., & Bengler, K. (2013). Why Should I Use ADAS? Advanced Driver Assistance Systems and The Elderly: Knowledge, Experience and Usage Barriers. *PROCEEDINGS of the Seventh International Driving Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design*.
Uddin, M., & Huynh, N. (2020). Injury severity analysis of truck-involved crashes under different weather conditions. *Accident Analysis and Prevention*, *141*. https://doi.org/10.1016/j.aap.2020.105529
Utriainen, R., Pollanen, M., & Liimatainen, H. (2020). The Safety Potential of Lane Keeping Assistance and Possible Actions to Improve the Potential. *IEEE Transactions on Intelligent Vehicles*, *5*(4), 556–564. https://doi.org/10.1109/TIV.2020.2991962
Vertlib, S. R., Rosenzweig, S., Rubin, O. D., & Steren, A. (2023). Are car safety systems associated with more speeding violations? Evidence from police records in Israel. *PLoS ONE*, *18*(8 August). https://doi.org/10.1371/journal.pone.0286622
Zou, R., Yang, H., Yu, W., Yu, H., Chen, C., Zhang, G., & Ma, D. T. (2023). Analyzing driver injury severity in two-vehicle rear-end crashes considering leading-following configurations based on passenger car and light truck involvement. *Accident Analysis and Prevention*, *193*. https://doi.org/10.1016/j.aap.2023.107298