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**POST-CRASH INJURY SEVERITY ANALYSIS
FOR CONVENTIONAL AND AUTONOMOUS
VEHICLES**

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PhD

The Hong Kong Polytechnic University

2026

The Hong Kong Polytechnic University
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**Post-Crash Injury Severity Analysis for Conventional
and Autonomous Vehicles**

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**A thesis submitted in partial fulfilment of the
requirements for the degree of Doctor of Philosophy**

August 2025

CERTIFICATE OF ORIGINALITY

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_____(Signed)

_____Qiaoqiao Ren_____(Name of student)

Dedication

Dedicated with love and gratitude to memorize my grandmother:

Thank you for teaching me how to love with sincerity.

Dedicated with love and gratitude to my grandfather:

Thank you for giving me endless courage to face the world.

Abstract

Road traffic crashes remain a significant concern, consistently ranking as one of the leading causes of death and disability worldwide. Analysing and reducing the crash injury and damage severities is essential for ensuring public safety and promoting sustainable economic development. A critical challenge in this issue lies in the complex and heterogeneous nature of crash causation and outcomes, which stem from the dynamic interplay of human, vehicle, road, and environmental factors. This complexity is further amplified by the emergence of autonomous vehicles (AVs), whose distinct crash patterns are not yet fully understood. To advance road safety, this thesis systematically analyses post-crash injury and damage severities for both conventional human-driven vehicles (HDVs) and AVs, thus forging evidence-based strategies that can contribute to a safer road traffic environment.

Firstly, to investigate the heterogeneous impact of factors determining different crash injury severity levels under adverse road conditions for conventional single-vehicle rollover crashes, the random parameters logit model with unobserved heterogeneity in means and variances was employed. A series of likelihood ratio tests and marginal effects were used to assess the temporal instability or impact location non-transferability of the explanatory variables. The results indicate an overall temporal and locational instability of model estimates while several determinants are identified to have consistent effects on injury severity outcomes, such as animal-involved collisions, old drivers, safety restraint usage, female drivers, and physically impaired drivers.

Secondly, to explore the safety interaction between conventional vehicles and railways and investigate crash injury severities at undivided two-way highway-railway grade crossings (HRGCs), the XGBoost model was applied to identify important features for various injury severity outcomes. The results indicate that some significant predictors overlap between the killed and injured models, such as old driver, driver was in vehicle, main track, went around the gate, adverse crossing surface, and truck, while the other significant factors reveal that the XGBoost model can distinguish between different severity levels. Moreover, to further compare factors affecting post-crash injury severities for conventional vehicles before and during the COVID-19 pandemic, a multinomial logit model was developed for 2018-2019 HRGC crashes, and a random parameters logit model was developed for the 2020-2021 HRGC crashes. The results

indicate that the old driver and illuminated crossing were identified as random parameters with heterogeneity in means during the pandemic. As for the pre-pandemic period, no significant random parameters were captured. Significant variables also differ markedly between these two periods, with no significant driver-related or vehicle-related indicators identified for 2018-2019.

Thirdly, to understand the heterogeneity and identify key factors influencing the damage severity in AV crashes, a methodology integrating the latent class analysis and multinomial logit model was employed to explore the heterogeneity in AV crash patterns. Two heterogeneous clusters were determined based on skewed distributions of vehicle status and driving mode. The model estimation results indicate that partitioning the AV crash dataset into heterogeneous subsets facilitates the identification of critical factors that remain obscured when the dataset is analysed as a whole, such as the evening indicator.

Fourthly, to disentangle the direct and mediation effects of key factors on AV crash damage severities, the structural equation modelling was employed with additional point-of-interest characteristics. The results indicate direct pathways between AV crash outcomes and multiple risk factors, such as dark with streetlights and bus stop count. Results also reveal the impacts of two mediator variables, including zebra crossing and vulnerable road user.

Fifthly, to uncover the combinations of contributing factors that frequently co-occur in AV rear-end crashes, the association rule mining was employed with supplementary built environment data. Besides, HDV rear-end crashes were also collected to conduct the comparative analysis between AV and HDV crashes. The results confirm the existence of distinct patterns, individual risk factors, and co-occurrence mechanisms that are unique to AV systems in real-world contexts. Critical factors such as roadside parking, two-way without medians, multiple vehicles, traffic signals, intersections, and land types play pivotal roles in AV rear-end crashes, while HDV crashes are more frequently influenced by behavioural context and land use type.

The findings of this thesis highlight the importance of accounting for unobserved heterogeneity, temporal instability, mediation effects, and built environment factors when analysing HDV and AV crash severity outcomes. These enhanced understandings of crash patterns can inform the development of evidence-based safety strategies.

Publications Arising from the Thesis

Publications

1. **Ren, Q.**, Xu, M*, 2023. Exploring variations and temporal instability of factors affecting driver injury severities between different vehicle impact locations under adverse road surface conditions. *Analytic Methods in Accident Research* 40, 100305.
2. **Ren, Q.**, Xu, M*, 2025. Heterogeneity in crash patterns of autonomous vehicles: The latent class analysis coupled with multinomial logit model. *Accident Analysis & Prevention* 209, 107827.
3. **Ren, Q.**, Hu, C., Xu, M*, Song, J., 2025. Association rule mining of damage severities in autonomous vehicle rear-end crashes with supplementary built environment information. *Reliability Engineering and System Safety*. (Accept)
4. **Ren, Q.**, Xu, M*, 2025. Exploring factors affecting the injury severity of highway-rail grade crossing crashes during the COVID-19 pandemic. *Transportation Letters* 17(5), 816–826.
5. **Ren, Q.**, Xu, M*, 2024. Injury severity analysis of highway-rail grade crossing crashes in non-divided two-way traffic scenarios: A random parameters logit model. *Multimodal Transportation* 3(1), 100109.
6. **Ren, Q.**, Xu, M*, Zhou, B., Chung, S. H., 2024. Traffic safety assessment and injury severity analysis for undivided two-way highway-rail grade crossings. *Mathematics* 12(4), 519.

Working Papers

1. **Ren, Q.**, Liang, F., Xu, M*, Chung, S. H., & Graham, D. J., 2025. Unveiling autonomous vehicle crash patterns with supplementary points of interest information: Insights from the structural equation modelling. *Reliability Engineering and System Safety*. (Under 1st Revision)

Conference Presentations

1. **Ren, Q.**, Li, C., & Xu, M*., 2024. Injury severity analysis of road traffic accidents in Hong Kong: A comparative study before and during the COVID-19 pandemic. *The 28th International Conference of Hong Kong Society for Transportation Studies*, Hong Kong, December 9-10, 2024.
2. **Ren, Q.**, Hu, C., & Xu, M*., 2025. Association rule mining of damage severities in autonomous vehicle rear-end crashes with supplementary built environment information. *2025 Safe Mobility Conference*, Madison, the United States, April 7-9, 2025.

Other Publications

1. **Ren, Q.**, Xu, M*., Yan, X., 2024. An investigation of heterogeneous impact, temporal stability, and aggregate shift in factors affecting the driver injury severity in single-vehicle rollover crashes. *Accident Analysis & Prevention* 200, 107562.
2. **Ren, Q.**, He, J., Liu, Z., Xu, M*., 2024. Traffic flow characteristics and traffic conflict analysis in the downstream area of expressway toll station based on vehicle trajectory data. *Asian Transport Studies* 10, 100138.
3. **Ren, Q.**, He, J., Liu, Z., & Xu, M*., 2023. Traffic flow characteristics and traffic conflict analysis in the downstream area of expressway toll station based on vehicle trajectory data. *The 15th International Conference of Eastern Asia Society for Transportation Studies*, Kuala Lumpur, Malaysia, September 4-7, 2023.

Acknowledgements

First and foremost, I would like to express my deepest gratitude to my chief supervisor, Prof. Min Xu, for her invaluable guidance and support throughout my Ph.D. journey. Over the past three years, Prof. Xu has not only guided me through the labyrinth of academic research but also profoundly shaped the way I learn and think. Her razor-sharp insights, relentless pursuit of excellence, and dedication to nurturing independent thinkers have left an indelible mark on my growth. I am endlessly grateful for the freedom she granted me to explore my research interests. I also deeply appreciate how she intentionally involved me in mentoring junior researchers. These valuable experiences have equipped me with essential skills for my future career.

I am thankful to my co-supervisor, Prof. Sai-Ho Chung (Nick), for his indispensable support. A special note of thanks also goes to Prof. Daniel J. Graham of Imperial College London, whose insightful comments and kind help during my six-month research visit became a cornerstone of this thesis. I would also like to extend my gratitude to the members of my Ph.D. thesis examining committee, including Prof. Helai Huang, Prof. Shimul (Md. Mazharul) Haque, and Prof. Nang Ngai Sze for their meticulous review and invaluable suggestions on my dissertation. Their commitment to scholarly excellence has set a standard I will strive to uphold in my future research.

My sincere gratitude also goes to the Hong Kong Polytechnic University and Prof. Xu for their financial support throughout my doctoral studies. These fundings were not merely an enabler of my research; it was a catalyst for my growth and transformation. The university's additional support also allows me to undertake a research visit to Imperial College London, which is a valuable experience that expanded my academic horizons and gifted me unforgettable cultural and professional growth.

My heartfelt thanks go to all wonderful friends in our research group for making this journey so rewarding—Dr. Shouguo Peng, Dr. Jiangyan Huang, Mr. Yilun Wang, Ms. Rumei Ji, Dr. Hang Su, Mr. Tanghong Ran, Ms. Xiaohua Chen, Ms. Lin Tu, Mr.

Xiong Ya, Mr. Donglei Rong, and Ms. Fayang Liang. Special thanks also go to my cherished friends, Dr. Jiatong Song and Mr. Shuai Liang, who brought laughter to my happy moments and light to my dark days throughout this three-year journey.

My sincere and deepest gratitude must go to my family—to my grandfather for always encouraging me to follow my heart and stay true to my path, ensuring I live with fewer regrets; to my grandmother for her unforgettable warmth that comforted me through every challenge; to my mother, whose tireless love and companionship gave me strength; to my father, who supports me to grow beyond my limits; and to my aunts for making me feel so loved and supported. I also want to thank my younger sister for always being by my side and for being a constant source of happiness.

This thesis represents a journey: One that has taken me far from home, through countless challenges, to where I stand today. I walked a long way and now present this work not as an endpoint, but as a milestone in a journey that continues. Each step to doctoral studies in Hong Kong has expanded my world in ways I once could scarcely imagine. There were moments of joy, periods of doubt, and times of pain over the last years. Thanks to myself!

Qiaoqiao Ren

August 2025

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Chapter 1 Introduction

1.1 Background of this study

Road traffic deaths and injuries in crashes remain a major global health and development challenge. There were an estimated 1.19 million road traffic deaths in 2021 (World Health Organization, 2022). This corresponds to a rate of 15 road traffic deaths per 100,000 population. Although the overall level of global road traffic safety is on the rise with the improvement of vehicle safety design level, the enhancement of driver safety awareness, and the improvement of regulations, the total number of traffic accidents still fall far short of what is needed to meet the target of the United Nations Decade of Action for Road Safety 2021–2030 (World Health Organization, 2020). With a growing and increasingly urban global population, the rising demand for mobility is set to overwhelm transport systems, particularly those that rely heavily on private vehicles. As a leading cause of death and major contributor to disability, road traffic accidents not only bring heavy emotional damage and economic burden to the victims and their families, but also impose an enormous economic cost on societies (Elamrani et al., 2020a). Some estimates put the global macroeconomic cost of road traffic injuries as high as 1.8 trillion dollars, roughly equivalent to 10–12% of global gross domestic product (Chen et al., 2019). Consequently, analyzing and reducing the severity of injuries and damages resulting from traffic crashes is of great importance to ensure public safety and promote sustainable economic development.

On the one hand, given the substantial proportion of conventional vehicles currently in use globally, crashes involving traditional vehicles remain a critical research area. Understanding injury severity patterns and risk factors associated with these vehicles is vital, as the findings directly inform targeted safety measures, vehicle design improvements, and policy interventions aimed at mitigating crash impacts. The COVID-19 pandemic has also significantly altered travel behaviours and traffic patterns, highlighting the vulnerability of traditional vehicles and infrastructures. For

instance, shifts toward remote work reduced overall traffic volumes yet paradoxically, some regions experienced an increase in speeding-related severe crashes due to emptier roads. Such dynamics underscore the need for accounting for evolving mobility trends.

On the other hand, the landscape of traffic safety is undergoing a significant transformation as we navigate the opportunities presented by autonomous vehicles (AVs). AVs promise to reduce human error, which accounts for the majority of traditional traffic accidents, and offer new possibilities for safer and more efficient transportation systems. However, the transition from conventional human-driven vehicles (HDVs) to AVs is fraught with complexities that necessitate a thorough understanding of their crash patterns. For example, while AVs may reduce certain high-severity crashes, their interactions with legacy vehicles during the transition period could create novel conflict scenarios. Additionally, the lack of standardized crash reporting frameworks for AVs complicates comparative analyses. Most existing studies rely on small-scale AV crash datasets. This data scarcity limits the ability to generalize findings, emphasizing the need for more reliable real-world AV deployment data to assess crash outcomes robustly.

Therefore, this new era calls for a holistic reimagining of the road traffic safety paradigm, one that seamlessly integrates the lessons learned from conventional vehicle crashes with the occurrence of AVs. A critical challenge in addressing this issue lies in the complex and heterogeneous nature of crash causation and outcomes, which stem from the dynamic interplay of human, vehicle, infrastructure, and environmental factors. This complexity is further amplified by the emergence of AVs, whose distinct crash patterns are not yet fully understood. To advance road safety, this thesis systematically analyses post-crash injury and damage severities for both HDVs and AVs, with the objectives of: 1) modelling and comparing injury severity determinants for HDVs across diverse contexts, and 2) developing and applying advanced methodologies to unravel the heterogeneity and causal mechanisms underlying AV crash damage severity. The ultimate aim is to forge evidence-based strategies that contribute to a safer road

traffic environment.

The analysis of crash severity is a critical facet of road safety research that seeks to understand the factors contributing to the outcomes of traffic accidents (Mannering et al., 2016). Over the years, researchers have applied a vast array of statistical methods to analyse accident-based data in an effort to reduce injury severities and damage resulting from motor-vehicle accidents (Behnood and Mannering, 2016; Mannering et al., 2020; Yan et al., 2021a; Alnawmasi and Mannering, 2022). Studies that have focused on the statistical analysis of accident data have traditionally addressed one or more of three general objectives: 1) data analysis with the sole intent of quantifying the effect of statistically significant determinants (explanatory variables) on the likelihood and severity of accidents; 2) data analysis with the intent of using the resulting parameter estimates of the statistical model to forecast future accident likelihoods and severities; and 3) analysis of before and after data to evaluate the effectiveness of a specific safety countermeasure or a change in a specific factor that may influence likelihoods and severities of accidents.

This intricate analysis encompasses various dimensions, such as the vehicle dynamic, road environment, driver behaviour, and post-crash emergency response, etc. (Champahom et al., 2020; Yu et al., 2020; Liu and Fan, 2021; Wang et al., 2022). Each of these elements has the potential to markedly affect the severity of injuries/damages sustained in a collision. For instance, vehicle speed at the time of a crash, safety features such as airbags and seatbelts, and the structural integrity of the vehicle all play pivotal roles in determining injury severity outcomes (Wang et al., 2022). Additionally, the road environment, including weather conditions, road design, and traffic density, can exacerbate or mitigate the severity of crash injuries (Umair et al., 2022). Driver behaviour, including reaction times, impairment due to alcohol or drugs, and adherence to traffic laws, is another crucial aspect of injury severity (Rashmi and Marisamynathan, 2023; Yadav and Velaga, 2022). Notably, risky behaviours such as speeding, distracted driving, and non-compliance with traffic signals could significantly increase the

likelihood of crashes with severe injury consequences (Wang et al., 2022). Furthermore, the promptness and quality of emergency response services following a crash significantly influence the survival and recovery prospects of injury victims (Guo et al., 2023).

The insights gleaned from crash severity analysis have far-reaching implications for public health policy, road engineering, vehicle design, and traffic law enforcement (Hamim and Ukkusuri, 2022). By understanding the multi-dimensional nature of crash injuries/damages, transportation administrators can tailor interventions to specific contexts and vulnerable road user groups. For example, improving roadway illumination and signage can reduce the risk of nighttime collisions (Bhagavathula and Gibbons, 2023), while targeted public awareness campaigns can address driver behaviours contributing to high-severity crashes (Ren and Xu, 2023a). Moreover, advancements in vehicle technology, such as collision avoidance systems and advanced driver assistance systems, are reshaping the landscape of injury prevention (Matin and Dia, 2023). Therefore, crash severity analysis represents a cornerstone of road safety research, providing valuable insights that drive the design and implementation of life-saving interventions.

1.2 Research objectives

In view of the aforementioned background, this thesis endeavours to analyse post-crash severities in the context of both HDVs and AVs across diverse contexts. These meticulous analyses will provide retrospective insights into factors leading to traffic incidents and associated injuries/damages, thus offering a robust foundation for developing more targeted and effective traffic safety strategies. To this end, the post-crash severity analyses are first conducted for conventional vehicles. Specifically,

(1) To investigate the variations in vehicle impact locations and temporal shifts of the factors that influence driver injury severities in the context of adverse road conditions:

- Identify observable factors affecting the driver injury severity for each disaggregated vehicle impact location (center/left/right) while effectively handling unobserved heterogeneity by employing the random parameters logit modelling framework.
- Quantify and characterize the net effect of aggregate year-to-year and location-to-location shifts through probability differences between out-of-sample predictions and within-sample observations.
- Investigate the temporal instability and impact location non-transferability of individual determinants on adverse-road-related driver injury severities across center, left-side, and right-side crashes.

(2) To investigate crash injury severities and assess COVID-19 pandemic-induced shifts in crash patterns for conventional vehicles at undivided two-way highway-railway grade crossings (HRGCs):

- Apply the machine learning model to compare prediction accuracy and extract critical features between different injury severity categories.
- Compare factors influencing injury severities pre- and during the pandemic.
- Account for potential unobserved heterogeneity.

Subsequently, the post-crash damage severity analyses are conducted in the context of AVs.

(1) To understand the heterogeneity in AV crash patterns:

- Develop a highly automatic and fast variable extraction framework to facilitate the conversion of PDF format AV crash records from the California Department of Motor Vehicles (CA DMV) into comma-separated formats, thereby enabling their compatibility with statistical software and scripting languages for subsequent in-depth analysis.
- Capture heterogeneous clusters inherent in AV crash data.

- Identify key factors influencing the damage severity in the pooled crashes and each identified cluster.

(2) To disentangle the direct and mediation effects of key factors on AV crash damage severities with supplementary points of interest (POI) information:

- Incorporate POI characteristics into AV crash analysis.
- Understand how related potential determinants influence different AV crash damage severities directly.
- Quantify the potential mediation effects of explanatory variables on AV crash damage severities indirectly through mediator variables.

(3) To offer a dedicated and comprehensive investigation of the most prevalent type of crashes involving AVs—rear-end crashes,

- Conduct a comparative analysis between AV and HDV rear-end crashes and highlight the uniqueness of AV systems.
- Uncover the combinations of contributing factors that frequently co-occur in AV and HDV rear-end crashes. Short-term association rules, including 2-item and 3-item rules, are identified across all rear-end crashes. Furthermore, association rules for different damage severities are also investigated.
- Explore the influence of built environment factors on the occurrence of AV rear-end crashes.

This thesis makes several key contributions. Methodologically, it demonstrates the critical value of employing heterogeneity models and data-driven techniques to move beyond associative insights toward causal understanding in safety science. Empirically, it provides comprehensive, methodologically rigorous comparisons of AV and HDV crash patterns, identifying AV-specific risk patterns tied to the operational design domain and interaction with the built environment. Practically, the findings offer actionable intelligence for policymakers and engineers, advocating for context-specific countermeasures for HDVs and highlighting the need for AV-focused infrastructure

adaptation and sensor fusion strategies to mitigate identified environmental and interaction-based risks. Collectively, this thesis advances the theoretical and practical framework for analysing crash severity in a transitioning mobility landscape.

1.3 Thesis organization

Chapter 1 provides an overview of this research by presenting the background and indicating the significance of post-crash severity analysis for HDVs and AVs. Additionally, the research objectives are stated.

Chapter 2 reviews the literature on various aspects of HDV and AV safety research, including factors influencing HDV safety, factors influencing AV safety, and analytic methods for post-crash injury/damage severity modelling. Besides, the research gaps are put forward.

Chapter 3 investigates the heterogeneous impacts, temporal instability, and non-transferability of various determinants on driver injury severities across different vehicle impact locations under adverse road surface conditions for HDVs. The impacts of year-to-year and location-to-location shifts are also examined by comparing the probability differences between out-of-sample predictions and within-sample observations.

Chapter 4 explores the safety interaction between conventional vehicles and railways and models crash injury severities at undivided two-way HRGCs. The eXtreme Gradient Boosting (XGBoost) model and interpretable SHapley Additive exPlanations (SHAP) are applied to compare the prediction accuracy and extract important features that were crucial for determining various injury severity outcomes. This chapter further examines how the COVID-19 pandemic altered crash patterns for conventional vehicles at HRGCs by conducting a comparative analysis of injury severity determinants before and during the pandemic. The potential unobserved heterogeneity is also considered under the framework of random parameter logit model.

Chapter 5 seeks to understand the heterogeneity in crash patterns of AVs. A

systematic framework for AV crash data extraction is developed to streamline the transformation of PDF crash records into comma-separated value formats. Moreover, a robust framework for capturing distinct clusters and identifying the significant factors that impact the AV damage severity is proposed.

Chapter 6 provides a holistic assessment of associated risk factors by incorporating additional POI characteristics into AV crash damage modelling. The structural equation modelling (SEM) framework is employed to disentangle the direct and mediation effects of key factors on AV crash damage severities.

Chapter 7 contributes to the existing body of research on AV safety by offering a dedicated and comprehensive investigation of rear-end crashes. The association rule mining is employed to uncover the combinations of contributing factors that frequently co-occur in AV and HDV rear-end crashes. This study incorporates built environment factors into the analysis of rear-end crashes involving AVs. The comparative analysis between AV and HDV rear-end crashes is conducted to highlight the unique crash patterns associated with autonomous driving systems.

Chapter 8 concludes this thesis with a summary of the findings, limitations, and future research directions.

Chapter 2 Literature review

This chapter systematically reviews the literature that covers following key aspects:

(i) Crash injury severity analysis for HDVs under adverse road surface conditions, at highway-rail grade crossing crashes, and in the context of the COVID-19 pandemic; (ii) Crash damage severity analysis for AVs, including crash determinant and crash pattern identification of AVs, crash damage analysis with supplementary built environment factors, and damage severity analysis in AV rear-end crashes; (iii) Analytic methods for post-crash severity modelling. Besides, the research gaps of this thesis are also pointed out.

2.1 Crash injury severity analysis for HDVs

2.1.1 HDV injury severity analysis under adverse road surface conditions

Numerous empirical studies have been conducted to disentangle the impact of adverse road surface conditions on the crash injury severity (Behnood and Mannering, 2019; Fountas et al., 2020; Hou and Chen, 2020; Islam and Mannering, 2020, 2021; Morgan and Mannering, 2011; Pang et al., 2022; Wang et al., 2018; Yan et al., 2021b). For instance, Islam and Mannering (2020) examined the variation of determinants in crash injury severities involving aggressive and non-aggressive driving behaviours. The analysis revealed that the wet surface indicator exhibited statistical significance with a higher likelihood of minor and severe injuries in non-aggressive driving crashes. Yan et al. (2021b) explored the spatiotemporal instability of driver injury severities in adverse weather conditions and discovered that the wet road surface indicator had positive marginal effects on severe injuries in the 2014 Ohio model due to the slippery pavement surface, while it was negatively associated with severe injuries in the 2013 Ohio model owing to the risk-compensating mechanism. Abohassan et al. (2021) employed the structural equation modeling method and path analysis to investigate the direct and indirect effects of weather variables and maintenance operations on pavement friction and collision occurrence during snowstorms. Their findings showed

that icy road surfaces and wet slippery conditions had a detrimental impact on pavement friction and contributed to an increased risk of collisions.

Nevertheless, only a limited number of studies have endeavored to disaggregate the adverse-road-related crashes at a specific individual level and explored the underlying mechanisms of how contributors determine the adverse-road-related driver injury severities. In the study conducted by Morgan and Mannering (2011), the mixed logit model was utilized to examine impacts of age and gender on the injury severity of single-vehicle crashes under different roadway surface conditions (dry, wet, and snow/ice-covered). The results indicated that female drivers and older male drivers exhibited an increased likelihood of severe injuries when crashes transpired on wet, snowy, or icy surfaces. Conversely, male drivers under 45 years old experienced a decreased probability of severe injuries under such conditions. Li et al. (2013) analysed the correlation between several key pavement condition scores and injury severities based on crash records in Texas. The results indicated that there was a proportional association between poor pavement condition scores and more severe crashes, yet very poor pavement conditions were associated with less severe crashes. Chen et al. (2017) explored the unobserved heterogeneity and safety effects of pavement conditions on rural-road-related injury severities using the multivariate random parameters negative binomial specification. The results unveiled that the poor surface condition variable was identified as a significant random parameter with normal distribution in the crash model.

It is crucial to investigate the variations in vehicle impact locations and temporal shifts of the factors that influence driver injury severities in the context of adverse road conditions while accounting for the unobserved heterogeneity. In addition to conventional likelihood ratio tests, recent studies have utilized the out-of-sample prediction to compare the group-to-group or year-to-year predictive differences (Hou et al., 2022; Xu et al., 2021). This approach aids in identifying shifts more accurately between different groups or periods and understanding the potential reasons underlying those shifts. For instance, Alnawmasi and Mannering (2022a) used out-of-sample

simulations to examine the effects of increasing speed limits on the frequency and severity of crashes on freeways in Kansas. Results indicated that the aggregate impact of the changing influences of explanatory variables on average injury severities was relatively small. While the increased likelihood of rollover crashes in single-vehicle crashes implied that the higher speeds following the increase in the speed limit might have influenced the single-vehicle injury severity. In a recent study conducted by Alnawmasi and Mannering (2022b), out-of-sample simulations were employed to investigate temporal shifts in the injury severity related to distracted driving. The findings suggested that distracted driving crashes have become less severe over time according to both the latent-class multinomial logit model and a random parameters logit model with heterogeneity in the means and variances, while the latter model yielded significantly different injury-severity predictions. Yan et al. (2023) examined the temporal shifts and age-related variations in contributing factors that determined various injury severity levels in nighttime crashes and analysed the disparities between out-of-sample and within-sample predictions. The findings revealed the instability in prediction directions among various age groups over time and highlighted the crucial need to account for temporal instability and age-related differences when predicting accident occurrences.

2.1.2 HDV injury severity analysis at highway-rail grade crossing crashes

Regarding the safety of HRGCs, extensive studies have been conducted on crash frequency analysis, injury severity modeling, crash risk prediction, and risk mitigation measures evaluation (Gao et al., 2021; Kutela et al., 2022; Liu et al., 2022; Yan et al., 2023). A range of analytical techniques using statistical and data-driven approaches have been utilized to identify factors contributing to crashes and make predictions based on aggregated crash records or their subsets. For example, Hao et al. (2015) utilized an ordered probit model to explore the effect of age and gender on motor vehicle driver injury severity at HRGCs, and the analysis found that there were noteworthy variations in behavioural and physical characteristics between male and female drivers who were

involved in accidents. In a comparative study conducted by Ghomi et al. (2016), the severity of vulnerable road users involved in HRGC crashes was assessed using three different methods, namely, an ordered probit model, association rules, and tree-based methods. The study results revealed that train speed, older road users, nighttime conditions, and female drivers were more likely to be associated with severe crashes. Mathew and Benekohal (2021) adopted the Zero Inflated Negative Binomial model and Empirical Bayes method for each type of warning device to predict HRGC crashes. The predicted values demonstrated better agreement with the field data in comparison to the newly released Federal Railroad Administration model. Based on the 19-year HRGC crash data in North Dakota, Gao et al. (2021) used the resampling approach to address the imbalanced data issue and employed several data-driven approaches to predict HRGC accidents. This study suggested that resample led to a considerable improvement in recall rate and the proposed deep learning approach exhibits superior predictive performance compared to other machine learning methods. Keramati et al. (2020) investigated the public HRGC crash severity in North Dakota from 1990 to 2018 by applying the random survival forest model. Their results indicated that installing audible devices to crossing with gates and standard flashing lights could result in a significant reduction of crash likelihood, PDO, injury, and fatal crashes by 49%, 52%, 46%, and 50%, respectively.

Only a few studies have sought to address the methodological challenges arising from the unobserved heterogeneity in the domain of HRGC crash-related analysis. For example, Kutela et al. (2022) utilized the HRGC crash data spanning from 1999 to 2018 to assess pre-crash driver behaviours using a mixed multinomial logit model. The study demonstrated a notable intra-class correlation coefficient, underscoring the need to integrate random-effect parameters into the model. Furthermore, the study unveiled that male drivers exhibit a tendency to ignore crossing gates, while older drivers tend to halt briefly and proceed before the train has entirely cleared the crossing. Ahmed et al. (2023) utilized the random parameters multinomial logit models with heterogeneity in the

means and variances to account for the unobserved heterogeneity and spatial instability in the analysis of crash injury severity at HRGC using the crash data from Texas and California. The results indicated vehicle, train, driver, weather, and crossing characteristics that could significantly affect injury severity outcomes in state-specific models.

Compared to statistical models, machine learning methods have the advantage of being capable of processing big data and capturing intricate relationships between input variables and outcome predictions (Goswamy et al., 2023; Mannering et al., 2020a). Although machine learning models have been extensively studied for real-time safety and mobility prediction (Arvin et al., 2021; Khan and Ahmed, 2020; Sun et al., 2020), the application of these models to analyse injury severity at non-divided two-way traffic highway crossings has not been explored to the best of the authors' knowledge. Additionally, it is worth noting some previous studies that have utilized the eXtreme Gradient Boosting (XGBoost) model to evaluate crash severity, although these studies may not specifically focus on non-divided two-way highway and railway crashes. Given that the XGBoost model could provide effective insights in crash severity analysis, the study focuses on the application of this algorithm to investigate the influence of various determinants on injury severity outcomes at non-divided two-way traffic highway crossings.

Despite these remarkable achievements, it should be noted that data-driven approaches may lack the interpretability needed for direct application in safety enhancement strategies (i.e., deeply comprehend the causal impact of certain characteristics on HRGC accident likelihoods and the corresponding probability of injury outcome). The interpretability of predictive models is critical, especially in domains where decision-making can have life-altering consequences. The advancement of machine learning methodologies has made it possible for SHAP values to provide a consistent and cohesive method of interpreting models (Lundberg and Lee, 2017). By attributing prediction output to individual features, SHAP values provide transparency

to otherwise ‘black-box’ models in the analysis of HRGC crashes. While SHAP’s use in various predictive modeling scenarios has been documented, its application in conjunction with the XGBoost model for undivided two-way traffic HRGC safety analysis remains minimal.

2.1.3 HDV injury severity analysis in the context of COVID-19 pandemic

The COVID-19 pandemic could have significant impacts on the travel behaviour and traffic safety characteristics, leading to changes in the frequency, severity, and nature of HRGC crashes (Chand et al., 2021; Gupta et al., 2023; Islam et al., 2023; Li and Zhao, 2022; Mokhtarimousavi et al., 2022; Monfort et al., 2021; Pawar et al., 2021; Rostami et al., 2023; Taheri et al., 2023; Zhang et al., 2021). This has been evidenced by a notable increase of 6.8% in the number of HRGC crashes from 33,487 in 2019 to 35,766 in 2020 (Federal Railroad Administration, 2022). Similar trends can also be observed in other countries, such as Canada, where there was a 10% increase in road fatalities from January to September 2020 compared to the same period in 2019, despite a decrease in traffic volume due to lockdown measures (Canadian Council of Motor Transport Administrators, 2021).

The outbreak of COVID-19 has the potential to affect HRGC crashes in several ways. Firstly, the lockdowns, stay-at-home orders, and remote work policies implemented to reduce the spread of COVID-19 have led to a significant reduction in traffic volumes on highways (Muley et al., 2021; Wu et al., 2021). Meanwhile, there was a large decline of 11% in Vehicle Miles Traveled from 2019 to 2020 as the nation shut down and vehicular travel declined during 2020 in response to the pandemic (Federal Railroad Administration, 2022). However, the number of traffic-related deaths in 2020 reached a peak (38,824) since 2007 (41,259), representing a remarkable rise after three consecutive years of reductions from 37,806 in 2016. Secondly, the outbreak of COVID-19 has had a profound impact on the travel behaviour, with many individuals opting for alternative modes of transportation, such as private cars and bicycles, to

avoid public transit and reduce their exposure to the virus (Awad-Núñez et al., 2021; Shelat et al., 2022). This shift in the travel behaviour may have impacts on the injury severity of HRGC crashes. Private cars and bicycles are vulnerable to collisions with trains, as they may not be as visible to train operators and may have difficulty crossing tracks quickly. Previous studies also revealed that the COVID-19 pandemic would cause an increased possibility of distracted driving, risky driving, and impaired driving, as well as an increase in stress and anxiety (Adanu et al., 2022; Yasin et al., 2021). Finally, the pandemic can also lead to sample selectivity issues as stated in many studies (Islam et al., 2023; Said et al., 2023), as those who choose to travel by private cars or bicycles may have different characteristics than those who use public transits, which may impact their risks of injury in HRGC crashes. This highlights the potential effects of changes in travel patterns, as well as the necessity to identify the underlying factors that contribute to HRGC crashes during the pandemic.

2.2 Crash damage severity analysis for AVs

2.2.1 Crash determinant and crash pattern identification of AVs

The investigation of AV crashes has emerged as a critical area of transportation safety research, particularly as AV technologies transit from controlled testing to real-world deployment. Previous foundational studies primarily focused on technological reliability, examining sensor failures (Zhao et al., 2024), perception system limitations (Jiang et al., 2022), and decision-making algorithms (Tang et al., 2022). These works established important baselines for understanding AV-specific crash patterns that fundamentally differ from human-error-driven conventional crashes (World Health Organization, 2022). The evolving AV crash landscape reveals more complex interactions. For example, CA DMV collision reports demonstrates that over 60% of AV-involved incidents occurring during interactions with human road users or in complex building environment (California Department of Motor Vehicles, 2024). These complexities have prompted researchers to examine comprehensive risk factors beyond

vehicle technology alone.

A variety of data-driven and statistical techniques have been applied to unravel crash patterns and identify determinants contributing to AV crash damage severities (Mannering et al., 2020; Washington et al., 2020). Specifically, data mining techniques, such as cluster analysis, regression algorithms, and association rule mining, have been utilized to explore AV crash data and conduct safety analysis. For example, 245 AV collision records were collected and a specialized cost-sensitive classification and regression tree model was constructed by Zhu and Meng (2022) to investigate contributing factors to the AV crash severity and address the class imbalance issue. In the study by Moradloo et al. (2024), the hierarchical clustering method was applied to analyse 189 observations of crashes involving vehicles equipped with automated driving systems, and 15 edge cases were identified as instances involving rare or complex scenarios. Ashraf et al. (2021) utilized the decision tree and association rule approaches to identify the patterns preceding 198 AV-related collisions. The findings highlighted that the predominant incidents were rear-end collisions, occurring mainly at intersections while the AVs were halted and set to autonomous mode. Zhou et al. (2023) proposed a deep embedded clustering framework to identify prevalent high-risk collision scenarios involving AVs and powered-two-wheelers (PTWs), utilizing dynamic pre-crash attributes from real-world crash data. Stacked autoencoders were first utilized to extract embedded features from high-dimensional data. These features were then clustered and analysed using k-means clustering, thus successfully categorizing 180 car-to-PTWs crashes into six typical collision scenarios. Liu et al. (2024) employed the association rule mining technique to identify contributory risk factors and their mutual dependencies, which frequently co-occur in crashes involving AVs. The derived association rules indicate that these accidents were typically caused by intricate interactions among road conditions, vehicle attributes, and environmental circumstances. These data-driven methods have been shown to allow for a comprehensive evaluation of the collected data to identify AV crash patterns. However,

unraveling the impact of specific attributes on the likelihood of accidents and deriving substantive inferences have traditionally been weaknesses of these methods (Mannering et al., 2020). Furthermore, these data-driven methods tend to require a large amount of data to identify reliable patterns and correlations (Mannering et al., 2020).

As for the statistical models, their advantages of uncovering causality are preferred among safety analysts, especially in the context of AV crash dataset with low observations. In this regard, Xu et al. (2019) collected 72 AV-involved crashes from the CA DMV and then developed a bootstrap based binary logistic regression model to examine the determinants influencing the type and severity of crashes involving AVs. The findings indicated that the severity of crashes involving AVs is primarily influenced by factors including the AV driving mode, rear-end collision, collision location, roadside parking, and one-way road. To understand the factors that contribute to AV crashes, Boggs et al. (2020) constructed a database using 124 manufacturer-reported collision reports and applied hierarchical Bayesian logit models for estimation. The analysis showed a significantly increased risk of rear-end collisions involving AVs when the automated driving system was activated or when the driver disengaged the automated system before the crash. Based on the Bayesian Network coupled with Markov Chain Monte Carlo methods, Novat et al. (2023) utilized a mixed dataset consisting of 127 crashes involving AVs and 865 incidents involving conventional vehicles to conduct a comparative analysis that aimed at identifying the factors that contribute to the various types of collisions between these vehicles. The findings indicated that AVs are 43% more prone to rear-end collisions and 16% and 27% less susceptible to sideswipe/broadside and head-on/object-hitting incidents, compared to conventional vehicles. These statistical models are capable to handle different crash outcome categories efficiently and yield interpretable estimation results with a small sample size (Washington et al., 2020), thus allowing for a comprehensive understanding of how specific characteristics impact the likelihood of different damage severities in AV accidents.

Nevertheless, a notable deficiency in existing research is that they predominantly focused on holistic dataset analysis, overlooking the heterogeneity embedded within the AV crash data (Mannering et al., 2016b). The heterogeneity in AV crash patterns is a critical research area that requires special attention, given the multifaceted nature of AV operations and the diverse range of scenarios in which these vehicles may encounter challenges. Conducting AV accident analysis on a heterogeneous dataset can obscure significant relations (Mannering et al., 2016b; Ren and Xu, 2023b). It can mask underlying patterns and significant relationships that are crucial for understanding the dynamics of AV accidents, thus resulting in biased parameter estimates and erroneous inferences (Mannering et al., 2016b). Some previous research efforts have been invested in a particular attribute of conventional vehicle accidents to mitigate heterogeneity within the data, such as distinct categories of crashes, certain age demographics, different periods, specific crash locations, and lighting conditions (Fountas et al., 2020; Ren et al., 2024a). Nonetheless, it is important to recognize that those pre-specified segmentations may not ensure homogeneity within each subgroup and heterogeneity across different subgroups (Kim and Mokhtarian, 2023).

2.2.2 AV crash damage mediation analysis with built environment factors

Mediation analysis offers a rigorous framework to quantify indirect causal pathways (Wang et al., 2020), elucidating latent mechanisms through which mediation variables influence AV crash outcomes. In this regard, the structural equation modelling (SEM) approach is gaining traction for modelling traditional human-driven vehicle crash severity due to its ability to address complex interactions among multiple dependent and independent variables, including indirect or latent relationships (Najaf et al., 2017). For example, Xu et al. (2018a) utilized the SEM to convert traffic-related variables into independent latent factors, establishing interrelationships between key determinants and crash risks. Their findings highlighted that the path in SEM can effectively capture both direct and indirect effects of traffic variables on traffic crash risks. Dong et al. (2022) utilized the multigroup SEM to identify latent driving

behaviour indicators and investigate their relationships with crash damage severities and other independent variables during the COVID-19 pandemic. The employed SEM approach also demonstrated superior model fit compared to traditional probit models. Failure to account for the aforementioned indirect relationships may result in Type I errors (false positives) in identifying risk factors or, more critically, Type II errors (false negatives) that overlook genuine safety threats for AV crashes (Washington et al., 2020). Therefore, the adoption of SEM in AV crash outcome analysis would hold substantial promise and can offer a robust framework to unravel the complex interdependencies that shape AV safety outcomes.

A growing body of literature underscores the influence of the built environment on traffic safety (Amini et al., 2022), yet its impact on AV operations remains underexplored. Points of interest (POI) attributes—such as intersections, pedestrian zones, and nearby public fatalities—could introduce heterogeneous traffic conditions that challenge AV perception systems (Kuo et al., 2024). Prior studies have established correlations between POI characteristics and conventional human-driven vehicle crashes (Merlin et al., 2020; Soto et al., 2022), but whether these relationships persist in AV-involved collisions is still unclear. It can be speculated that building environment elements would influence AV performance in ways that diverge from human-driven vehicles. Bridging this knowledge gap through a holistic analysis of AV crash determinants is essential for developing context-aware safety frameworks tailored to AV operations and safety.

In the context of traditional human-driven vehicle crashes, research indicated that factors such as intersections, road surface conditions, and road types can significantly influence drivers' decision-making and safety attitudes (Peng et al., 2023). Besides, the number and layout of lanes affect drivers' reaction times and behavioural choices (Chen et al., 2022). The presence or absence of traffic signals also has significant impacts on crash damage severities (Peng et al., 2023). Additionally, many studies intricately that land-use configurations and traffic settings not only perplex human drivers but also

interfere with the decision-making processes of autonomous driving systems (Kuo et al., 2024), thus depicting the AVs' reaction to the surrounding environment. At the same time, well-designed crosswalk facilities can enhance pedestrians' sense of safety when crossing the street and reduce the occurrence of traffic accidents (Ihssian and Ismail, 2023). When it comes to AVs, the presence of various POIs such as commercial zones, educational institutions, recreational areas, and transit hubs presents unique challenges for AV perception and response mechanisms. Land-use patterns and urban design can also shape AV navigation, influencing crash rates and risk exposure. Recent analyses of AV collision reports also indicate that a substantial proportion of incidents could occur in complex urban environments, underscoring the necessity of a dedicated study to explore the interplay between AVs and their operational environments (Ren and Xu, 2025).

2.2.3 Analysis of variable co-occurrence patterns in AV rear-end crashes

Rear-end crashes have been identified as one of the most pressing safety concerns associated with AVs, accounting for nearly half of AV-related traffic crashes and often leading to severe damage outcomes (Xu et al., 2019). Researchers such as Liu et al. (2024a) and Ashraf et al. (2021) both found that AV rear-end crashes tend to be more severe compared to other crash types. Furthermore, studies using naturalistic driving data (Ren and Xu, 2025) and AV simulation frameworks (Wu et al., 2024) have also emphasized the significant proportion of rear-end crashes.

Despite the growing interest in AV safety, empirical research on rear-end crash mechanisms remains limited due to the novelty of AV technologies and data scarcity (Liu and Feng, 2024). Existing research has primarily relied on simulation data (Feng et al., 2023), small-scale real-world crash records (Liu et al., 2024a; Ren and Xu, 2025; C. Zhu et al., 2023), reconstructed scenarios (Zhou et al., 2023), field testing (Lee and Hess, 2020), and traffic flow analysis (Pan et al., 2024) to understand the safety performance of AVs. For example, an intelligent simulated testing environment using

dense deep reinforcement learning was developed by Feng et al. to significantly accelerate the AV safety validation process, thus enabling efficient evaluation and training of autonomous systems through AI-based agents that simulate real-world safety-critical scenarios (Feng et al., 2023). Using 245 AV collision records, Zhu and Meng employed a cost-sensitive classification and regression tree model to explore the factors influencing crash damage severities and solve the associated class imbalance (Zhu et al., 2023). In the study conducted by Zhou et al. (2023), a clustering framework based on deep embedding was used to identify six high-risk crash scenarios involving AVs and powered two-wheelers. Few studies have specifically investigated the mechanisms and risk factors underlying AV rear-end crashes, highlighting the urgent necessity for targeted empirical research to mitigate potential risks and prevent crashes.

While many studies examined the correlation between specific variables and AV crashes, there is a notable lack of research specifically focusing on the interrelationships among multiple factors in the context of AV rear-end crashes. Addressing this gap is crucial, as AV rear-end crash scenarios often involve complex and multifaceted interactions between risk factors. In this regard, the association rule mining technique, a complementary data mining method, has gained increasing attention in traffic safety research for its ability to reveal complex interdependencies among crash-related variables. Unlike conventional regression-based models (Chen et al., 2022, 2025; Xu et al., 2018; Zhang and Lin, 2025), association rule mining is an unsupervised learning technique that can discover frequent variable co-occurrence patterns within crash datasets. This makes it particularly well-suited for identifying multifactorial crash scenarios that may be overlooked by traditional statistical methods. For example, Mimi et al. (2025) conducted a six-year analysis (2017–2022) of Texas crash records using association rule mining to uncover significant patterns influencing crash severity among elderly pedestrians aged 65–74 and over 74, particularly under different lighting environments. Lan et al. (2023) integrated association rule mining with complex networks to explore the correlation among risk factors and predict the severity of ship

crashes. This study not only identified critical risk interactions but also demonstrated the value of combining association rule mining with network modeling for safety assessments. Under the framework of association rule mining technique, Çakır et al. (2021) applied Apriori, Predictive Apriori, and FP-Growth algorithms to analyze tugboat crash data, revealing frequent co-occurrence patterns such as the link between aging vessels and hull damage. Besides, Lan et al. (2022) investigated total loss maritime crashes using the association rule mining, identifying crash types such as machinery damage and foundering as critical patterns contributing to significant loss outcomes. These studies demonstrate that association rule mining can not only complement traditional modeling by uncovering multiple variable associations but also can enhance policy relevance through its interpretability and actionable rule-based outputs, thus providing a powerful tool for holistic safety assessments for AV rear-end crashes.

2.3 Analytic methods for post-crash injury severity modelling

In recent years, many studies have used historical accident data to formulate safety countermeasures and reduce the crash injury severities. Early accident analysis models mostly focused on accident frequency models, such as accident frequency prediction, accident black spot identification, etc. (El-Basyouny and Sayed, 2009; Ghadi and Török, 2019). Accident frequency prediction mainly considered the non-negativity and integer of accident frequency by counting models, and the identification of accident black spots was realized by calculating the relatively frequent points of road network accidents in a certain statistical period. However, neither accident frequency prediction nor black spot identification can reflect the logical process of accident occurrence, and the severity of accident is not divided. Therefore, the medium-term accident analysis model begins to use multivariate discrete selection model to explore the cause and severity of accident. The commonly used models include multivariate logit/probit models, ordered logit/probit models, negative binomial models, etc. (Lapparent, 2008; Khattak and Rocha, 2003; Wang and Abdel-Aty, 2008). These models are usually incompatible with multi-source and heterogeneous traffic accident data, thus resulting in large estimation biases.

In order to solve the aforementioned problems, models integrating heterogeneity and endogeneity were proposed, such as random parameter logit models and latent classification logit models (Cerwick et al., 2014; Kim et al., 2013; Li et al., 2019; Morgan and Mannering, 2011; Wu et al., 2014; Yu et al., 2019), but mathematical statistical models are usually difficult to deal with massive data. Therefore, many studies began to use data-driven methods for accident prediction (Elamrani et al., 2020b; Sameen and Pradhan, 2017; Yu et al., 2021; Yu et al., 2020; Zheng et al., 2019). To sum up, accident analysis methods can be basically summarized into four categories: traditional mathematical statistical model, endogenous/heterogeneous model, data-driven method and causal inference model.

(1) Traditional mathematical statistical models: Statistical methods and limited accident data are usually used to predict the impact of various traffic safety improvement measures on accident risk and crash injuries (Mannering et al., 2016). However, traditional mathematical statistical models usually have certain deviations in model estimation due to the failure to solve the problems of missing data, temporal instability of parameters, and accident heterogeneity. In order to solve the above problems, researchers began to use endogeneity model and heterogeneity model to replace the traditional mathematical statistics model (Azimi et al., 2020; Dabbour et al., 2017; Yu et al., 2020b).

(2) Endogenous/heterogeneity models: The endogenous model explains the endogeneity between accident-related variables, that is, considering the potential correlation between model dependent variables. The heterogeneity model mainly excavates the non-observed variables that affect the injury severity of accident casualties. Generally speaking, the model integrating endogeneity and heterogeneity has higher requirements for data. The richer the accident variables, the higher the interpretability of the model. However, it often brings more computational constraints when the complexity of the model increases, which results in the decline of the generalization ability of the model. To estimate highly complex endogenous and heterogeneous models, simulation method and approximate estimation method are usually used for numerical integration. Although researchers have made some progress in such methods in recent years, there are still many challenges in model estimation when facing a huge data system (Mannering, 2018a).

(3) Data-driven methods: These methods refer to machine learning, deep learning, reinforcement learning, etc., which can process massive data and have high prediction accuracy. However, most data-driven models are non-parametric models, also known as “smart black boxes”, which usually cannot explain the mechanism of accidents and injury severities. The accident causal relationship mined by existing data-driven models is not generalizable and universal. Typical non-parametric models can usually be divided into regularization algorithms, decision tree algorithms, Bayesian networks, clustering algorithms, association rule algorithms, artificial neural network, dimensionality reduction algorithms, ensemble algorithms and reinforcement learners, etc. (Mannering et al., 2020c; Tang et al., 2020).

(4) Causal inference models: The model reveals that historical accidents and injury severities may have a certain tendency and representativeness, resulting in the deviation of results. In addition, the prediction performance of causal inference model is poor and has the characteristics of time series, which is easy to produce large analysis biases (Tang et al., 2020). It is rarely used in traffic accident analysis, but it has a certain application foundation in other fields.

Generally, we need to consider not only how to achieve the balance between model predictability and model explanatory power, but also the applicability of data when selecting models. For example, the prediction performance and explanatory power of endogenous and heterogeneous models are higher than those of traditional mathematical statistical models, but they have high requirements for input data, and there are some difficulties in practical application. On the contrary, the traditional mathematical statistical model has lower requirements for input data and it is easier to apply, but there are also shackles such as low prediction accuracy of the model.

These four analytical approaches—traditional, endogeneity/heterogeneity, data-driven, and causal models—differ significantly in their data dependencies. The intended purpose of the modelling exercise further informs the method selection. While endogeneity and heterogeneity models generally offer superior predictive and causal insights compared to traditional models, their application demands highly granular data and involves greater complexity. Traditional safety models, in contrast, are less data-intensive and simpler to implement, but this practicality compromises their predictive accuracy and causal explanatory power, often introducing inferential bias.

When dealing with extremely large datasets, such as those from naturalistic driving studies, the estimation of traditional, advanced endogeneity/heterogeneity, and causal models becomes computationally challenging. In such “big data” contexts, data-driven methods frequently emerge as the most feasible option. Although applicable across various data scales, data-driven approaches are less favoured with smaller datasets where other methods excel at uncovering causal relationships. A key limitation of purely data-driven methods is their potential detachment from domain-specific knowledge, leading to inferences based predominantly on statistical patterns. The rise of artificial intelligence offers a pathway to integrate automated forms of domain expertise, refining models built on statistical reasoning. Ultimately, however, human judgment and domain expertise remain indispensable, particularly for establishing causal inference frameworks where variable relationships are theorized from prior knowledge.

Consider modelling factors influencing traffic fatalities, where the rare event problem is pronounced—fatalities constitute only about 0.6% of reported accidents. Deriving meaningful policy insights requires massive datasets to adequately represent non-traditional variables (e.g., those related to impaired driving or proximity to alcohol venues). A purely data-driven model might overlook crucial variables if not originally encoded in the data. Domain expertise guides the inclusion of such access-related measures, informed by the established causal link between alcohol impairment and fatality risk. Similarly, literature suggests correlations between economic cycles and fatality rates—a contextual insight absent in purely statistical models. This illustrates a potential “model-data disconnect” in big data analytics, where relevant variables may be omitted, creating a form of hidden missing data. While AI may mitigate some of this gap, human expertise is still required to frame the problem correctly.

This leads to a critical consideration: if big data modelling aims to generate novel insight, its value hinges on the quality of inference it enables. Thus, it transcends merely handling vast datasets or identifying correlations; the paramount challenge is achieving “big inference”—high-quality, actionable understanding. The drunk-driving example demonstrates a case where big inference is limited without accounting for unobserved heterogeneity. Another limitation arises from conflating correlation with causation, potentially prompting misguided policies. These are instances of constrained big inference in the absence of domain-informed model structuring. Conversely, big data

can itself be a source of valuable heterogeneity through previously unmeasured, fine-grained variables. In naturalistic driving studies, for instance, it enables the use of non-traditional metrics like precise lane positioning or vehicle dynamics for risk modelling.

2.4 Research gaps

Based on the literature review of HDV crash severity analysis, AV crash severity analysis, and methods for crash severity analysis, several research gaps have been identified:

(1) While extensive studies have been undertaken to understand the influence of adverse road conditions on HDV driver injury severities, it cannot be ignored that they may not sufficiently accommodate the potential temporal instability and unobserved heterogeneity arising from various factors in adverse-road-related crashes, especially concerning individual vehicle impact location. Besides, combining near-side and far-side collisions together may overlook the inhomogeneous injury outcomes and cause misinterpretations. However, to date, few studies have attempted to uncover the internal mechanism between deteriorating road surfaces and vehicle impact locations on the driver injury severity in single-vehicle crashes at a disaggregate level. Furthermore, the current knowledge regarding whether the determinants influencing adverse-road-related crash injury severities vary across different impact locations and the underlying mechanism behind such divergence is rather limited.

(2) Despite being critical for the smooth operation and safety of multimodal transportation systems, non-divided two-way HRGCs are rarely specifically explored in previous studies. Additionally, previous studies on the injury severity analysis of HRGC crashes did not fully take into account the unobserved heterogeneity and potential variable interactive effects. The outbreak of COVID-19 pandemic has also led to significant changes in the traffic volume, driver behaviour, and sample selectivity, which could alter the transportation pattern and influence the injury severity of HRGC crashes. Despite the disproportionately high percentage of injuries and fatalities, very limited research has been conducted to investigate the injury severity in HRGC crashes during the COVID-19 pandemic.

(3) A notable deficiency in existing research is that they predominantly focused on holistic dataset analysis, overlooking the heterogeneity embedded within the AV

crash data. The heterogeneity in AV crash patterns is a critical research area that requires special attention, given the multifaceted nature of AV operations and the diverse range of scenarios in which these vehicles may encounter challenges. Conducting AV accident analysis on a heterogeneous dataset can obscure mask underlying patterns and significant relationships that are crucial for understanding the dynamics of AV accidents, thus resulting in biased parameter estimates and erroneous inferences.

(4) The nascent stage of AV technology development and limited availability of comprehensive AV crash records have constrained current safety analyses to primarily exploratory investigations. While numerous studies have identified factors affecting the severity and frequency of human-driven vehicle crashes, few studies have explored the impact of built environment characteristics on AV crash damage severities. Besides, direct and mediation effects of key factors on AV crash severities remain underexplored.

(5) While existing literature has emphasized the dominance of rear-end crashes in the context of AVs, limited attention has specifically been given to the contributing factors that lead to this AV crash type. As AV rear-end crash scenarios often involve complex and multifaceted interactions between risk factors, it is necessary to uncover the combinations of contributing factors that frequently co-occur in AV rear-end crashes.

Chapter 3 Temporal instability of factors affecting driver injury severities between different vehicle impact locations under adverse road surface conditions

3.1 Introduction

The adverse road surface condition has been widely acknowledged as a vital determinant that has a remarkable impact on the likelihood of accident occurrences and injury severities. Accompanied by deteriorating driving conditions such as decreased visibility, irregular yaw rate feedback, and poor emergency braking performance (Koylu and Tural, 2021), driving in unfavorable road circumstances could dramatically increase the frequency of driving errors and dangerous driving behaviours (Alnawmasi and Mannering, 2019; Yan et al., 2021a). According to the Federal Highway Administration (FHWA, 2022), there is approximately 75% of automobile accidents occurred on wet pavements every year in the United States. Specifically, almost 5,700 people are killed and over 544,700 are wounded in these crashes. Meanwhile, snowy, slushy, and icy pavements account for 24% of all weather-related vehicle collisions each year, with over 1,300 people being killed and over 116,800 people being injured. Note that other than serious safety issues, adverse road surfaces could also cause traffic delays and inflict damage to roadway infrastructure (FHWA, 2022). In this context, special emphasis should be given to uncover the underlying mechanism of how related factors affect the driver injury severity outcomes in adverse-road-related crashes, which has the potential to improve road safety and minimize associated expenditures.

In addition to adverse roadway surfaces, the vehicle impact location could also have a considerable influence on the injury severity sustained by drivers as indicated in previous studies (Lai et al., 2012; Champahom et al., 2020; Yu et al., 2020; Liu and Fan, 2021; Wang et al., 2022). Note that although Wang et al. (2022) investigated contributing factors of driver injury severities between rear-end and non-rear-end crashes, it is undeniable that drivers are more prone to sustaining severe injuries in near-side crashes than in far-side collisions due to the direct impact and significantly restricted survival space. Combining near-side and far-side

collisions together may overlook the inhomogeneous injury outcomes and cause misinterpretations. However, to date, few studies have attempted to uncover the internal mechanism between deteriorating road surfaces and vehicle impact locations on the driver injury severity in single-vehicle crashes at a disaggregate level. Furthermore, the current knowledge regarding whether the determinants influencing adverse-road-related crash injury severities vary across different impact locations and the underlying mechanism behind such divergence is rather limited.

3.2 Data description

The crash data utilized in the study is provided by the Highway Safety Information System, which contains single-vehicle crash records that occurred under adverse road surface conditions in Ohio from January 1, 2015, to December 31, 2017. In this research, adverse-road-related crashes refer to crashes that happen on wet, snowy, icy, or mud-sand road surfaces. Regarding the detailed classification of different vehicle impact locations, the “Center Front” and “Rear Center” samples are classified as the center crashes; the “Left Front”, “Left Side”, and “Left Rear” samples are identified as the left-side crashes; and the “Right Front”, “Right Side”, and “Right Rear” samples are categorized as the right-side crashes. Meanwhile, the accident sub-dataset and the vehicle sub-dataset are merged based on the corresponding accident identification number to comprehensively identify the determinants of driver injury severities over the observed years. After screening out observations with missing data in variables, the final dataset contains 12,013, 6,532, and 10,628 records for 2015, 2016, and 2017, respectively.

Three categories are utilized to represent driver injury severity outcomes: no injury, minor injury, and severe injury. Multiple variables including crash characteristics, driver characteristics, temporal characteristics, vehicle characteristics, roadway characteristics, and environment characteristics are identified as explanatory variables determining different levels of driver injury severities associated with adverse-road-related crashes. Table 3.1 and Figure 3.1 show the driver injury severity distribution of different vehicle impact locations by year

(78.68%, 19.56%, and 1.76% for no injury, minor injury, and severe injury in total center crashes, 81.58%, 16.76%, and 1.66% in total left-side crashes, while 84.71%, 14.27%, and 1.02% in total right-side crashes). Specifically, center crashes make up the largest proportion of all injury levels throughout the observed years. It should be noted that the proportion of no injuries in center crashes is the smallest compared to that in left-side and right-side crashes. Typically, the proportions of minor and severe injuries in center and left-side crashes are greater than those in right-side crashes. Table 3.2 presents the descriptive statistics of independent variables in the center, left-side, and right-side crashes across different years.

Table 3.1. Crash injury frequency distribution for impact locations by year.

Year	Center crashes			Left-side crashes			Right-side crashes			Total
	NI	MI	SI	NI	MI	SI	NI	MI	SI	
2015	3455	871	73	3097	630	60	3280	517	30	12013
2016	1969	493	41	1605	338	25	1736	296	29	6532
2017	3254	793	80	2677	548	65	2692	485	34	10628

Remarks: NI = No Injury; MI = Minor Injury; SI = Severe Injury.

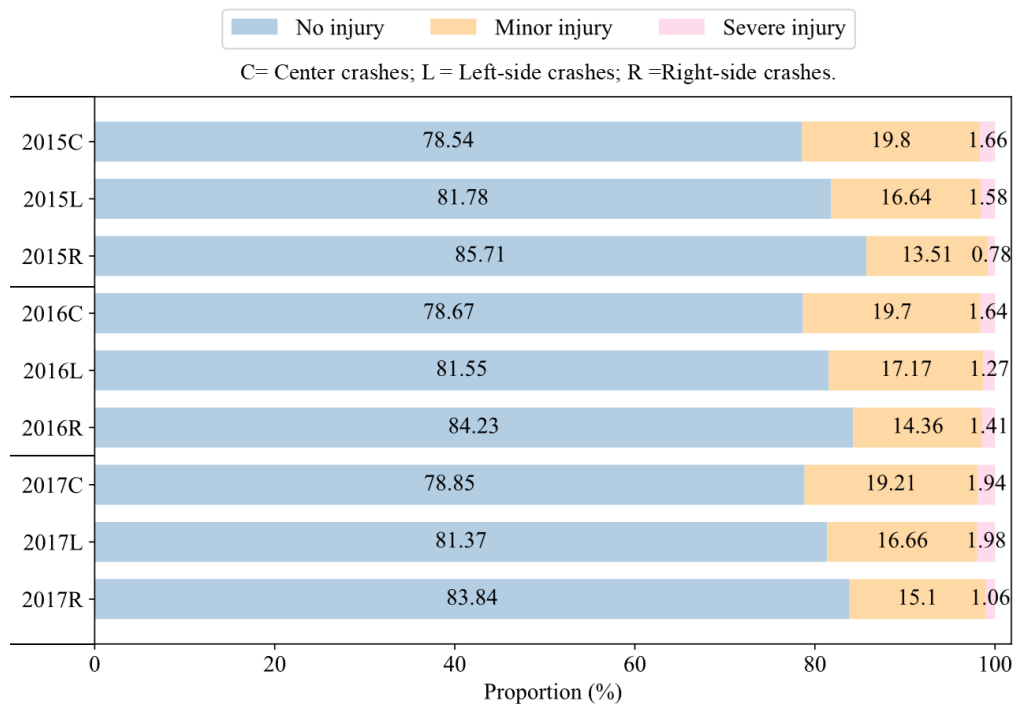


Figure 3.1. Adverse-road-related crash injury severity distribution for different impact locations over the years.

Table 3.2. Descriptive statistics of independent variables (Std. Dev. in parentheses).

Variables	IL	2015			2016			2017		
		NI	MI	SI	NI	MI	SI	NI	MI	SI
Crash characteristics										
Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise)	C	0.744 (0.436)	0.944 (0.230)	0.973 (0.164)	0.775 (0.418)	0.917 (0.276)	0.927 (0.264)	0.743 (0.437)	0.913 (0.282)	0.937 (0.243)
	L	0.751 (0.433)	0.884 (0.320)	0.950 (0.219)	0.762 (0.426)	0.893 (0.309)	0.840 (0.374)	0.729 (0.444)	0.909 (0.288)	0.923 (0.267)
	R	0.798 (0.402)	0.905 (0.293)	0.900 (0.302)	0.810 (0.392)	0.892 (0.311)	0.897 (0.310)	0.790 (0.407)	0.911 (0.284)	1.000 (0.000)
Collision with non-fixed object indicator (1 if collided with non-fixed object as the first harmful event, 0 otherwise)	C	0.223 (0.416)	0.035 (0.184)	0.000 (0.000)	0.195 (0.396)	0.034 (0.183)	0.000 (0.000)	0.225 (0.418)	0.042 (0.200)	0.050 (0.218)
	L	0.186 (0.389)	0.019 (0.138)	0.017 (0.128)	0.173 (0.378)	0.030 (0.170)	0.040 (0.200)	0.217 (0.412)	0.035 (0.183)	0.000 (0.000)
	R	0.147 (0.354)	0.035 (0.184)	0.000 (0.000)	0.146 (0.353)	0.030 (0.172)	0.000 (0.000)	0.157 (0.364)	0.027 (0.162)	0.000 (0.000)
Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise)	C	0.033 (0.178)	0.026 (0.160)	0.027 (0.164)	0.030 (0.171)	0.049 (0.215)	0.073 (0.264)	0.031 (0.174)	0.045 (0.208)	0.013 (0.111)
	L	0.064 (0.244)	0.081 (0.273)	0.033 (0.180)	0.065 (0.247)	0.077 (0.267)	0.120 (0.332)	0.054 (0.226)	0.057 (0.231)	0.077 (0.267)
	R	0.055 (0.229)	0.075 (0.264)	0.100 (0.302)	0.044 (0.206)	0.078 (0.268)	0.103 (0.310)	0.053 (0.224)	0.062 (0.241)	0.000 (0.000)
Animal indicator (1 if animal involved in the crash, 0 otherwise)	C	0.203 (0.402)	0.022 (0.146)	0.000 (0.000)	0.176 (0.381)	0.020 (0.141)	0.000 (0.000)	0.209 (0.406)	0.033 (0.178)	0.025 (0.156)
	L	0.169 (0.374)	0.029 (0.167)	0.000 (0.000)	0.158 (0.365)	0.024 (0.152)	0.000 (0.000)	0.200 (0.400)	0.026 (0.158)	0.000 (0.000)
	R	0.126 (0.332)	0.015 (0.123)	0.000 (0.000)	0.126 (0.331)	0.027 (0.162)	0.000 (0.000)	0.139 (0.346)	0.023 (0.149)	0.000 (0.000)
Non-functional damage indicator (1 if damage to vehicle is non-functional, 0 otherwise)	C	0.230 (0.421)	0.056 (0.230)	0.014 (0.117)	0.203 (0.402)	0.057 (0.232)	0.000 (0.000)	0.192 (0.394)	0.052 (0.221)	0.013 (0.111)
	L	0.248 (0.432)	0.063 (0.244)	0.017 (0.128)	0.229 (0.420)	0.095 (0.293)	0.080 (0.277)	0.225 (0.418)	0.051 (0.220)	0.031 (0.173)
	R	0.254 (0.435)	0.093 (0.290)	0.033 (0.181)	0.258 (0.438)	0.111 (0.315)	0.069 (0.258)	0.231 (0.422)	0.060 (0.237)	0.029 (0.170)
Functional damage indicator (1 if damage to vehicle is functional, 0 otherwise)	C	0.286 (0.452)	0.166 (0.373)	0.068 (0.253)	0.270 (0.444)	0.148 (0.356)	0.049 (0.218)	0.258 (0.437)	0.122 (0.328)	0.025 (0.156)
	L	0.335 (0.472)	0.198 (0.399)	0.033 (0.180)	0.326 (0.469)	0.216 (0.412)	0.040 (0.200)	0.317 (0.465)	0.188 (0.391)	0.062 (0.241)
	R	0.333 (0.471)	0.195 (0.397)	0.233 (0.425)	0.312 (0.464)	0.193 (0.395)	0.034 (0.186)	0.318 (0.466)	0.179 (0.384)	0.235 (0.426)
Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise)	C	0.484 (0.500)	0.777 (0.416)	0.918 (0.275)	0.527 (0.499)	0.795 (0.404)	0.951 (0.218)	0.551 (0.497)	0.826 (0.379)	0.962 (0.190)
	L	0.417 (0.493)	0.738 (0.440)	0.950 (0.219)	0.445 (0.497)	0.689 (0.463)	0.880 (0.332)	0.458 (0.498)	0.761 (0.427)	0.908 (0.290)
	R	0.413 (0.492)	0.712 (0.453)	0.733 (0.445)	0.430 (0.495)	0.696 (0.461)	0.897 (0.310)	0.451 (0.498)	0.761 (0.427)	0.735 (0.443)
Straight driving indicator (1 if the vehicle was going straight preceding the crash, 0 otherwise)	C	0.782 (0.413)	0.750 (0.433)	0.699 (0.460)	0.743 (0.437)	0.740 (0.439)	0.780 (0.419)	0.761 (0.427)	0.715 (0.452)	0.713 (0.454)
	L	0.765 (0.424)	0.730 (0.444)	0.683 (0.466)	0.748 (0.434)	0.692 (0.462)	0.640 (0.490)	0.741 (0.438)	0.730 (0.444)	0.754 (0.432)
	R	0.752 (0.432)	0.721 (0.448)	0.833 (0.375)	0.762 (0.426)	0.716 (0.452)	0.586 (0.501)	0.738 (0.440)	0.711 (0.453)	0.676 (0.470)
Other movements indicator (1 if vehicle was making turns or other movements preceding the crash, 0 otherwise)	C	0.218 (0.413)	0.250 (0.433)	0.301 (0.460)	0.257 (0.437)	0.260 (0.439)	0.220 (0.419)	0.239 (0.427)	0.285 (0.452)	0.288 (0.454)
	L	0.218 (0.413)	0.250 (0.433)	0.301 (0.460)	0.252 (0.434)	0.308 (0.462)	0.360 (0.490)	0.259 (0.438)	0.270 (0.444)	0.246 (0.432)
	R	0.248 (0.432)	0.279 (0.448)	0.167 (0.375)	0.238 (0.426)	0.284 (0.452)	0.414 (0.501)	0.262 (0.440)	0.289 (0.453)	0.324 (0.470)
Driver characteristics										
Young driver indicator (1 if driver age below 30 years, 0 otherwise)	C	0.466 (0.499)	0.514 (0.500)	0.384 (0.487)	0.493 (0.500)	0.477 (0.500)	0.366 (0.488)	0.491 (0.500)	0.488 (0.500)	0.362 (0.482)
	L	0.470 (0.499)	0.483 (0.500)	0.450 (0.499)	0.485 (0.500)	0.503 (0.501)	0.480 (0.510)	0.470 (0.499)	0.474 (0.499)	0.385 (0.488)
	R	0.459 (0.498)	0.509 (0.500)	0.433 (0.498)	0.463 (0.499)	0.446 (0.498)	0.379 (0.494)	0.463 (0.499)	0.468 (0.499)	0.529 (0.502)
Middle-aged driver indicator (1 if driver age between 30–50 years, 0 otherwise)	C	0.335 (0.472)	0.290 (0.454)	0.301 (0.460)	0.311 (0.463)	0.329 (0.470)	0.317 (0.471)	0.308 (0.462)	0.333 (0.471)	0.300 (0.459)
	L	0.323 (0.468)	0.343 (0.475)	0.283 (0.452)	0.334 (0.472)	0.314 (0.465)	0.280 (0.458)	0.318 (0.466)	0.356 (0.479)	0.338 (0.474)
	R	0.337 (0.473)	0.296 (0.457)	0.300 (0.461)	0.331 (0.471)	0.328 (0.470)	0.414 (0.501)	0.329 (0.470)	0.320 (0.466)	0.147 (0.356)
Old driver indicator (1 if driver age over 50, 0 otherwise)	C	0.200 (0.400)	0.195 (0.396)	0.315 (0.466)	0.197 (0.397)	0.195 (0.396)	0.317 (0.471)	0.201 (0.401)	0.179 (0.383)	0.338 (0.474)
	L	0.207 (0.405)	0.175 (0.380)	0.267 (0.443)	0.181 (0.385)	0.183 (0.388)	0.240 (0.436)	0.213 (0.409)	0.170 (0.375)	0.277 (0.449)
	R	0.205 (0.404)	0.195 (0.397)	0.267 (0.445)	0.206 (0.405)	0.226 (0.419)	0.207 (0.412)	0.208 (0.406)	0.212 (0.409)	0.324 (0.470)
	C	0.961 (0.193)	0.878 (0.327)	0.671 (0.471)	0.957 (0.203)	0.854 (0.354)	0.537 (0.505)	0.952 (0.213)	0.860 (0.347)	0.688 (0.464)

Variables	IL	2015			2016			2017		
		NI	MI	SI	NI	MI	SI	NI	MI	SI
Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise)	L	0.961 (0.195)	0.894 (0.308)	0.600 (0.491)	0.958 (0.201)	0.926 (0.262)	0.640 (0.490)	0.963 (0.188)	0.903 (0.296)	0.692 (0.463)
	R	0.952 (0.213)	0.882 (0.323)	0.400 (0.493)	0.959 (0.199)	0.885 (0.319)	0.414 (0.501)	0.954 (0.210)	0.868 (0.339)	0.559 (0.499)
Gender indicator (1 if driver was female, 0 otherwise)	C	0.373 (0.484)	0.486 (0.500)	0.466 (0.500)	0.371 (0.483)	0.454 (0.498)	0.244 (0.435)	0.377 (0.485)	0.464 (0.499)	0.412 (0.493)
	L	0.376 (0.484)	0.490 (0.500)	0.317 (0.466)	0.361 (0.480)	0.485 (0.501)	0.400 (0.500)	0.369 (0.482)	0.513 (0.500)	0.446 (0.498)
	R	0.371 (0.483)	0.495 (0.500)	0.333 (0.474)	0.369 (0.483)	0.524 (0.500)	0.379 (0.494)	0.372 (0.483)	0.499 (0.500)	0.500 (0.502)
Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise)	C	0.059 (0.236)	0.171 (0.377)	0.338 (0.474)	0.071 (0.256)	0.181 (0.385)	0.390 (0.494)	0.058 (0.233)	0.178 (0.382)	0.413 (0.493)
	L	0.059 (0.236)	0.171 (0.377)	0.338 (0.474)	0.054 (0.226)	0.121 (0.327)	0.240 (0.436)	0.059 (0.235)	0.128 (0.334)	0.215 (0.412)
	R	0.067 (0.249)	0.133 (0.340)	0.289 (0.456)	0.068 (0.252)	0.122 (0.327)	0.207 (0.412)	0.060 (0.237)	0.142 (0.349)	0.294 (0.458)
Temporal characteristics										
Weekday indicator (1 if crash occurred during the weekday, 0 otherwise)	C	0.648 (0.478)	0.659 (0.474)	0.685 (0.466)	0.682 (0.466)	0.692 (0.462)	0.561 (0.502)	0.708 (0.455)	0.728 (0.445)	0.688 (0.464)
	L	0.636 (0.481)	0.654 (0.476)	0.567 (0.497)	0.685 (0.465)	0.722 (0.449)	0.560 (0.507)	0.737 (0.440)	0.728 (0.445)	0.800 (0.401)
	R	0.651 (0.477)	0.660 (0.474)	0.733 (0.445)	0.696 (0.460)	0.703 (0.458)	0.759 (0.435)	0.740 (0.439)	0.720 (0.449)	0.824 (0.383)
Early morning indicator (1 if time of day is between 12 AM to 5:59 AM, 0 otherwise)	C	0.192 (0.394)	0.166 (0.373)	0.164 (0.371)	0.196 (0.397)	0.211 (0.408)	0.220 (0.419)	0.189 (0.391)	0.197 (0.398)	0.250 (0.434)
	L	0.185 (0.388)	0.175 (0.380)	0.200 (0.401)	0.186 (0.389)	0.142 (0.350)	0.240 (0.436)	0.192 (0.394)	0.170 (0.375)	0.185 (0.389)
	R	0.187 (0.390)	0.149 (0.356)	0.267 (0.445)	0.184 (0.387)	0.155 (0.363)	0.172 (0.384)	0.180 (0.384)	0.190 (0.392)	0.059 (0.236)
Morning indicator (1 if time of day is between 6AM to 11:59 AM, 0 otherwise)	C	0.316 (0.465)	0.323 (0.468)	0.219 (0.415)	0.268 (0.443)	0.278 (0.448)	0.244 (0.435)	0.290 (0.454)	0.290 (0.454)	0.288 (0.454)
	L	0.320 (0.467)	0.329 (0.470)	0.267 (0.443)	0.312 (0.463)	0.299 (0.458)	0.280 (0.458)	0.302 (0.459)	0.325 (0.468)	0.200 (0.401)
	R	0.333 (0.471)	0.358 (0.480)	0.233 (0.425)	0.309 (0.462)	0.338 (0.474)	0.241 (0.435)	0.298 (0.457)	0.334 (0.472)	0.412 (0.495)
Afternoon indicator (1 if time of day is between 12 PM to 6:59 PM, 0 otherwise)	C	0.271 (0.444)	0.302 (0.459)	0.370 (0.484)	0.307 (0.461)	0.296 (0.457)	0.390 (0.494)	0.279 (0.449)	0.277 (0.448)	0.250 (0.434)
	L	0.284 (0.451)	0.305 (0.460)	0.333 (0.473)	0.290 (0.454)	0.355 (0.479)	0.320 (0.476)	0.278 (0.448)	0.296 (0.456)	0.308 (0.463)
	R	0.268 (0.443)	0.292 (0.455)	0.300 (0.461)	0.281 (0.450)	0.307 (0.462)	0.276 (0.455)	0.299 (0.458)	0.291 (0.454)	0.324 (0.470)
Evening indicator (1 if time of day is between 7 PM to 11:59 PM, 0 otherwise)	C	0.221 (0.415)	0.209 (0.407)	0.247 (0.432)	0.230 (0.421)	0.215 (0.411)	0.146 (0.358)	0.242 (0.428)	0.236 (0.425)	0.212 (0.410)
	L	0.210 (0.407)	0.192 (0.394)	0.200 (0.401)	0.213 (0.410)	0.204 (0.404)	0.160 (0.374)	0.228 (0.420)	0.210 (0.407)	0.308 (0.463)
	R	0.212 (0.409)	0.201 (0.401)	0.200 (0.402)	0.226 (0.418)	0.199 (0.400)	0.310 (0.471)	0.223 (0.416)	0.186 (0.389)	0.206 (0.406)
Spring indicator (1 if crash occurred during the spring, 0 otherwise)	C	0.142 (0.349)	0.162 (0.368)	0.205 (0.405)	0.190 (0.392)	0.181 (0.385)	0.146 (0.358)	0.163 (0.370)	0.199 (0.400)	0.225 (0.418)
	L	0.139 (0.345)	0.176 (0.381)	0.200 (0.401)	0.177 (0.382)	0.169 (0.375)	0.240 (0.436)	0.161 (0.368)	0.159 (0.366)	0.185 (0.389)
	R	0.137 (0.344)	0.172 (0.378)	0.267 (0.445)	0.181 (0.386)	0.247 (0.432)	0.172 (0.384)	0.150 (0.357)	0.210 (0.408)	0.176 (0.383)
Summer indicator (1 if crash occurred during the summer, 0 otherwise)	C	0.088 (0.284)	0.123 (0.328)	0.096 (0.295)	0.105 (0.307)	0.130 (0.336)	0.049 (0.218)	0.118 (0.323)	0.134 (0.340)	0.112 (0.317)
	L	0.090 (0.286)	0.114 (0.318)	0.133 (0.341)	0.108 (0.311)	0.154 (0.361)	0.080 (0.277)	0.108 (0.310)	0.128 (0.334)	0.154 (0.362)
	R	0.085 (0.279)	0.108 (0.311)	0.100 (0.302)	0.113 (0.317)	0.159 (0.366)	0.207 (0.412)	0.119 (0.324)	0.163 (0.369)	0.059 (0.236)
Autumn indicator (1 if crash occurred during the autumn, 0 otherwise)	C	0.214 (0.410)	0.207 (0.405)	0.233 (0.424)	0.318 (0.466)	0.298 (0.458)	0.268 (0.449)	0.275 (0.446)	0.231 (0.421)	0.325 (0.469)
	L	0.193 (0.395)	0.187 (0.390)	0.183 (0.388)	0.320 (0.466)	0.308 (0.462)	0.400 (0.500)	0.270 (0.444)	0.228 (0.420)	0.154 (0.362)
	R	0.193 (0.395)	0.162 (0.369)	0.167 (0.375)	0.308 (0.462)	0.233 (0.424)	0.207 (0.412)	0.272 (0.445)	0.227 (0.419)	0.265 (0.443)
Winter indicator (1 if crash occurred during the winter, 0 otherwise)	C	0.555 (0.497)	0.509 (0.500)	0.466 (0.500)	0.386 (0.487)	0.391 (0.489)	0.537 (0.505)	0.443 (0.497)	0.436 (0.496)	0.338 (0.474)
	L	0.578 (0.494)	0.522 (0.500)	0.483 (0.501)	0.395 (0.489)	0.370 (0.483)	0.280 (0.458)	0.461 (0.499)	0.485 (0.500)	0.508 (0.501)
	R	0.584 (0.493)	0.557 (0.497)	0.467 (0.502)	0.397 (0.490)	0.361 (0.481)	0.414 (0.501)	0.460 (0.498)	0.400 (0.490)	0.500 (0.502)
Vehicle characteristics										
Passenger car involvement indicator (1 if passenger car being involved in the crash, 0 otherwise)	C	0.595 (0.491)	0.637 (0.481)	0.521 (0.501)	0.597 (0.491)	0.586 (0.493)	0.415 (0.499)	0.607 (0.488)	0.608 (0.488)	0.625 (0.485)
	L	0.558 (0.497)	0.492 (0.500)	0.467 (0.500)	0.535 (0.499)	0.586 (0.493)	0.600 (0.500)	0.561 (0.496)	0.558 (0.497)	0.492 (0.501)
	R	0.536 (0.499)	0.569 (0.495)	0.533 (0.502)	0.544 (0.498)	0.591 (0.492)	0.517 (0.509)	0.536 (0.499)	0.528 (0.499)	0.529 (0.502)
	C	0.226 (0.418)	0.185 (0.388)	0.315 (0.466)	0.213 (0.410)	0.221 (0.415)	0.390 (0.494)	0.207 (0.405)	0.190 (0.393)	0.163 (0.370)

Variables	IL	2015			2016			2017		
		NI	MI	SI	NI	MI	SI	NI	MI	SI
Truck involvement indicator (1 if truck being involved in the crash, 0 otherwise)	L	0.258 (0.437)	0.254 (0.435)	0.333 (0.473)	0.255 (0.436)	0.213 (0.410)	0.320 (0.476)	0.238 (0.426)	0.215 (0.411)	0.308 (0.463)
	R	0.263 (0.440)	0.230 (0.421)	0.333 (0.474)	0.241 (0.428)	0.179 (0.384)	0.241 (0.435)	0.271 (0.444)	0.256 (0.436)	0.206 (0.406)
Sport Utility Vehicle (SUV) involvement indicator (1 if SUV being involved in the crash, 0 otherwise)	C	0.179 (0.384)	0.178 (0.383)	0.164 (0.371)	0.189 (0.392)	0.193 (0.395)	0.195 (0.401)	0.186 (0.389)	0.202 (0.401)	0.213 (0.410)
	L	0.184 (0.388)	0.254 (0.435)	0.200 (0.401)	0.211 (0.408)	0.201 (0.401)	0.080 (0.277)	0.201 (0.401)	0.226 (0.419)	0.200 (0.401)
	R	0.202 (0.401)	0.201 (0.401)	0.133 (0.342)	0.215 (0.411)	0.230 (0.421)	0.241 (0.435)	0.193 (0.395)	0.216 (0.412)	0.265 (0.443)
Insurance indicator (1 if vehicle was insured, 0 otherwise)	C	0.823 (0.382)	0.698 (0.459)	0.493 (0.501)	0.815 (0.388)	0.659 (0.474)	0.585 (0.499)	0.814 (0.389)	0.653 (0.476)	0.525 (0.500)
	L	0.836 (0.370)	0.759 (0.428)	0.483 (0.501)	0.829 (0.376)	0.692 (0.462)	0.600 (0.500)	0.843 (0.364)	0.719 (0.450)	0.569 (0.496)
	R	0.837 (0.369)	0.735 (0.441)	0.633 (0.485)	0.824 (0.381)	0.757 (0.430)	0.621 (0.494)	0.821 (0.384)	0.703 (0.457)	0.618 (0.488)
Vehicle age indicator (1 if the vehicle age is less than 5 years, 0 otherwise)	C	0.222 (0.416)	0.147 (0.354)	0.137 (0.345)	0.201 (0.401)	0.142 (0.349)	0.024 (0.156)	0.241 (0.428)	0.193 (0.395)	0.300 (0.459)
	L	0.232 (0.422)	0.170 (0.376)	0.100 (0.301)	0.201 (0.401)	0.136 (0.343)	0.160 (0.374)	0.277 (0.448)	0.193 (0.395)	0.154 (0.362)
	R	0.217 (0.412)	0.157 (0.364)	0.333 (0.474)	0.194 (0.395)	0.159 (0.366)	0.034 (0.186)	0.256 (0.436)	0.204 (0.403)	0.176 (0.383)
Vehicle age indicator (1 if the vehicle age is between 5 and 10 years, 0 otherwise)	C	0.320 (0.466)	0.312 (0.464)	0.329 (0.471)	0.306 (0.461)	0.325 (0.469)	0.341 (0.480)	0.271 (0.445)	0.241 (0.428)	0.188 (0.391)
	L	0.323 (0.467)	0.308 (0.462)	0.267 (0.443)	0.317 (0.465)	0.266 (0.443)	0.280 (0.458)	0.245 (0.430)	0.248 (0.432)	0.200 (0.401)
	R	0.334 (0.472)	0.288 (0.453)	0.233 (0.425)	0.322 (0.467)	0.284 (0.452)	0.069 (0.258)	0.245 (0.430)	0.227 (0.419)	0.294 (0.458)
Vehicle age indicator (1 if the vehicle age is older than 10 years, 0 otherwise)	C	0.458 (0.498)	0.541 (0.498)	0.534 (0.500)	0.493 (0.500)	0.533 (0.499)	0.634 (0.488)	0.488 (0.500)	0.566 (0.496)	0.513 (0.501)
	L	0.446 (0.497)	0.522 (0.500)	0.633 (0.483)	0.482 (0.500)	0.598 (0.491)	0.560 (0.507)	0.477 (0.500)	0.558 (0.497)	0.646 (0.479)
	R	0.449 (0.497)	0.555 (0.497)	0.433 (0.498)	0.484 (0.500)	0.557 (0.498)	0.897 (0.310)	0.500 (0.500)	0.569 (0.495)	0.529 (0.502)
Roadway characteristics										
Traffic controls indicator (1 if traffic control functioned, 0 otherwise)	C	0.831 (0.375)	0.815 (0.388)	0.822 (0.383)	0.834 (0.372)	0.811 (0.392)	0.805 (0.401)	0.838 (0.368)	0.830 (0.376)	0.937 (0.243)
	L	0.834 (0.372)	0.813 (0.390)	0.900 (0.301)	0.832 (0.374)	0.861 (0.347)	0.800 (0.408)	0.858 (0.349)	0.836 (0.371)	0.831 (0.376)
	R	0.830 (0.376)	0.843 (0.364)	0.800 (0.402)	0.840 (0.367)	0.831 (0.375)	0.966 (0.186)	0.863 (0.344)	0.837 (0.369)	0.882 (0.324)
The number of lanes indicator (1 if the number of lanes is 1–3, 0 otherwise)	C	0.446 (0.497)	0.397 (0.489)	0.411 (0.493)	0.441 (0.497)	0.444 (0.497)	0.561 (0.502)	0.447 (0.497)	0.372 (0.483)	0.538 (0.500)
	L	0.409 (0.492)	0.368 (0.482)	0.467 (0.500)	0.411 (0.492)	0.411 (0.493)	0.440 (0.507)	0.405 (0.491)	0.378 (0.485)	0.523 (0.501)
	R	0.473 (0.499)	0.507 (0.500)	0.467 (0.502)	0.494 (0.500)	0.490 (0.501)	0.586 (0.501)	0.467 (0.499)	0.474 (0.500)	0.412 (0.495)
The number of lanes indicator (1 if the number of lanes is 4–6, 0 otherwise)	C	0.499 (0.500)	0.502 (0.500)	0.507 (0.501)	0.496 (0.500)	0.475 (0.500)	0.366 (0.488)	0.492 (0.500)	0.530 (0.499)	0.387 (0.488)
	L	0.537 (0.499)	0.576 (0.494)	0.483 (0.501)	0.521 (0.500)	0.515 (0.501)	0.440 (0.507)	0.524 (0.499)	0.533 (0.499)	0.338 (0.474)
	R	0.478 (0.500)	0.449 (0.498)	0.500 (0.503)	0.455 (0.498)	0.439 (0.497)	0.345 (0.484)	0.481 (0.500)	0.462 (0.499)	0.529 (0.502)
The number of lanes indicator (1 if the number of lanes is greater than 6, 0 otherwise)	C	0.054 (0.227)	0.101 (0.301)	0.082 (0.275)	0.063 (0.243)	0.081 (0.273)	0.073 (0.264)	0.061 (0.240)	0.098 (0.298)	0.075 (0.264)
	L	0.054 (0.225)	0.056 (0.229)	0.050 (0.219)	0.068 (0.252)	0.074 (0.262)	0.120 (0.332)	0.070 (0.256)	0.089 (0.285)	0.138 (0.346)
	R	0.049 (0.215)	0.044 (0.206)	0.033 (0.181)	0.051 (0.221)	0.071 (0.257)	0.069 (0.258)	0.051 (0.221)	0.064 (0.245)	0.059 (0.236)
Freeway indicator (1 if crash occurred on the freeway, 0 otherwise)	C	0.432 (0.495)	0.467 (0.499)	0.452 (0.499)	0.426 (0.495)	0.430 (0.496)	0.220 (0.419)	0.436 (0.496)	0.502 (0.500)	0.300 (0.459)
	L	0.472 (0.499)	0.497 (0.500)	0.400 (0.491)	0.447 (0.497)	0.491 (0.501)	0.360 (0.490)	0.472 (0.499)	0.511 (0.500)	0.431 (0.496)
	R	0.403 (0.490)	0.381 (0.486)	0.300 (0.461)	0.376 (0.484)	0.372 (0.484)	0.310 (0.471)	0.408 (0.491)	0.408 (0.492)	0.382 (0.488)
Speed limit <30 mph indicator (1 if speed limit < 30 mph, 0 otherwise)	C	0.045 (0.207)	0.059 (0.235)	0.041 (0.199)	0.041 (0.197)	0.034 (0.183)	0.049 (0.218)	0.039 (0.193)	0.061 (0.239)	0.075 (0.264)
	L	0.036 (0.187)	0.025 (0.157)	0.033 (0.180)	0.023 (0.150)	0.018 (0.132)	0.000 (0.000)	0.029 (0.168)	0.027 (0.163)	0.015 (0.123)
	R	0.049 (0.216)	0.046 (0.210)	0.000 (0.000)	0.050 (0.218)	0.034 (0.181)	0.034 (0.186)	0.040 (0.196)	0.047 (0.213)	0.000 (0.000)
Speed limit 30-60 mph indicator (1 if speed limit is between 30 and 60 mph, 0 otherwise)	C	0.675 (0.469)	0.688 (0.464)	0.808 (0.395)	0.689 (0.463)	0.728 (0.445)	0.805 (0.401)	0.678 (0.467)	0.668 (0.471)	0.713 (0.454)
	L	0.643 (0.479)	0.689 (0.463)	0.717 (0.452)	0.687 (0.464)	0.704 (0.457)	0.720 (0.458)	0.654 (0.476)	0.659 (0.474)	0.754 (0.432)
	R	0.666 (0.472)	0.712 (0.453)	0.833 (0.375)	0.687 (0.464)	0.696 (0.461)	0.724 (0.455)	0.669 (0.470)	0.699 (0.459)	0.853 (0.356)
Speed limit >60 mph indicator (1 if speed limit > 60 mph, 0 otherwise)	C	0.280 (0.449)	0.254 (0.435)	0.151 (0.359)	0.271 (0.444)	0.237 (0.426)	0.146 (0.358)	0.283 (0.451)	0.271 (0.445)	0.213 (0.410)
	L	0.321 (0.467)	0.286 (0.452)	0.250 (0.434)	0.290 (0.454)	0.278 (0.449)	0.280 (0.458)	0.317 (0.465)	0.314 (0.464)	0.231 (0.422)

Variables	IL	2015			2016			2017		
		NI	MI	SI	NI	MI	SI	NI	MI	SI
Rural state indicator (1 if crash occurred in the rural state, 0 otherwise)	R	0.285 (0.452)	0.242 (0.428)	0.167 (0.375)	0.263 (0.441)	0.270 (0.445)	0.241 (0.435)	0.290 (0.454)	0.254 (0.435)	0.147 (0.356)
	C	0.662 (0.473)	0.551 (0.497)	0.548 (0.499)	0.638 (0.481)	0.584 (0.493)	0.659 (0.480)	0.645 (0.478)	0.540 (0.499)	0.588 (0.493)
	L	0.657 (0.475)	0.629 (0.483)	0.617 (0.488)	0.652 (0.477)	0.636 (0.482)	0.560 (0.507)	0.653 (0.476)	0.617 (0.486)	0.723 (0.449)
Municipal street indicator (1 if crash occurred on the municipal street, 0 otherwise)	R	0.679 (0.467)	0.669 (0.471)	0.767 (0.425)	0.653 (0.476)	0.645 (0.479)	0.655 (0.484)	0.673 (0.469)	0.629 (0.483)	0.676 (0.470)
	C	0.308 (0.462)	0.421 (0.494)	0.452 (0.499)	0.341 (0.474)	0.400 (0.490)	0.341 (0.480)	0.323 (0.468)	0.425 (0.494)	0.387 (0.488)
	L	0.305 (0.460)	0.335 (0.472)	0.350 (0.478)	0.334 (0.472)	0.340 (0.474)	0.400 (0.500)	0.314 (0.464)	0.352 (0.478)	0.262 (0.441)
Turnpike indicator (1 if crash occurred on the turnpike, 0 otherwise)	R	0.287 (0.452)	0.306 (0.461)	0.233 (0.425)	0.329 (0.470)	0.331 (0.471)	0.310 (0.471)	0.290 (0.454)	0.332 (0.471)	0.324 (0.470)
	C	0.030 (0.172)	0.028 (0.164)	0.000 (0.000)	0.020 (0.141)	0.016 (0.126)	0.000 (0.000)	0.032 (0.176)	0.035 (0.185)	0.025 (0.156)
	L	0.038 (0.191)	0.037 (0.188)	0.033 (0.180)	0.014 (0.119)	0.024 (0.152)	0.040 (0.200)	0.033 (0.178)	0.031 (0.173)	0.015 (0.123)
Intersection indicator (1 if crash occurred on the intersection, 0 otherwise)	R	0.034 (0.182)	0.025 (0.157)	0.000 (0.000)	0.018 (0.132)	0.024 (0.152)	0.034 (0.186)	0.037 (0.188)	0.039 (0.194)	0.000 (0.000)
	C	0.318 (0.466)	0.359 (0.480)	0.342 (0.476)	0.315 (0.465)	0.333 (0.472)	0.146 (0.358)	0.326 (0.469)	0.371 (0.483)	0.250 (0.434)
	L	0.362 (0.481)	0.371 (0.483)	0.300 (0.460)	0.337 (0.473)	0.367 (0.483)	0.320 (0.476)	0.355 (0.478)	0.385 (0.487)	0.262 (0.441)
Environment characteristics	R	0.309 (0.462)	0.282 (0.450)	0.133 (0.342)	0.274 (0.446)	0.291 (0.455)	0.241 (0.435)	0.309 (0.462)	0.309 (0.462)	0.176 (0.383)
	C	0.661 (0.473)	0.674 (0.469)	0.603 (0.490)	0.691 (0.462)	0.682 (0.466)	0.537 (0.505)	0.687 (0.464)	0.686 (0.464)	0.587 (0.493)
	L	0.683 (0.465)	0.687 (0.464)	0.567 (0.497)	0.678 (0.467)	0.598 (0.491)	0.640 (0.490)	0.683 (0.465)	0.703 (0.457)	0.662 (0.474)
Daylight indicator (1 if lighting condition is daylight, 0 otherwise)	R	0.685 (0.464)	0.704 (0.457)	0.667 (0.474)	0.688 (0.464)	0.628 (0.484)	0.621 (0.494)	0.699 (0.459)	0.666 (0.472)	0.647 (0.480)
	C	0.442 (0.497)	0.505 (0.500)	0.425 (0.495)	0.432 (0.495)	0.456 (0.499)	0.488 (0.506)	0.415 (0.493)	0.470 (0.499)	0.425 (0.495)
	L	0.460 (0.498)	0.535 (0.499)	0.500 (0.501)	0.460 (0.499)	0.530 (0.500)	0.400 (0.500)	0.426 (0.495)	0.511 (0.500)	0.369 (0.484)
Dawn/dusk indicator (1 if lighting condition is dawn/dusk, 0 otherwise)	R	0.459 (0.498)	0.563 (0.496)	0.467 (0.502)	0.461 (0.499)	0.530 (0.500)	0.448 (0.506)	0.447 (0.497)	0.495 (0.500)	0.588 (0.495)
	C	0.062 (0.241)	0.069 (0.253)	0.068 (0.253)	0.067 (0.249)	0.069 (0.254)	0.000 (0.000)	0.063 (0.243)	0.049 (0.216)	0.050 (0.218)
	L	0.062 (0.242)	0.043 (0.203)	0.067 (0.250)	0.068 (0.252)	0.038 (0.193)	0.000 (0.000)	0.065 (0.246)	0.064 (0.245)	0.108 (0.311)
Dark-lighted indicator (1 if lighting condition is dark-lighted, 0 otherwise)	R	0.066 (0.248)	0.046 (0.210)	0.033 (0.181)	0.059 (0.235)	0.091 (0.288)	0.103 (0.310)	0.061 (0.240)	0.072 (0.259)	0.088 (0.285)
	C	0.151 (0.358)	0.194 (0.396)	0.233 (0.424)	0.176 (0.381)	0.207 (0.405)	0.220 (0.419)	0.170 (0.376)	0.240 (0.427)	0.213 (0.410)
	L	0.143 (0.350)	0.179 (0.384)	0.183 (0.388)	0.163 (0.370)	0.160 (0.367)	0.280 (0.458)	0.163 (0.370)	0.181 (0.385)	0.138 (0.346)
Dark-unlighted indicator (1 if lighting condition is dark-unlighted, 0 otherwise)	R	0.143 (0.350)	0.149 (0.356)	0.233 (0.425)	0.153 (0.360)	0.142 (0.350)	0.138 (0.351)	0.159 (0.366)	0.171 (0.377)	0.029 (0.170)
	C	0.346 (0.476)	0.232 (0.422)	0.274 (0.447)	0.326 (0.469)	0.268 (0.443)	0.293 (0.461)	0.352 (0.478)	0.241 (0.428)	0.313 (0.464)
	L	0.334 (0.472)	0.243 (0.429)	0.250 (0.434)	0.308 (0.462)	0.272 (0.446)	0.320 (0.476)	0.346 (0.476)	0.245 (0.430)	0.385 (0.488)
	R	0.332 (0.471)	0.242 (0.428)	0.267 (0.445)	0.328 (0.470)	0.236 (0.426)	0.310 (0.471)	0.333 (0.471)	0.262 (0.440)	0.294 (0.458)

Remarks: IL = Impact Location; SI = Severe Injury; MI = Minor Injury; NI = No Injury; C = Center crashes; L = Left-side crashes; R = Right-side crashes.

3.3 Methods

The random parameters multinomial logit model with the heterogeneity in the means and variances can explicitly address observation-related variations of explanatory variables although existing data sources cover only a small fraction of a wide variety of factors that affect the injury severities (Behnood and Mannering, 2017). To investigate significant contributing factors and identify the possible unobserved heterogeneity in adverse-road-related crashes, this model is employed in this study. The linear utility function is defined as follows to determine the specific injury severity level k in crash n (Alnawmasi and Mannering, 2019):

$$U_{kn} = \boldsymbol{\beta}_k \mathbf{X}_{kn} + \varepsilon_{kn} \quad (3.1)$$

where U_{kn} is the severity function that determines the probability of injury severity level k in crash n , $\boldsymbol{\beta}_k$ is the vector of parameters estimated for the driver injury severity level k , $\mathbf{X}_{kn}$ is the vector of explanatory variables influencing driver injury severities in single-vehicle crash n , and ε_{kn} is a stochastic error term.

If the disturbance term is assumed to be generalized extreme value distributed, which allows parameters to vary across observations, a standard multinomial logit model can be defined as (McFadden, 1981):

$$P_{kn} = \int \frac{\exp(\boldsymbol{\beta}_k \mathbf{X}_{kn})}{\sum \exp(\boldsymbol{\beta}_k \mathbf{X}_{kn})} f(\boldsymbol{\beta}|\boldsymbol{\varphi}) d\boldsymbol{\beta} \quad (3.2)$$

where P_{kn} is the probability of injury severity outcome k in crash n , $f(\boldsymbol{\beta}|\boldsymbol{\varphi})$ is the probability density function of vector $\boldsymbol{\beta}$ and $\boldsymbol{\varphi}$ is a vector of parameters describing the density function, while the other terms have been defined previously.

When the heterogeneity in means and variances exists among random parameters, the vector $\boldsymbol{\beta}_{kn}$ that allows estimated parameters to vary across accidents can be defined as (Al-Bdairi et al., 2020; Islam and Mannering, 2020; Alnawmasi and Mannering, 2023):

$$\boldsymbol{\beta}_{kn} = \boldsymbol{\beta}_k + \boldsymbol{\delta}_k \mathbf{Z}_{kn} + \sigma_k \exp(\boldsymbol{\omega}_k \mathbf{W}_{kn}) \mathbf{v}_{kn} \quad (3.3)$$

where β_k represents the constant term (constant across all observations for injury severity k), Z_{kn} is the vector of crash-specific variables with the heterogeneity in the mean that determines the driver injury severity k , δ_k is a corresponding vector of estimable parameters, W_{kn} is another vector of crash-specific explanatory variables explaining the heterogeneity in the standard deviation σ_k with the corresponding parameter vector ω_k , and u_{kn} is the error term.

A simulation-based maximum likelihood method is used to estimate the model parameters. Previous studies (Halton, 1960; Bhat, 2000; Behnood and Al-Bdairi, 2020) have shown that 1000 Halton draws could effectively estimate coefficients for the distribution of the random parameters and compute the probabilities by stochastically drawing values. Meanwhile, a variety of parameter density functions (e.g., uniform, lognormal, normal, and triangular distributions) have been empirically evaluated in previous studies, which recommended that the model with a normal distribution is statistically superior in its capability to describe the central tendency and variations of random variables compared to models using other distributions (Behnood and Al-Bdairi, 2020; Islam and Mannering, 2020). Therefore, the identified random parameters are set to be normally distributed in this study.

To directly interpret the effects of significant variables X_{kn} on the probability of driver injury outcome k , marginal effects are also computed. Specifically, the marginal effect denotes the effect that every one-unit increase of an explanatory variable X_{knl} has on the k -th severity outcome probability (Washington et al., 2020), which is calculated by averaging the marginal effects over all crash observations:

$$\frac{\partial P_{kn}}{\partial X_{knl}} = \overline{P_{kn}} [\text{given } X_{knl} = 1] - \overline{P_{kn}} [\text{given } X_{knl} = 0] \quad (3.4)$$

3.4 Temporal stability and impact location transferability tests

To statistically investigate the stability of the influence that significant determinants have on adverse-road-related crash injury severities, two groups of likelihood ratio tests were conducted. The first series were employed to compare the models developed for two individual years and examine if the parameter estimates of the center, left-side, and right-side crash injury

severities were stable over observed years, which can be defined as (Washington et al., 2020):

$$\chi_l^2 = -2[LL(\beta_{year_2 year_1}) - LL(\beta_{year_1})] \quad (3.5)$$

where $year_1$ and $year_2$ are two observed individual years; $LL(\beta_{year_2 year_1})$ is the log-likelihood of a model containing converged parameters from $year_2$ while using data from $year_1$; $LL(\beta_{year_1})$ is the log-likelihood at convergence of the model containing converged parameters using $year_1$'s data (parameters are no longer restricted to subset data $year_2$'s converged parameters as is the case for $LL(\beta_{year_2 year_1})$).

Table 3.3. Likelihood ratio test results for center, left-side, and right-side crashes between different years (χ^2 values with degrees of freedom in parenthesis and confidence level in brackets).

$year_1$	$year_2$								
	Center			Left			Right		
	2015	2016	2017	2015	2016	2017	2015	2016	2017
2015	-	71.874	71.657	-	88.868	52.350	-	85.035	62.994
	-	(20)	(19)	-	(18)	(22)	-	(17)	(20)
	-	[>99.99%]	[>99.99%]	-	[>99.99%]	[99.97%]	-	[>99.99%]	[>99.99%]
2016	91.705	-	48.474	47.159	-	43.827	35.400	-	62.860
	(20)	-	(19)	(21)	-	(22)	(21)	-	(20)
	[>99.99%]	-	[99.98%]	[99.91%]	-	[99.63%]	[97.45%]	-	[>99.99%]
2017	70.870	78.947	-	45.978	108.294	-	41.909	70.153	-
	(20)	(20)	-	(21)	(18)	-	(21)	(17)	-
	[>99.99%]	[>99.99%]	-	[99.87%]	[>99.99%]	-	[99.57%]	[>99.99%]	-

The test was also conducted by reversing $year_1$'s data and $year_2$'s data to provide two test results for each model comparison. The test follows a χ^2 distribution with the degrees of freedom equaling to the number of estimated parameters in $\beta_{year_2 year_1}$. The resulting χ^2 statistic can be utilized to determine whether the null hypothesis that the parameters are stable in the two years should be rejected or accepted (Behnood and Mannering, 2015). Table 3.3 presents the results of hypothesis tests across different collision locations over the years. There is a significant level of confidence that the models' specifications and estimated parameters are not temporally stable among the year-to-year combinations, as shown by the fact that 17 out of the 18 tests produced confidence levels that were larger than 99%. Besides, one test of year-on-year comparison illustrated that the null hypothesis (the parameters were the same) could be rejected at the 95% confidence level (this was the 2016 data using the 2015 parameter estimates for right-side crashes). As such, the overall high degree of confidence indicates the obvious temporal instability of the estimated parameters for each impact location group.

Similarly, the transferability of estimated parameters between center, left-side, and right-side crash models can be validated with (Alnawmasi and Mannering, 2022b):

$$\chi_t^2 = -2[LL(\beta_{l_2l_1}) - LL(\beta_{l_1})] \quad (3.6)$$

where l_1 and l_2 are two individual vehicle impact locations; $LL(\beta_{l_2l_1})$ is the log-likelihood of a model containing converged parameters from l_2 while using data from l_1 ; $LL(\beta_{l_1})$ is the log-likelihood at convergence of the model containing converged parameters using l_1 's data (parameters are no longer restricted to subset data l_2 's converged parameters as is the case for $LL(\beta_{l_2l_1})$).

Table 3.4 presents the results of hypothesis tests for three years between different vehicle impact locations. These tests consistently yielded confidence levels exceeding 99%, indicating a substantial lack of transferability in the models' specifications and estimated parameters across different location combinations. Therefore, the null hypothesis that center, left-side, and right-side crash models can be transferred to each other should be rejected.

Table 3.4. Likelihood ratio test results for three years between different vehicle impact locations (χ^2 values with degrees of freedom in parenthesis and confidence level in brackets).

l_1	l_2								
	2015			2016			2017		
	Center	Left	Right	Center	Left	Right	Center	Left	Right
Center	-	99.466 (21) [>99.99%]	265.846 (21) [>99.99%]	-	55.997 (18) [>99.99%]	118.057 (17) [>99.99%]	-	66.840 (22) [>99.99%]	163.156 (20) [>99.99%]
Left	72.904 (20) [>99.99%]	-	145.173 (21) [>99.99%]	44.915 (20) [99.89%]	-	59.782 (17) [>99.99%]	58.748 (19) [>99.99%]	-	107.861 (20) [>99.99%]
Right	172.275 (20) [>99.99%]	115.310 (21) [>99.99%]	-	80.736 (20) [>99.99%]	58.117 (18) [>99.99%]	-	103.322 (19) [>99.99%]	87.045 (22) [>99.99%]	-

3.5 Net effect between out-of-sample predictions and within-sample observations

Examining the net effect of temporal shifts could provide more insightful results than solely focusing on likelihood ratio tests or marginal effects (Alnawmasi et al., 2024; Alnawmasi and Mannering, 2022a, 2022b; Hou et al., 2022; Xu et al., 2021). To this end, the out-of-sample prediction was first conducted. That is, parameters of one year's center/left-side/right-side crash model were used to predict the driver injury severity with center/left-side/right-side data from a different year. Meanwhile, the within-sample observation (the calculated probability

from one year's data using the same year's estimated model) was also obtained to provide the comparison benchmark. The simulation of out-of-sample prediction was carried out using the similar method in estimating parameters from the base sample, and 1,000 Halton draws were employed to compute driver injury severity probabilities (Yan et al., 2023a). The means of differences between the out-of-sample probability and within-sample probability could reveal the aggregate net effects of year-to-year temporal shifts, which are calculated through:

$$\Delta P(k_l) = P_{year_2 year_1}(k_l) - P_{year_1}(k_l) \quad (3.7)$$

where $P_{year_2 year_1}(k_l)$ is the estimated probability of the driver injury severity k belonging to location category l (center/left/right) in $year_2$ (2015/2016/2017) using the estimated injury severity model based on $year_1$'s (2015 or 2016) data, and $P_{year_1}(k_l)$ denotes the probability of the injury severity k of location category l in $year_1$ using $year_1$'s estimated model.

Likewise, to assess the aggregate injury severity differences among location-to-location (center/left-side/right-side) combinations, parameters of one group's crash model will be used to predict the driver injury severity probabilities with the other two groups' data in the same year. The means of differences between the out-of-sample probability and within-sample probability for each year can be calculated as:

$$\Delta P(k_{year}) = P_{l_2 l_1}(k_{year}) - P_{l_1}(k_{year}) \quad (3.8)$$

where $P_{l_2 l_1}(k_{year})$ is the estimated probability of driver injury severity k belonging to $year$ (2015/2016/2017) in location category l_2 (center/left-side/right-side) using the estimated driver injury severity model based on l_1 's (center/left-side/right-side) data, and $P_{l_1}(k_{year})$ denotes the probability of injury severity k of location category l_1 in $year$ (2015/2016/2017) using the l_1 's estimated model.

With respect to temporal shifts, Table 3.5 presents the means of probability differences between out-of-sample predictions and within-sample observations over different years. For example, if the 2015 center crash model parameters are used to predict 2016 center crash injury severities, there will be an increase in the probabilities of minor injuries and severe injuries by

0.0158 and 0.0018, while the probability of no injuries will decrease by 0.0176. However, if these parameters are used to predict 2017 center crash injury severities, the probability of no injuries and severe injuries will be underestimated by 0.0176 and 0.0019, while the probabilities of minor injuries will be overestimated by 0.0195. Similarly, both the means of probability differences between the within-sample and out-of-sample predictions for left-side and right-side crashes show an unstable trend, indicating the necessity to account for the temporal instability in forecasting the driver injury severity of single-vehicle crashes (Alogaili and Mannering, 2022a; Mannering, 2018b).

Table 3.5. Means of probability differences in predicting the injury severity between different years.

Observed year	Severity	Predicted year					
		2016			2017		
		Center	Left	Right	Center	Left	Right
2015	NI	-0.0176	-0.0060	0.0054	-0.0176	0.0043	0.0072
	MI	0.0158	0.0030	0.0003	0.0195	-0.0001	-0.0050
	SI	0.0018	0.0030	-0.0057	-0.0019	-0.0042	-0.0022
2016	NI	-	-	-	0.0004	0.0026	0.0013
	MI	-	-	-	0.0027	0.0048	-0.0054
	SI	-	-	-	-0.0031	-0.0074	0.0041

Table 3.6. Means of probability differences in predicting the injury severity between different impact location groups.

Observed group	Severity	Predicted group								
		Center			Left			Right		
		2015	2016	2017	2015	2016	2017	2015	2016	2017
Center	NI	-	-	-	-0.0188	-0.0090	-0.0048	-0.0589	-0.0410	-0.0362
	MI	-	-	-	0.0196	0.0091	0.0090	0.0506	0.0399	0.0296
	SI	-	-	-	-0.0008	-0.0001	-0.0042	0.0083	0.0011	0.0066
Left	NI	0.0317	0.0150	0.0093	-	-	-	-0.0409	-0.0284	-0.0309
	MI	-0.0329	-0.0141	-0.0131	-	-	-	0.0338	0.0288	0.0206
	SI	0.0012	-0.0009	0.0038	-	-	-	0.0071	-0.0004	0.0103
Right	NI	0.0644	0.0469	0.0363	0.0404	0.0302	0.0287	-	-	-
	MI	-0.0559	-0.0457	-0.0295	-0.0321	-0.0312	-0.0196	-	-	-
	SI	-0.0085	-0.0012	-0.0068	-0.0083	0.0010	-0.0091	-	-	-

Regarding the non-transferability of vehicle impact locations,

Table 3.6 provides the means of probability differences in predicting the driver injury severity across different impact location groups. Likewise, it can be found that the observed probabilities will be overestimated or underestimated in all location-to-location comparisons. However, it is important to note that almost identical directions of differences within the specific injury category are captured across different years. For instance, using the parameters of center crash model in 2015 to predict the left-side crash injury severity will underestimate no injuries and severe injuries, whereas using the same parameters to forecast the minor injury

of left-side crashes will overestimate the probability. This finding is also applicable to the years 2016 and 2017 in the context of the same driver injury severity levels, excluding the cases of 2016 left-to-center, 2016 left-to-right, and 2016 right-to-left combinations. Nevertheless, there are variations in the magnitudes of probability differences across different years, which further indicates the temporal instability and non-transferability of the impact location. Another insight from the out-of-sample predictions is that the parameters of center crash models would underestimate the probability of severe injuries in left-side accidents across all periods, while using the same parameters to predict the severe injury of right-side crashes will overestimate the probability. Likewise, utilizing the left-side crash model parameters will result in an overestimation of the likelihood of severe injuries in right-side and center crashes, with slight variations in cases of 2016 left-to-center and 2016 left-to-right predictions. This conversion rule also generally applies to results predicted by the right-side crash models. Consequently, the net effects of aggregate year-to-year and location-to-location shifts are successfully quantified through probability differences between out-of-sample predictions and within-sample observations. This consistent finding also highlights the necessity to make more efforts in mitigating driver injury severities for left-side and center accidents.

To further characterize the net effect, Figure 3.2 shows the detailed distribution of differences between predicted probabilities and observed probabilities concerning three driver injury severity outcomes over different years. The mean differences of each injury-severity category are connected by the blue line in each pairwise comparison subplot. The deviation of each line from the vertical line at 0 provides an intuitive understanding of the aggregate differences in predictions. For example, it could be observed that the overall out-of-sample prediction biases between different years in the center crash models are greater than the prediction differences in the left-side and right-side models. Meanwhile, the kernel density plots of severity prediction differences in each paired comparison subplot can quantify the magnitude of the dispersion. For instance, the dispersion of the probability differences in forecasting injury severities for 2017C using the 2015C model is greater than that of the probability differences in predicting injury severities for 2017L using the 2015L model, as

shown in Figure 3.2 (a) and Figure 3.2 (e).

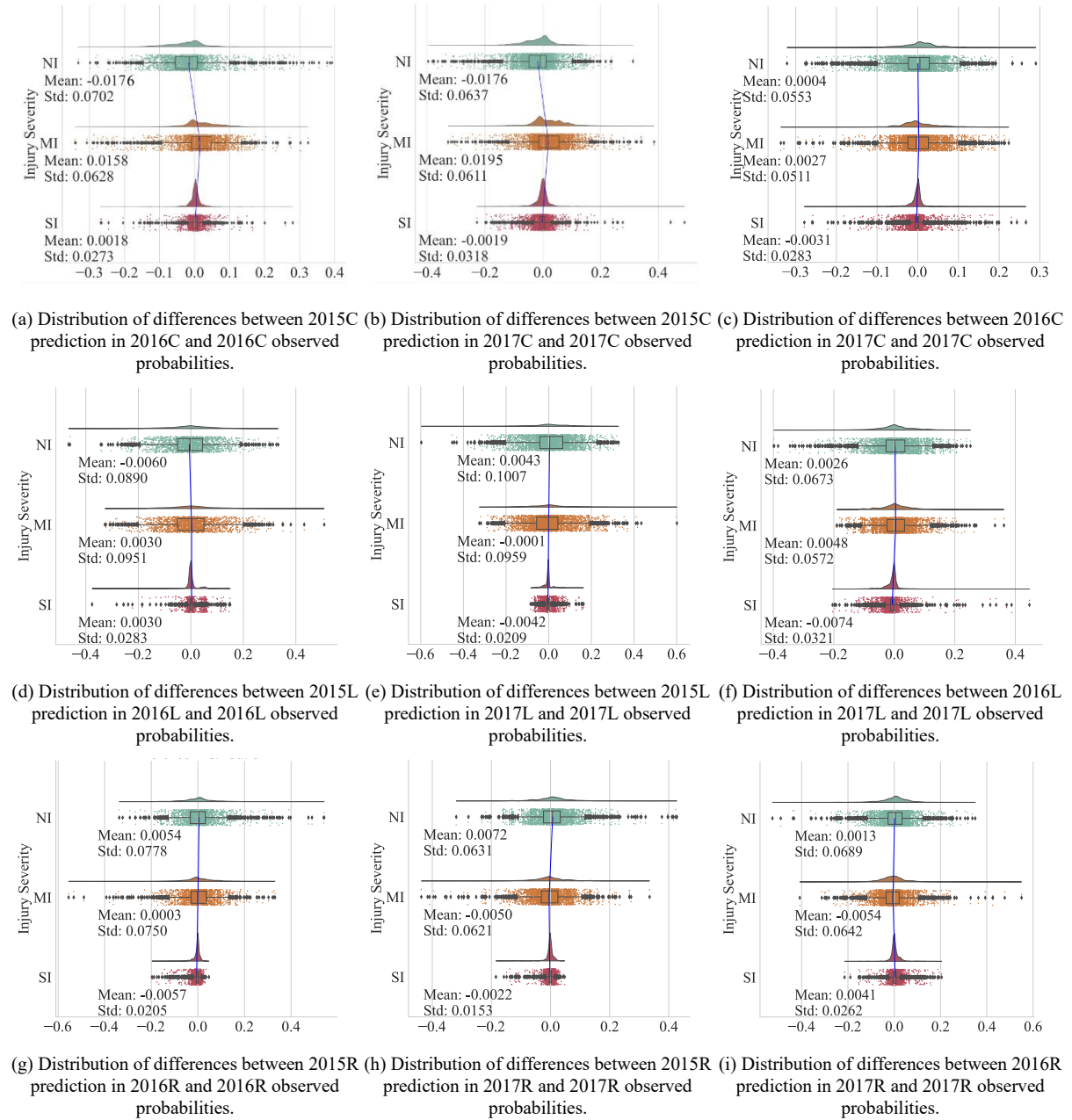


Figure 3.2. Distribution of differences between predicted probabilities and observed probabilities over different years.

To depict the distribution features of the net effect between different years more accurately, Table 3.7 further tabulates the skewness and kurtosis of these probability differences. Specifically, skewness measures the degree of asymmetry in the distribution of data. A negative skewness indicates a left-skewed distribution, a positive skewness indicates a right-skewed distribution, and a skewness of 0 indicates a symmetric distribution. Kurtosis measures the degree of peakedness and thickness of the tails in a data distribution. A positive kurtosis

Table 3.7. Frequency distribution characteristics of probability differences in predicting the injury severity between different years.

Observed year	Severity	Predicted year											
		2016						2017					
		Center		Left		Right		Center		Left		Right	
		Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
2015	NI	-0.9824	5.2927	-0.2689	1.4660	1.0988	6.3233	-0.7243	4.3558	-0.4073	1.3764	0.7600	6.0304
	MI	0.7489	4.7537	0.2141	1.3494	-0.8853	6.8081	0.0860	4.1783	0.4325	1.4765	-0.6152	6.0172
	SI	-1.0883	32.1429	-2.4676	38.6673	-4.0466	23.1214	1.6661	37.0251	1.4614	10.9905	-4.8028	36.9795
2016	NI	-	-	-	-	-	-	-0.7235	3.4619	-0.6134	3.4807	-0.6689	6.0578
	MI	-	-	-	-	-	-	0.0481	3.8709	0.4686	2.3652	0.6924	7.5888
	SI	-	-	-	-	-	-	-0.1239	23.6252	2.9124	42.4957	1.0837	16.5791

Table 3.8. Frequency distribution characteristics of probability differences in predicting the injury severity between different impact location groups.

Observed Severity year		Predicted year																	
		Center						Left						Right					
		2015		2016		2017		2015		2016		2017		2015		2016		2017	
Skewness		Kurtosis		Skewness		Kurtosis		Skewness		Kurtosis		Skewness		Kurtosis		Skewness		Kurtosis	
Center	NI	-	-	-	-	-	-	0.1839	0.6443	-1.0662	4.9354	-1.5818	6.2768	-1.2730	3.0330	-0.7224	1.4619	-2.2076	9.1958
	MI	-	-	-	-	-	-	-0.2333	0.2055	0.8498	3.1926	1.5407	7.6349	0.9494	1.9338	0.4679	1.5879	1.2703	10.3441
	SI	-	-	-	-	-	-	0.6982	14.1082	-0.3144	68.2955	3.1685	34.5727	6.5012	72.1255	4.1671	41.3463	4.5506	33.0885
Left	NI	-0.1819	0.7377	1.2433	3.8167	1.7416	5.6175	-	-	-	-	-	-	-0.3365	1.1180	-0.1543	3.5299	0.6171	4.8153
	MI	0.2602	0.2302	-1.1182	3.2991	-1.4004	5.5862	-	-	-	-	-	-	0.1558	1.1271	-0.6132	6.3740	-1.4806	8.9486
	SI	-1.5468	16.7142	-0.6554	53.8579	-3.2231	25.5707	-	-	-	-	-	-	3.2337	12.0266	7.1003	91.6221	1.5079	9.3259
Right	NI	1.2129	2.9782	0.7287	1.1168	1.9853	7.6009	0.3542	1.5519	0.0231	3.4325	-0.3654	4.1431	-	-	-	-	-	-
	MI	-0.8945	2.0921	-0.5430	1.0752	-1.0142	8.1493	-0.0873	1.3930	0.9309	8.3671	1.3839	8.3683	-	-	-	-	-	-
	SI	-4.8706	33.2350	-4.3485	31.3375	-4.1148	27.3005	-3.0844	11.1450	-6.8693	86.9108	-1.6662	9.6826	-	-	-	-	-	-

suggests a distribution that is more peaked and has thicker tails than a normal distribution, while a negative kurtosis indicates a distribution that is flatter than a normal distribution. These two indices, representing the differences in out-of-sample predictions for each year's samples, are annotated with different colors to indicate their positive or negative values, with darker colors signifying larger values.

It can be seen that the probability differences in using the 2015 center and left models to predict no injury outcome for the corresponding positions in 2016 and 2017 are left-skewed, while the probability differences in using the 2015 right crash model to predict no injury outcomes for the corresponding positions in 2016 and 2017 are right-skewed. Moreover, the magnitude of the right-skewed values is greater than that of the left-skewed values, further indicating the non-transferability of the collision location parameters. Additionally, a nearly opposite direction of skewness is observed in predicting no injuries and severe injuries between different years, and the magnitude of skewness values in no injuries are generally greater than the corresponding probability differences for severe injuries. This suggests that there are significant differences between the out-of-sample prediction results for different severity levels due to the imbalanced dataset. As for the kurtosis, it is found that the kurtosis of minor injuries is comparable to that of no injuries among all the year-to-year prediction differences, whereas the kurtosis of the prediction differences in severe injuries is significantly greater than those of the previous two, indicating that there is a greater degree of peakedness and thickness in the tails of the distribution of the prediction differences for severe injuries.

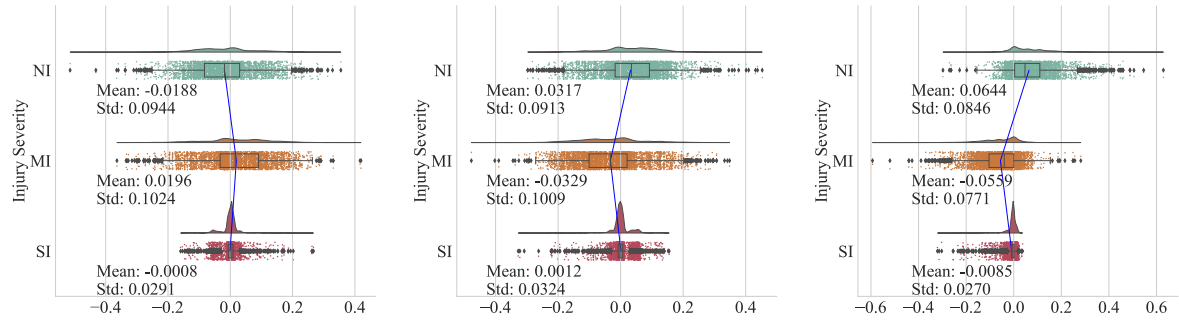
Similarly, Figures. 3.3–3.5 depict the detailed distribution of differences between predicted probabilities and observed probabilities regarding three driver injury severity outcomes over different impact locations for three years. Table 3.8 also presents the skewness and kurtosis of these probability differences. Apart from the findings that are similar to those presented earlier, it can be seen from blue mean curves that the prediction differences between different positions in the same year are markedly larger than the out-of-sample prediction bias for the same impact location across different years, in comparison to Figure 3.2. This implies that the non-transferability of the collision location has a greater impact on the prediction than the temporal

instability. Meanwhile, it is noteworthy that the out-of-sample prediction differences of each injury severity outcome across different impact positions in 2015 are generally larger than the prediction differences in the other two years. These findings further highlight the importance of considering both temporal instability and location non-transferability in the driver injury severity analysis as both have significant impacts on the accuracy of severity predictions.

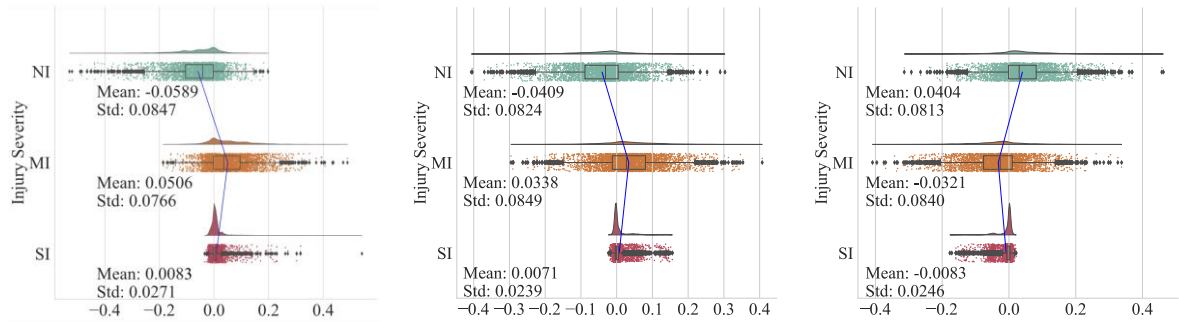
To further quantify the impact of changes in mean differences on the performance of out-of-sample prediction models, the out-of-sample predictive accuracy is also compared to the within-sample observation accuracy. Figure 3.6 illustrates the disparity in out-of-sample prediction accuracy and within-sample observation accuracy between groups within the same collision location but in different years. It can be seen that the majority of accuracy differences predominantly display negative values, indicating a reasonable decrease in overall prediction accuracy. In terms of numerical values, the largest prediction difference is found in the severe injury level, followed by minor injuries and no injuries. However, there are slight discrepancies in the prediction results across different impact locations. Specifically, there is an observed increment in the prediction accuracy for minor injuries in center crashes, concomitant with an increase in the prediction accuracy for no injuries in right-side crashes. By contrast, the prediction accuracy of left-side accidents decreases for all severity levels. These variations imply the existence of divergent temporal effects across impact locations, which can be influenced by factors such as location-specific characteristics and temporal changes in injury patterns. Figure 3.7 showcases the contrasts in out-of-sample prediction accuracy and within-sample observation accuracy between groups in the same year but in a different collision location. The prediction differences show both positive and negative values, which is different from the consistent decrease in accuracy observed in Figure 3.6. It is worth noting that the direction of the prediction differences is almost consistent with the means of probability differences reported in

Table 3.6 for predicting injury severity between different impact location groups, whereas this phenomenon is not observed in the analysis of accuracy differences over different years. This notable discrepancy may be attributed to the substantial variations in probability

differences across three impact locations.

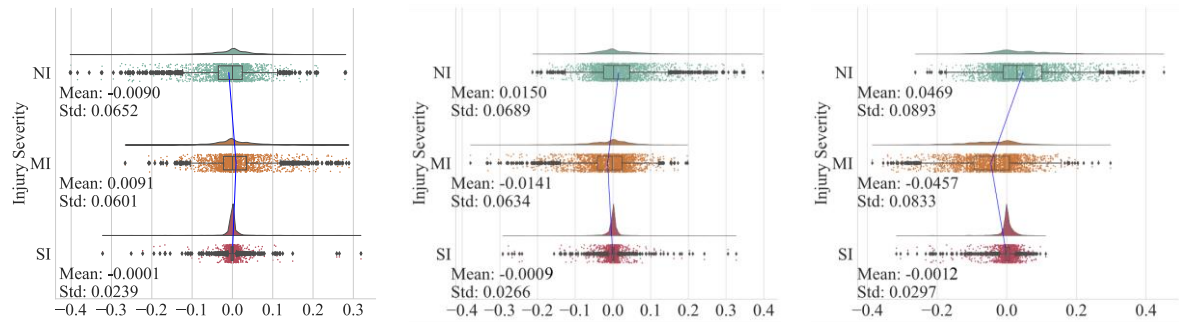


(a) Distribution of differences between 2015C prediction in 2015L and 2015L observed probabilities. (b) Distribution of differences between 2015L prediction in 2015C and 2015C observed probabilities. (c) Distribution of differences between 2015R prediction in 2015C and 2015C observed probabilities.

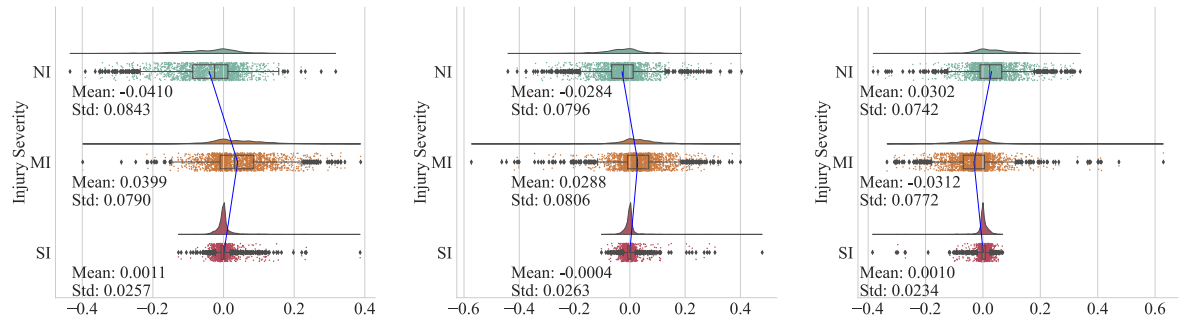


(d) Distribution of differences between 2015C prediction in 2015R and 2015R observed probabilities. (e) Distribution of differences between 2015L prediction in 2015R and 2015R observed probabilities. (f) Distribution of differences between 2015R prediction in 2015L and 2015L observed probabilities.

Figure 3.3. Distribution of differences between predicted probabilities and observed probabilities over groups in 2015.

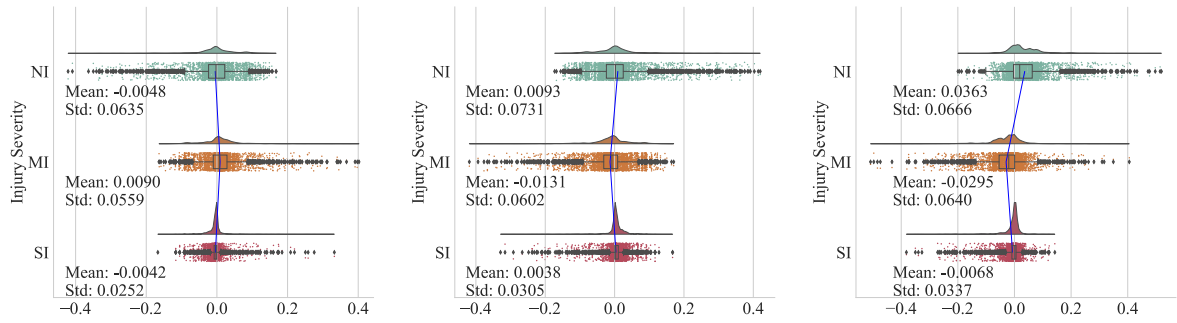


(a) Distribution of differences between 2016C prediction in 2016L and 2016L observed probabilities. (b) Distribution of differences between 2016L prediction in 2016C and 2016C observed probabilities. (c) Distribution of differences between 2016R prediction in 2016C and 2016C observed probabilities.

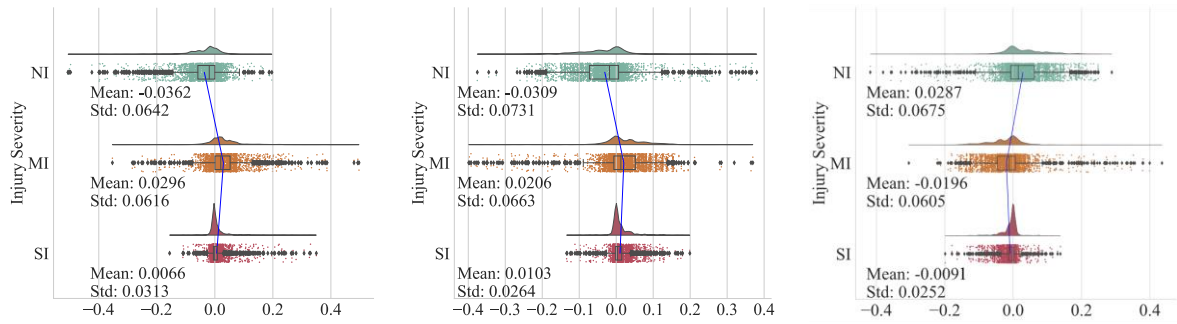


(d) Distribution of differences between 2016C prediction in 2016R and 2016R observed probabilities. (e) Distribution of differences between 2016L prediction in 2016R and 2016R observed probabilities. (f) Distribution of differences between 2016R prediction in 2016L and 2016L observed probabilities.

Figure 3.4. Distribution of differences between predicted probabilities and observed probabilities over groups in 2016.



(a) Distribution of differences between 2017C prediction in 2017L and 2017L observed probabilities. (b) Distribution of differences between 2017L prediction in 2017C and 2017C observed probabilities. (c) Distribution of differences between 2017C prediction in 2017C and 2017C observed probabilities.



(d) Distribution of differences between 2017C prediction in 2017R and 2017R observed probabilities. (e) Distribution of differences between 2017L prediction in 2017R and 2017R observed probabilities. (f) Distribution of differences between 2017C prediction in 2017L and 2017L observed probabilities.

Figure 3.5. Distribution of differences between predicted probabilities and observed probabilities over groups in 2017.

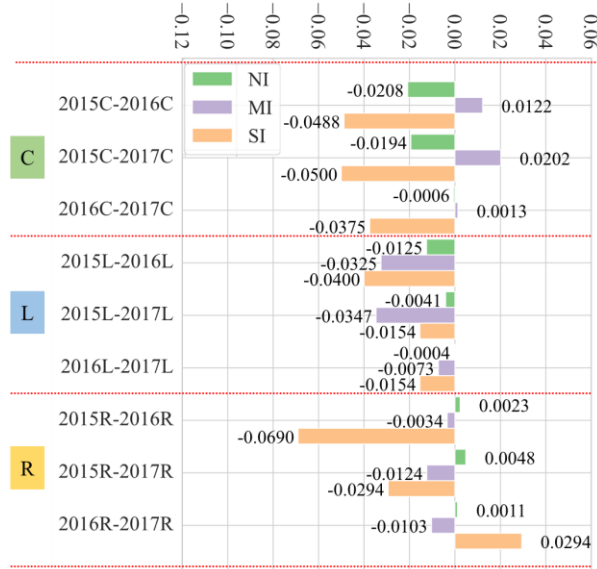


Figure 3.6. Differences between predicted accuracy and observed accuracy over different years.



Figure 3.7. Differences between predicted accuracy and observed accuracy over different impact location groups.

3.6 Results and discussions

Table 3.9 presents a comparative analysis of four competitive models, namely the fixed parameters multinomial logit model (MNL), the random parameters multinomial logit model (RPL), the random parameters multinomial logit model with the heterogeneity in the means (RPLM), and the random parameters multinomial logit model with the heterogeneity in the means and variances (RPLMV). The specifications of all models were confirmed through a series of likelihood ratio tests to ensure that the included variables and parameters could significantly improve the converged log-likelihood (Washington et al., 2020). To evaluate these models' performance, four different criteria were used: log-likelihood value, ρ^2 value, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). Specifically, the log-likelihood value serves as a measure of how accurately the model describes the observed data. A higher log-likelihood value indicates a better fit between the model and the data. The ρ^2 quantifies the proportion of variance explained by the model, with a higher value signifying a better fit as well. The AIC and BIC are measures of model complexity, with lower values indicating a better tradeoff between model fit and complexity (Akaike, 1974; Schwarz, 1978). The comparative analysis reveals that the random parameters model with the heterogeneity in the means (and variances) outperforms the other models in terms of these four criteria (except for the 2016 center crash model where the heterogeneity in the means and variances is not captured). This model has the highest log-likelihood and ρ^2 values, indicating a better fit to the

crash data. Meanwhile, the AIC and BIC scores for this model are competitive. Additionally, a series of likelihood ratio tests were employed to compare the random parameters model with heterogeneity in means (and variances) to the other models (Fountas and Anastasopoulos, 2018). The results illustrate that the null hypothesis that the random parameters model with the heterogeneity in the means (and variances) is the same as its counterparts can be rejected at the 95 % confidence level. Therefore, the discussion in this study is based on these superior models.

The estimates of random parameters logit models with the heterogeneity in the means (and variances) across different impact locations in three years are presented in Tables 4.10–4.12, which indicate an overall satisfactory statistical fit with p^2 values ranging from 0.550 to 0.644. Notably, although the heterogeneity in the means of random parameters was consistently significant (except for the 2016 center crash model), the heterogeneity in the variances was not found to be statistically significant across three collision locations in years 2016 and 2017. The factors identified to be significant also exhibited discrepancy between the center, left-side, and right-side crash models. Table 3.13 shows the marginal effects of the significant variables (arranged by variable classification). The remainder of this section presents a detailed discussion of the estimation results from the variable-level perspective.

Table 3.9. Comparison results of four competitive models (MNL: multinomial logit model, RPL: random parameters multinomial logit model, RPLM: random parameters multinomial logit model with the heterogeneity in the means, RPLMV: random parameters multinomial logit model with the heterogeneity in the means and variances).

	2015				2016			2017		
	MNL	RPL	RPLM	RPLMV	MNL	RPL	RPLM	MNL	RPL	RPLM
Center crashes										
K (Number of parameters)	17	18	19	20	19	20	-	17	18	19
Log-likelihood at zero (LL(0))	-4832.795	-4832.795	-4832.795	-4832.795	-2749.827	-2749.827	-	-4533.973	-4533.973	-4533.973
Converged log-likelihood (LL(β))	-2178.458	-2169.249	-2167.216	-2160.907	-1235.320	-1226.689	-	-2055.221	-2044.768	-2042.455
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.5492	0.5511	0.5516	0.5529	0.5508	0.5539	-	0.5467	0.5490	0.5495
AIC	4390.9	4374.5	4372.4	4361.8	2492.6	2493.4	-	4144.4	4125.5	4122.9
BIC	4499.5	4489.5	4493.8	4489.6	2603.3	2609.9	-	4252.0	4239.4	4243.1
Likelihood ratio test	MNL vs RPLMV 35.102 (3) [>99.99%]	RPL vs RPLMV 16.684 (2) [99.98%]	RPLM vs RPLMV 12.617 (1) [99.96%]		MNL vs RPL 17.262 (1) [>99.99%]			MNL vs RPLM 25.533 (2) [>99.99%]	RPL vs RPLM 4.627 (1) [96.85%]	
Left-side crashes										
K (Number of parameters)	18	19	20	21	16	17	18	18	19	22
Log-likelihood at zero (LL(0))	-4160.445	-4160.445	-4160.445	-4160.445	-2162.069	-2162.069	-2162.069	-3614.434	-3614.434	-3614.434
Converged log-likelihood (LL(β))	-1821.187	-1819.024	-1814.100	-1804.044	-921.197	-917.155	-913.491	-1565.234	-1562.377	-1552.717
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.5623	0.5628	0.5640	0.5664	0.5739	0.5758	0.5775	0.5669	0.5677	0.5704
AIC	3678.4	3676.0	3668.2	3650.1	1866.4	1864.3	1863.0	3166.5	3162.8	3149.4
BIC	3790.7	3794.6	3793.0	3781.1	1955.8	1959.3	1963.5	3276.2	3278.6	3283.6
Likelihood ratio test	MNL vs RPLMV 34.285 (3) [>99.99%]	RPL vs RPLMV 29.960 (2) [>99.99%]	RPLM vs RPLMV 20.113 (1) [>99.99%]		MNL vs RPLM 15.412 (2) [99.95%]	RPL vs RPLM 7.328 (1) [99.32%]		MNL vs RPLM 25.034 (4) [>99.99%]	RPL vs RPLM 19.320 (3) [99.98%]	
Right-side crashes										
K (Number of parameters)	17	18	19	21	15	16	17	18	19	20
Log-likelihood at zero (LL(0))	-4204.389	-4204.389	-4204.389	-4204.389	-2264.240	-2264.240	-2264.240	-3527.644	-3527.644	-3527.644
Converged log-likelihood (LL(β))	-1506.977	-1504.443	-1501.249	-1497.669	-877.448	-874.578	-869.450	-1367.873	-1365.666	-1358.826
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.6416	0.6422	0.6429	0.6438	0.6125	0.6137	0.6160	0.6122	0.6129	0.6148
AIC	3048.0	3044.9	3038.5	3037.3	1784.9	1781.2	1772.9	2771.7	2769.3	2757.7
BIC	3154.2	3157.4	3157.2	3168.6	1869.4	1871.3	1868.6	2881.1	2884.7	2879.1
Likelihood ratio test	MNL vs RPLMV 18.617 (4) [99.91%]	RPL vs RPLMV 13.548 (3) [99.64%]	RPLM vs RPLMV 7.161 (2) [97.21%]		MNL vs RPLM 15.997 (2) [99.97%]	RPL vs RPLM 10.257 (1) [99.86%]		MNL vs RPLM 18.094 (2) [>99.99%]	RPL vs RPLM 13.680 (1) [99.98%]	

3.6.1 Heterogeneity in the means and variances of random parameters

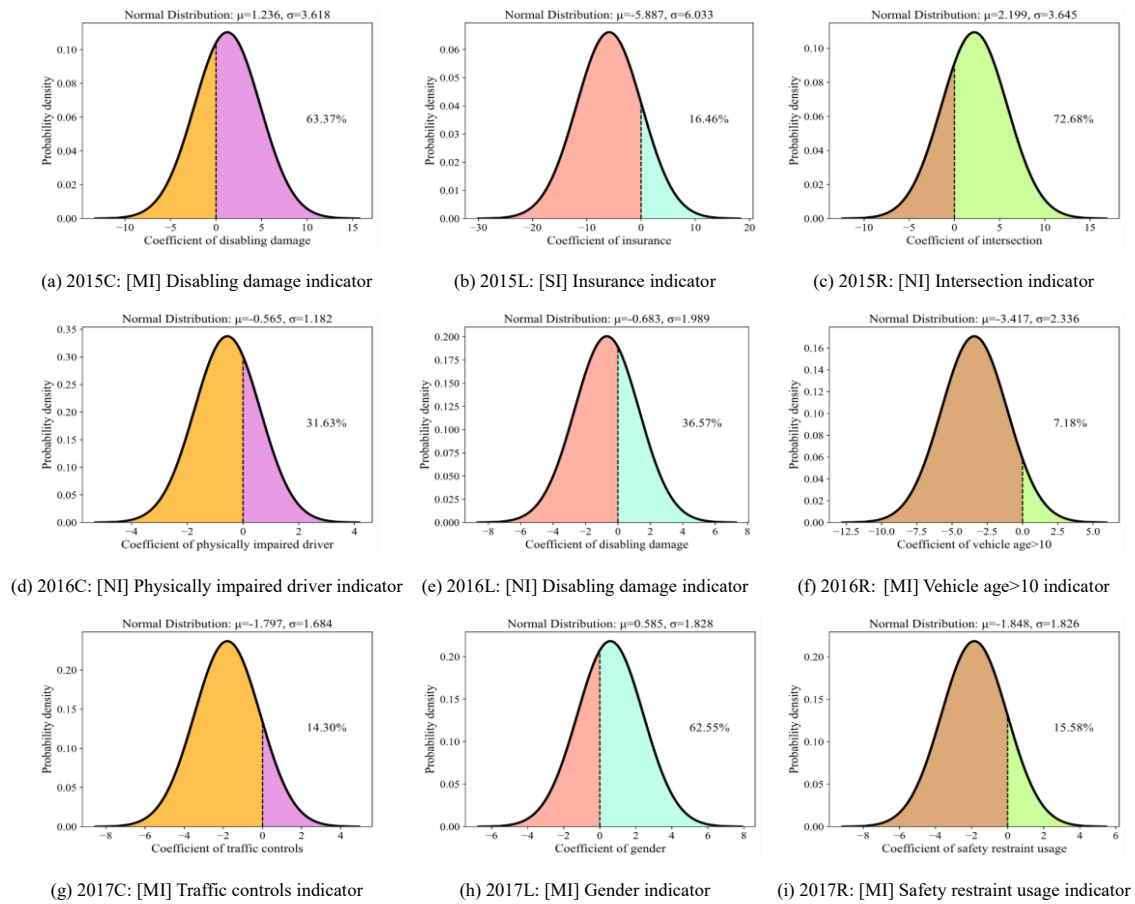


Figure 3.8. Distribution of the random parameters.

As indicated in Table 3.10, three variables were identified as random parameters with normal distributions in center crash models: the disabling damage indicator, physically impaired driver indicator, and traffic controls indicator, whereas in left-side crash models, the insurance indicator, disabling damage indicator, as well as gender indicator were identified as significant random parameters, as shown in Table 3.11. Concerning right-side collision models in Table 3.12, it was discovered that the intersection indicator, vehicle age>10 indicator, and safety restraint usage indicator produced random parameters with heterogeneous means or variances. The results demonstrate that a varying influence of the unobserved characteristics on the driver injury severity between different vehicle impact locations is captured by these random parameters (Mannering et al., 2020). Figure 3.8 presents the probability density diagrams of these identified normally distributed random parameters. Taking the 2017

center crash model as an example, the traffic control indicator defined to minor injury outcome produces a random parameter that is normally distributed with a mean of -1.797 and a standard deviation of 1.684 . This implies that the parameter of this variable is negative with a probability of 85.70% and positive with a probability of 14.30% for each observation.

As for the heterogeneity in the means, the presence of roadway with more than six lanes was observed to decrease the means of heterogeneity in the disabling damage indicator for minor injury outcomes in the 2015 center crash model, whereas the insurance indicator would increase the mean of the random parameter generated by the traffic controls indicator specific to minor injuries in 2017 center crashes. It is worth noting that no explanatory variable was found to have significant influences on the heterogeneity in the means of physically impaired driver indicator defined to no injuries in the 2016 center crash model. Turning to the heterogeneity in the means of left-side crash models, the physically impaired driver indicator was observed to decrease the mean of its random parameter, resulting in a decreased likelihood of no injuries in 2016. On the other hand, this indicator would elevate the mean of the insurance indicator in the 2015 left-side crash model, thereby increasing the possibility of severe injury outcomes. In the presence of 4–6 lanes and animals, the mean of female drivers for minor injury would decrease in 2017 left-side crashes, making minor injury less likely. By contrast, when the first harmful event was identified as the non-colliding object such as a rollover, there was an observed increment in the mean, consequently amplifying the likelihood of minor injuries. Different from the 2017 left-side crash model, the female driver indicator was found to be a significant variable that increased the means of heterogeneity in the vehicle age older than 10 years indicator for minor injury outcomes in the 2016 right-side crash model. Regarding the 2015 right-side crash model, the mean of intersection indicator defined to no injury would increase when the traffic control was functioning. In the 2017 right-side crash model, middle-aged drivers were found to be associated with increased mean of the safety restraint usage indicator,

making minor injuries more likely.

With regard to the heterogeneity in the variances, none of explanatory variables had significant impacts on the variances of the random parameters across all 2016 and 2017 crash models, as shown in Tables 4.10–4.12. The insured vehicle indicator was found to statistically decrease the variance of the random parameter produced by the disabling damage indicator for minor injury in 2015 center crashes, leading to more observations decreasing the likelihood of minor injury. Turning to the 2015 left-side crash model, the variances of insurance indicator specific to severe injury would decline if safety restraints were utilized by drivers in these single-vehicle accidents. Regarding right-side crashes in 2015, it was observed that the disabling damage led to an increase in the variance of the random parameters relating to the intersection indicator for no injury, while insured vehicles exhibited a significant association with decreased variance.

3.6.2 Crash characteristics

The collision with fixed object indicator consistently resulted in more severe injuries (with positive marginal effects for minor injuries or severe injuries) in 2015 and 2017. It can be speculated that the tire-road friction coefficient under adverse road conditions is smaller than that of dry surfaces, thus limiting the effectiveness of braking systems in hazardous situations. Consequently, there is greater kinetic energy dissipation during a collision with fixed objects, thereby increasing the likelihood of fatal and minor injuries (Roque et al., 2015). Regarding the non-collision indicator, it was also observed to be associated with an increased possibility of more severe injury for each location in one or two years, further reflecting the potential temporal stability and transferability of this indicator. This could be attributed to the inherent seriousness of this crash type, that is, non-collision accidents such as overturns are typically associated with strong lateral impact, thus resulting in injuries and fatalities (Yan et al., 2022). Nevertheless, considerable variations in the combination of different damage

locations and years were captured, indicating the complexity of interaction mechanism. It is also noteworthy that although the estimated parameter of the animal-involved collision indicator consistently led to less severe injury (with positive values for no injury and negative values for minor injury or severe injury) across three observed years, this indicator was found to be significant in all center crash models but only significant in one or two side-wipe crash models, demonstrating the slight diversity across impact locations.

The non-functional damage indicator was identified as a determinant to be negatively associated with the occurrence of minor injuries or severe injuries in 2017 center and right-side crash models, while the functional damage indicator was statistically significant in all models except for the 2016 right-side crash model. Furthermore, it was observed that the disabling damage indicator had a significant impact on the severity of crashes across all combinations of years and locations. Notably, this indicator consistently correlated with more severe driver injuries (with positive values indicating minor or severe injuries). These findings suggest that the disabling damage indicator is not only consistent over time but also transferable across different crash locations. The results were intuitive since the driver injury severity and the vehicle damage severity were positively related when crashes happened. With respect to indicators reflecting the movement type preceding the crashes, the straight driving indicator would increase the possibility of more severe injury in 2016 center and 2017 left-side crash models, whereas these indicators were found to be statistically insignificant in right-side crash models. This interesting phenomenon can be explained by the fact that drivers typically bear indirect damage in left-hand drive vehicles when right-side crashes happen, thus sharing lower risks and being less sensitive to this movement indicator compared to collisions occurring in the other two impact positions.

3.6.3 Driver characteristics

For age-related indicators, it was observed that young and middle-aged drivers

were associated with a decreased probability of severe injuries in 2017 crash models. However, these two variables were not found to be significant in 2015 and 2016 models. In contrast, the old driver indicator was observed to maintain a positive relationship with more severe injury crashes. Besides, it is noteworthy that this variable was identified as a rather consistent characteristic among three impact locations from 2015 to 2017. These findings are in line with previous studies (Alnawmasi and Mannering, 2022b; Chen et al., 2016). A possible explanation is that the declined perception and reaction ability of old drivers would cause serious obstacles in dealing with complicated traffic environments and subsequently lead to more serious injuries.

The safety restraint usage indicator was also found to be temporally and positionally stable across different collision locations, making minor or severe injuries less likely. Previous findings also found that using protection such as the belt or helmet can significantly decrease injury severities in traffic accidents (Wang and Abdel-Aty, 2008; Li et al., 2019). The results suggested that stricter regulations should be formulated to increase the proportion of drivers with seatbelts on. With respect to drivers' gender attributes, female drivers consistently demonstrated temporal stability and location transferability throughout the observed year, with a positive effect on minor or severe injuries due to their susceptibility to traffic accidents (Alnawmasi and Mannering, 2022).

Regarding the physically impaired indicators, the marginal effects showed that impaired drivers tended to increase the possibility of minor or severe injuries (Behnood and Mannering, 2017). Compared to left-side and right-side crashes, severe injury crashes might be more likely to occur in center crashes when the driver was in the physically impaired condition. Empirical studies have shown that drivers' driving skills, including attention, scanning, and information processing ability, would deteriorate even at low blood alcohol concentration levels (European Commission, 2018; Yan et al., 2021a). Therefore, the joint effect of the diminished capacity to avoid risks in case of danger and more aggressive driving behaviours such as speeding would result in

more severe injuries, especially in head-on collisions with the fastest energy decay rate under adverse road surface conditions.

3.6.4 Temporal characteristics

The season-of-year indicators generally yielded respective consistent marginal effects across different impact locations over the years. Regarding the marginal effects of the spring indicator, minor or severe injuries were more likely to occur in the variable-significant models over three different impact locations. The summer indicator was also found to be positively associated with a decreased possibility of no injuries while making minor injuries more likely. By contrast, it was observed that the autumn would result in less likelihood of severe injury in 2015 left-side crashes. The possible reason underlying such divergency is that adverse weather conditions (e.g., typhoons and rainstorms) that typically occur in spring and summer can significantly deteriorate the driving environment (Wang et al., 2022), whereas the autumn indicator is generally associated with fine weather with low precipitation, adequate sunlight, and comfortable temperature in Ohio (Weather Atlas, 2022).

The early morning indicator was only statistically significant in 2015 and 2017 right-side crash models, which demonstrated positive marginal effects in relation to minor or severe injuries. This phenomenon can be explained from two perspectives. On the one hand, major causes of catastrophic collisions, such as speeding, fatigue, and drowsy driving, are more prevalent in the early morning hours (Siebert et al., 2019). Another alternative explanation might be the reduced visibility during early morning periods (Yan et al., 2021b), which significantly increased risks of right-side crashes compared to left-side and center collisions on adverse road surfaces. Note that only the 2016 left-side crash model captured the negative effect of the afternoon indicator, which is associated with the increased likelihood of minor injuries and severe injuries. Apart from the similar issues of distracted and fatigued driving in the early morning, afternoons usually witness high traffic volumes during rush hours. The increased

number of vehicles can result in road congestion and traffic jams, subsequently raising the probability of accidents. Compared to weekends, the weekday indicator was observed to make severe injuries less likely among 2016 left-side crashes, which aligns with previous empirical findings (Yan et al., 2021a; Behnood and Al-Bdairi, 2020).

3.6.5 Vehicle characteristics

The passenger car involvement indicator was identified as a significant determinant only in the 2015 left-side and 2016 center crash models with a higher possibility of no injuries, while it was not identified as a significant variable in right-side accidents. Compared to trucks and SUVs, passenger cars equipped with specialized safety features, such as advanced airbag systems, crumple zones, and side impact beams, are more effective in mitigating impact forces and reducing the risk of injuries, especially in destructive left-side and center crashes. Being the insured vehicle was found to significantly influence driver injury severities across various combinations of different impact locations and years under poor road surface conditions, demonstrating a high level of temporal consistency and impact location transferability. It was found to be stably associated with a decreased probability of more severe injury since most insured drivers may have higher safety awareness (Yan et al., 2021a). Distinct findings also revealed that insurance made drivers more likely to sustain more severe injuries (Zhang et al., 2014). This might be caused by the driving-compensating principle that insured drivers were less cautious and more likely to engage in dangerous driving behaviours.

With respect to the vehicle age, the 5–10 years old indicator was observed to be of temporal and positional instability. In the 2016 center crash model, it was found to have a positive impact on severe injuries, whereas it turned out to be negatively related to the incidence of severe injuries in the 2015 right-side crash models. This indicates that, even for well-functioned automobiles, the vehicle's kinetic energy could instantaneously transfer to drivers and result in more severe injuries in center crashes. By contrast, the vehicle's kinetic energy might be distributed between the vehicle and

the driver in right-side collisions, thus resulting in less severe injuries. The 0–5 years old indicator was observed to be positively related to severe injury severities in the variable-significant model while producing subtle differences in their marginal effects owing to the divergences of estimated parameter categories. Likewise, when crashes involving more than 10 years older vehicles, the likelihood of severe injuries was observed to increase but only generated statistical significance in the 2016 right-side crash model. It is understandable that vehicles over ten years were typically associated with poor mechanical properties and low stability, which might cause potential safety hazards and result in a higher probability of more severe injury outcomes (Yan et al., 2021a).

3.6.6 Roadway characteristics

In 2015 right-side and 2017 center crashes, the results showed that there was a lower possibility of more severe injuries if the accident occurred on the road section with traffic controls functioning. This is consistent with previous findings that signal controls implemented at intersections with complex traffic conditions can effectively regulate the traffic flow in orderliness (Wang and Abdel-Aty, 2008). For the number of lanes indicator, it is noteworthy that these variables were all found to be statistically insignificant in right-side crashes and 2016 crashes, indicating the sensitivity and non-transferability to different impact locations and years. It was observed that being 1–3 lane roadways and greater than 6 lane roadways generally produced consistent findings for center and left-side crashes in 2015 and 2017, resulting in more severe outcomes. In contrast, crashes occurred in 4–6 lane roadways would result in less severe injuries for the 2015 left-side combination. One possible reason for this remarkable difference is the relatively narrower driving space on 1–3 lane roadways and the more aggressive driving behaviours of drivers on wider roads (Se et al., 2021).

Regarding the variables reflecting roadway types, the freeway indicator was only found to be statistically significant in the 2016 center crash model, making more severe

injury less likely, whereas the municipal street indicator sustained less severe injuries in 2016 left-side crashes. Municipal streets were also found to be negatively associated with minor injuries and severe injuries in right-side crashes (in 2015 and 2016). One rationale lies in the fact that highways and municipal roads typically feature spacious lanes, medians, and effective traffic management systems, which help reduce traffic congestion and the risk of accidents. An alternative reason is that these roads are subject to stringent regulation and enforcement measures. Traffic police and surveillance systems regularly patrol and monitor highways and municipal roads to ensure compliance with traffic rules and speed limits. Besides, it was found that the intersection indicator was positively correlated with the no injury or minor injury outcomes in the 2015 right-side crash model. One possible explanation is that drivers tended to be more cautious with a slower speed when driving near intersections with wet, snowy, or icy road surfaces (Pervaz et al., 2022), thereby decreasing the possibility of severe injuries.

Despite being insignificant in three impact location models of 2016, the speed limit of 30–60 mph showed the potential impact location transferability of corresponding parameter estimates, which was negatively associated with no injuries and positively associated with the minor injuries or severe injuries in 2015 center and left-side collisions, as well as that in 2017 right-side crashes. This is reasonable since the braking distance of vehicles would significantly increase under adverse road conditions. Even within lower speed limits, drivers may still be unable to stop in a timely manner if there are obstacles or other vehicles on the road, resulting in collisions and serious injuries (Li et al., 2018). Furthermore, maintaining vehicle stability can also be challenging in unfavorable surface scenarios, as vehicles are prone to losing balance or experiencing skidding, thereby increasing the risk of rollovers and collisions.

3.6.7 Environment characteristics

Regarding the environmental attributes, only the dark-unlighted indicator specific

to minor injuries and the adverse weather condition indicator specific to no injuries were found to generate significance statistically. The former variable exhibited marginal effects in the 2015 left-side crash model, where it was positively associated with no injuries and severe injuries. However, it was not identified as a significant variable in all center and right-side crash models, demonstrating the diversity across different damage locations. It can be assumed that compared to far-side crashes, near-side accidents were more sensitive to the impact of lighting conditions. Therefore, the lighting condition should be improved to reduce the occurrence of such accidents (Chang et al., 2022). Another insightful understanding is the extreme nature of this variable. Namely, even though drivers tended to compensate for adverse visibility conditions by modifying their driving behaviours to maintain an acceptable level of risk, there was still a higher likelihood of severe injury severities once the crash happened.

Note that the adverse weather condition consistently exhibited a negative correlation to minor and severe injuries in 2016 crashes across all impact locations, whereas it was not identified as a significant variable in 2015 and 2017 crash models. This implies the presence of temporal shifts between disaggregated years, highlighting the importance of considering temporal dynamics when implementing targeted injury prevention strategies. This is consistent with findings of historical empirical studies where drivers were found to behave more carefully under unfavorable driving conditions due to the risk-compensating mindset (Behnood and Mannering, 2019; Islam and Mannering, 2020, 2021; Pang et al., 2022; Wang et al., 2018).

Table 3.10. Model estimation results of random parameters logit models with heterogeneity in the means and variances in center crashes over the years.

Variable	2015		2016		2017	
	Parameter	t-Stat	Parameter	t-Stat	Parameter	t-Stat
[MI] Constant	-3.805	-8.86	-1.836	-6.02	-	-
[SI] Constant	-3.798	-8.27	-2.655	-6.52	-5.938	-7.60
Random parameters (normally distributed)						
[MI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise)	1.236	4.97	-	-	-	-
Standard deviation	3.618	4.50	-	-	-	-
[MI] Traffic controls indicator (1 if traffic control functioned, 0 otherwise)	-	-	-	-	-1.797	-3.58
Standard deviation	-	-	-	-	1.684	3.90
[NI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise)	-	-	-0.565	-2.70	-	-
Standard deviation	-	-	1.182	1.65	-	-
Heterogeneity in the means of random parameters						
[MI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise): The number of lanes indicator (1 if the number of lanes is greater than 6, 0 otherwise)	-0.927	-2.33	-	-	-	-
[MI] Traffic controls indicator (1 if traffic control functioned, 0 otherwise): Insurance indicator (1 if vehicle was insured, 0 otherwise)	-	-	-	-	0.504	2.31
Heterogeneity in the variances of random parameters						
[MI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise): Insurance indicator (1 if vehicle was insured, 0 otherwise)	-0.638	-3.26	-	-	-	-
Crash characteristics						
[NI] Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise)	-1.315	-4.07	-	-	-	-
[NI] Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise)	-	-	-0.506	-1.94	-	-
[NI] Animal indicator (1 if animal involved in the crash, 0 otherwise)	-	-	2.199	6.50	2.080	6.84
[MI] Animal indicator (1 if animal involved in the crash, 0 otherwise)	-1.677	-3.75	-	-	-	-
[NI] Non-functional damage indicator (1 if damage to vehicle is non-functional, 0 otherwise)	-	-	-	-	2.051	6.99
[MI] Functional damage indicator (1 if damage to vehicle is functional, 0 otherwise)	0.885	4.92	0.965	3.95	-1.342	-6.98
[NI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise)	-	-	-1.884	-8.64	-	-
[SI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise)	-	-	-	-	2.696	4.48
[NI] Straight driving indicator (1 if the vehicle was going straight preceding the crash, 0 otherwise)	-	-	-0.281	-2.25	-	-
Driver characteristics						
[MI] Middle-aged driver indicator (1 if driver age between 30–50 years, 0 otherwise)	-	-	-	-	0.263	2.09
[NI] Old driver indicator (1 if driver age over 50, 0 otherwise)	-1.005	-3.70	-1.067	-2.88	-1.109	-4.23
[MI] Old driver indicator (1 if driver age over 50, 0 otherwise)	-0.630	-2.14	-0.691	-1.85	-0.785	-2.72
[NI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise)	1.853	6.67	2.635	7.25	1.570	5.52
[MI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise)	0.825	2.54	1.611	4.63	0.701	2.34
[NI] Gender indicator (1 if driver was female, 0 otherwise)	-0.833	-7.20	-0.540	-4.75	-0.646	-5.62
[NI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise)	-1.234	-7.10	-	-	-1.260	-6.69
Temporal characteristics						
[NI] Spring indicator (1 if crash occurred during the spring, 0 otherwise)	-0.337	-2.27	-	-	-	-

Variable	2015		2016		2017	
	Parameter	t-Stat	Parameter	t-Stat	Parameter	t-Stat
[MI] Summer indicator (1 if crash occurred during the summer, 0 otherwise)	0.475	2.50	-	-	-	-
Vehicle characteristics						
[SI] Passenger car involvement indicator (1 if passenger car being involved in the crash, 0 otherwise)	-	-	-0.676	-2.01	-	-
[NI] Insurance indicator (1 if vehicle was insured, 0 otherwise)	-	-	0.479	3.76	0.990	6.45
[SI] Insurance indicator (1 if vehicle was insured, 0 otherwise)	-1.029	-4.16	-	-	-	-
[SI] Vehicle age indicator (1 if the vehicle age is less than 5 years, 0 otherwise)	-	-	-	-	0.646	2.40
[NI] Vehicle age indicator (1 if the vehicle age is between 5 and 10 years, 0 otherwise)	-	-	-0.196	-1.65	-	-
Roadway characteristics						
[NI] Traffic controls indicator (1 if traffic control functioned, 0 otherwise)	-	-	-	-	-1.070	-2.26
[SI] The number of lanes indicator (1 if the number of lanes is 1–3, 0 otherwise)	-	-	-	-	0.834	3.43
[MI] The number of lanes indicator (1 if the number of lanes is greater than 6, 0 otherwise)	1.051	3.77	-	-	-	-
[NI] Freeway indicator (1 if crash occurred on the freeway, 0 otherwise)	-	-	0.984	2.48	-	-
[MI] Freeway indicator (1 if crash occurred on the freeway, 0 otherwise)	-	-	0.760	1.91	-	-
[NI] Speed limit 30–60 mph indicator (1 if speed limit is between 30 and 60 mph, 0 otherwise)	-0.321	-2.70	-	-	-	-
Environment characteristics						
[NI] Adverse weather condition indicator (1 if weather condition is adverse, 0 otherwise)	-	-	0.216	1.77	-	-
Model statistics						
Number of observations (<i>N</i>)	4399		2503		4127	
Number of estimated parameters (<i>K</i>)	20		20		19	
Log-likelihood at zero, <i>LL</i> (0)	-4832.795		-2749.827		-4533.973	
Log-likelihood at convergence, <i>LL</i> (β)	-2160.907		-1226.689		-2042.455	
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.553		0.554		0.550	
Akaike information criterion (AIC)	4361.8		2493.4		4122.9	
Bayesian Information Criterion (BIC)	4489.6		2609.9		4243.1	

Table 3.11. Model estimation results of random parameters logit models with heterogeneity in the means and variances in left-side crashes over the years.

Variable	2015		2016		2017	
	Parameter	t-Stat	Parameter	t-Stat	Parameter	t-Stat
[MI] Constant	-2.855	-8.85	-1.402	-3.46	-4.654	-10.68
[SI] Constant	-7.998	-7.01	-2.101	-3.65	-6.878	-10.72
Random parameters (normally distributed)						
[NI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise)	-	-	-0.683	-1.71	-	-
<i>Standard deviation</i>	-	-	1.989	2.78	-	-
[SI] Insurance indicator (1 if vehicle was insured, 0 otherwise)	-5.887	-1.65	-	-	-	-
<i>Standard deviation</i>	6.033	2.26	-	-	-	-
[MI] Gender indicator (1 if driver was female, 0 otherwise)	-	-	-	-	0.585	2.21
<i>Standard deviation</i>	-	-	-	-	1.828	3.34
Heterogeneity in the means of random parameters						
[NI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise): Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise)	-	-	-0.982	-1.70	-	-
[SI] Insurance indicator (1 if vehicle was insured, 0 otherwise): Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise)	2.844	2.13	-	-	-	-
[MI] Gender indicator (1 if driver was female, 0 otherwise): Non-collision indicator (1 if first harmful	-	-	-	-	1.650	1.65

Variable	2015		2016		2017	
	Parameter	t-Stat	Parameter	t-Stat	Parameter	t-Stat
event was identified as non-colliding object such as a rollover, etc., 0 otherwise)						
[MI] Gender indicator (1 if driver was female, 0 otherwise): The number of lanes indicator (1 if the number of lanes is 4–6, 0 otherwise)	-	-	-	-	-0.656	-2.86
[MI] Gender indicator (1 if driver was female, 0 otherwise): Animal indicator (1 if animal involved in the crash, 0 otherwise)	-	-	-	-	-3.313	-2.93
Heterogeneity in the variances of random parameters						
[SI] Insurance indicator (1 if vehicle was insured, 0 otherwise): Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise)	-0.625	-3.11	-	-	-	-
Crash characteristics						
[NI] Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise)	-1.691	-7.27	-	-	-	-
[MI] Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise)	-	-	-	-	1.540	4.44
[SI] Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise)					1.825	3.37
[NI] Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise)	-1.754	-6.26	-	-	-1.589	-4.05
[NI] Animal indicator (1 if animal involved in the crash, 0 otherwise)	-	-	2.109	4.65	-	-
[MI] Functional damage indicator (1 if damage to vehicle is functional, 0 otherwise)	-0.568	-5.01	0.696	3.05	1.224	4.85
[NI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise)	-	-	-	-	-2.268	-9.09
[SI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise)	3.851	3.58	-	-	-	-
[NI] Straight driving indicator (1 if the vehicle was going straight preceding the crash, 0 otherwise)	-	-	-	-	-0.237	-1.89
Driver characteristics						
[NI] Young driver indicator (1 if driver age below 30 years, 0 otherwise)	-	-	-	-	0.318	2.57
[NI] Old driver indicator (1 if driver age over 50, 0 otherwise)	-	-	-0.427	-2.09	-0.539	-1.78
[MI] Old driver indicator (1 if driver age over 50, 0 otherwise)	-	-	-	-	-0.661	-2.09
[SI] Old driver indicator (1 if driver age over 50, 0 otherwise)	0.934	2.40	-	-	-	-
[NI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise)			2.373	4.61		
[MI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise)	-0.751	-4.50	1.828	3.76	-	-
[NI] Gender indicator (1 if driver was female, 0 otherwise)			-0.794	-4.66		
[MI] Gender indicator (1 if driver was female, 0 otherwise)	0.588	6.37	-	-	-	-
[NI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise)	-	-	-2.340	-3.72	-	-
[MI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise)	0.575	3.76	-1.320	-2.34	0.531	2.86
Temporal characteristics						
[SI] Weekday indicator (1 if crash occurred during the weekday, 0 otherwise)	-	-	-0.768	-1.77	-	-
[NI] Afternoon indicator (1 if time of day is between 12 PM to 6:59 PM, 0 otherwise)	-	-	-0.376	-2.21	-	-
[MI] Spring indicator (1 if crash occurred during the spring, 0 otherwise)	0.373	2.89	-	-	-	-
[MI] Summer indicator (1 if crash occurred during the summer, 0 otherwise)	0.349	2.32	-	-	-	-
[MI] Autumn indicator (1 if crash occurred during the autumn, 0 otherwise)	0.236	1.89	-	-	-	-

Variable	2015		2016		2017	
	Parameter	t-Stat	Parameter	t-Stat	Parameter	t-Stat
Vehicle characteristics						
[MI] Passenger car involvement indicator (1 if passenger car being involved in the crash, 0 otherwise)	-0.368	-4.00	-	-	-	-
[NI] Insurance indicator (1 if vehicle was insured, 0 otherwise)	-	-	0.758	3.75	1.215	4.59
[MI] Insurance indicator (1 if vehicle was insured, 0 otherwise)	-	-	-	-	0.643	2.26
Roadway characteristics						
[SI] The number of lanes indicator (1 if the number of lanes is 1–3, 0 otherwise)	-	-	-	-	1.066	3.78
[MI] The number of lanes indicator (1 if the number of lanes is 4–6, 0 otherwise)	0.221	2.13	-	-	-	-
[NI] The number of lanes indicator (1 if the number of lanes is greater than 6, 0 otherwise)	-	-	-	-	-1.074	-2.60
[MI] The number of lanes indicator (1 if the number of lanes is greater than 6, 0 otherwise)	-	-	-	-	-1.179	-2.64
[MI] Speed limit 30–60 mph indicator (1 if speed limit is between 30 and 60 mph, 0 otherwise)	0.382	3.55	-	-	-	-
[NI] Municipal street indicator (1 if crash occurred on the municipal street, 0 otherwise)	-	-	0.346	1.93	-	-
Environment characteristics						
[SI] Dark-lighted indicator (1 if lighting condition is dark-lighted, 0 otherwise)	-0.214	-1.97	-	-	-	-
[NI] Adverse weather condition indicator (1 if weather condition is adverse, 0 otherwise)	-	-	0.556	3.19	-	-
Model statistics						
Number of observations (N)	3787		1968		3290	
Number of estimated parameters (K)	21		18		22	
Log-likelihood at zero, $LL(0)$	-4160.445		-2162.069		-3614.434	
Log-likelihood at convergence, $LL(\beta)$	-1804.044		-913.491		-1552.717	
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.566		0.577		0.570	
Akaike information criterion (AIC)	3650.1		1863.0		3149.4	
Bayesian Information Criterion (BIC)	3781.1		1963.5		3283.6	

Table 3.12. Model estimation results of random parameters logit models with heterogeneity in the means and variances in right-side crashes over the years.

Variable	2015		2016		2017	
	Parameter	t-Stat	Parameter	t-Stat	Parameter	t-Stat
[MI] Constant	-2.371	-8.36	-1.172	-3.67	-2.322	-4.10
[SI] Constant	-4.990	-19.13	-4.855	-7.45	-5.493	-9.60
Random parameters (normally distributed)						
[MI] Vehicle age indicator (1 if the vehicle age is older than 10 years, 0 otherwise)	-	-	-3.417	-3.99	-	-
Standard deviation	-	-	2.336	3.63	-	-
[NI] Intersection indicator (1 if crash occurred on the intersection, 0 otherwise)	2.199	1.75	-	-	-	-
Standard deviation	3.645	2.30	-	-	-	-
[MI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise)	-	-	-	-	-1.848	-3.72
Standard deviation	-	-	-	-	1.826	2.61
Heterogeneity in the means of random parameters						
[NI] Intersection indicator (1 if crash occurred on the intersection, 0 otherwise): Traffic controls indicator (1 if traffic control functioned, 0 otherwise)	1.471	2.46	-	-	-	-
[MI] Vehicle age indicator (1 if the vehicle age is older than 10 years, 0 otherwise): Gender indicator (1 if driver was female, 0 otherwise)			1.113	2.74		
[MI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise): Middle-aged driver indicator (1 if driver age between 30–50 years, 0 otherwise)	-	-	-	-	1.204	3.57
Heterogeneity in the variances of random parameters						
[NI] Intersection indicator (1 if crash occurred on the intersection, 0 otherwise): Disabling damage	0.249	1.83	-	-	-	-

Variable	2015		2016		2017	
	Parameter	t-Stat	Parameter	t-Stat	Parameter	t-Stat
indicator (1 if damage to vehicle is disabling, 0 otherwise)						
[NI] Intersection indicator (1 if crash occurred on the intersection, 0 otherwise): Insurance indicator (1 if vehicle was insured, 0 otherwise)	-0.317	-1.85	-	-	-	-
Crash characteristics	-	-	-	-	-	-
[MI] Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise)	-	-	-	-	1.914	3.94
[NI] Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise)	-	-	-0.685	-2.30	-	-
[MI] Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise)					2.062	3.52
[NI] Animal indicator (1 if animal involved in the crash, 0 otherwise)	2.010	4.82	1.417	3.32	-	-
[MI] Non-functional damage indicator (1 if damage to vehicle is non-functional, 0 otherwise)	-	-	-	-	-2.257	-5.04
[MI] Functional damage indicator (1 if damage to vehicle is functional, 0 otherwise)	0.552	2.82	-	-	-1.221	-4.73
[NI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise)	-1.558	-8.89	-1.391	-7.45	-	-
[SI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise)	-	-	-	-	1.270	3.20
Driver characteristics						
[NI] Middle-aged driver indicator (1 if driver age between 30–50 years, 0 otherwise)	-	-	-	-	1.080	3.57
[NI] Old driver indicator (1 if driver age over 50, 0 otherwise)	-	-	-	-	-0.448	-2.41
[MI] Old driver indicator (1 if driver age over 50, 0 otherwise)	-	-	0.393	1.98	-	-
[NI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise)	-	-	1.768	6.61	-	-
[MI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise)	-0.663	-3.62	-	-	-	-
[NI] Gender indicator (1 if driver was female, 0 otherwise)	-	-	-0.495	-2.72	-	-
[MI] Gender indicator (1 if driver was female, 0 otherwise)	0.778	6.48	-	-	0.870	4.41
[NI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise)	-0.671	-3.81	-1.006	-2.89	-1.958	-4.77
[MI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise)	-	-	-	-	-1.262	-2.79
Temporal characteristics						
[MI] Early morning indicator (1 if time of day is between 12 AM to 5:59 AM, 0 otherwise)	-0.499	-3.19	-	-	-	-
[SI] Early morning indicator (1 if time of day is between 12 AM to 5:59 AM, 0 otherwise)	-	-	-	-	-1.733	-2.32
[NI] Spring indicator (1 if crash occurred during the spring, 0 otherwise)	-0.418	-2.76	-0.534	-2.77	-	-
[MI] Spring indicator (1 if crash occurred during the spring, 0 otherwise)	-	-	-	-	0.570	2.79
[NI] Summer indicator (1 if crash occurred during the summer, 0 otherwise)	-	-	-0.539	-2.47	-	-
[MI] Summer indicator (1 if crash occurred during the summer, 0 otherwise)	-	-	-	-	0.442	2.01
Vehicle characteristics						
[NI] Insurance indicator (1 if vehicle was insured, 0 otherwise)	0.309	2.21	-	-	0.490	2.79
[MI] Vehicle age indicator (1 if the vehicle age is less than 5 years, 0 otherwise)	-0.406	-2.46	-	-	-	-
[NI] Vehicle age indicator (1 if the vehicle age is between 5 and 10 years, 0 otherwise)	0.346	2.64	-	-	-	-
[NI] Vehicle age indicator (1 if the vehicle age is older than 10 years, 0 otherwise)	-	-	-1.927	-3.12	-	-
Roadway characteristics						

Variable	2015		2016		2017	
	Parameter	t-Stat	Parameter	t-Stat	Parameter	t-Stat
[MI] Traffic controls indicator (1 if traffic control functioned, 0 otherwise)	0.445	2.69	-	-	-	-
[SI] Speed limit 30-60 mph indicator (1 if speed limit is between 30 and 60 mph, 0 otherwise)	-	-	-	-	0.976	1.98
[NI] Municipal street indicator (1 if crash occurred on the municipal street, 0 otherwise)	0.296	2.19	0.372	2.18	-	-
[MI] Intersection indicator (1 if crash occurred on the intersection, 0 otherwise)	1.088	1.90	-	-	-	-
Environment characteristics						
[NI] Adverse weather condition indicator (1 if weather condition is adverse, 0 otherwise)	-	-	0.393	2.39	-	-
Model statistics						
Number of observations (N)	3827		2061		3211	
Number of estimated parameters (K)	21		17		20	
Log-likelihood at zero, $LL(0)$	-4204.389		-2264.240		-3527.644	
Log-likelihood at convergence, $LL(\beta)$	-1497.669		-869.450		-1358.826	
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.644		0.616		0.615	
Akaike information criterion (AIC)	3037.3		1772.9		2757.7	
Bayesian Information Criterion (BIC)	3168.6		1868.6		2879.1	

Table 3.13. The marginal effects of contributing factors in different impact location models.

Variable	Center			Left			Right		
	NI	MI	SI	NI	MI	SI	NI	MI	SI
2015									
Crash characteristics									
[NI] Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise)	-0.1276	0.1130	0.0146	-0.2021	0.1885	0.0136	-	-	-
[NI] Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise)	-	-	-	-0.0182	0.0169	0.0013	-	-	-
[NI] Animal indicator (1 if animal involved in the crash, 0 otherwise)	-	-	-	-	-	-	0.0036	-0.0034	-0.0002
[MI] Animal indicator (1 if animal involved in the crash, 0 otherwise)	0.0052	-0.0052	0.0000	-	-	-	-	-	-
[MI] Functional damage indicator (1 if damage to vehicle is functional, 0 otherwise)	-0.0219	0.0227	-0.0008	0.0159	-0.0159	0.0000	-0.0110	0.0111	-0.0001
[NI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise)	-	-	-	-	-	-	-0.0951	0.0886	0.0065
[MI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise)	-0.1198	0.1227	-0.0029	-	-	-	-	-	-
[SI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise)	-	-	-	-0.0329	-0.0099	0.0428	-	-	-
Driver characteristics									
[NI] Old driver indicator (1 if driver age over 50, 0 otherwise)	-0.0216	0.0178	0.0038	-	-	-	-	-	-
[MI] Old driver indicator (1 if driver age over 50, 0 otherwise)	0.0112	-0.0118	0.0006	-	-	-	-	-	-
[SI] Old driver indicator (1 if driver age over 50, 0 otherwise)	-	-	-	-0.0221	-0.0006	0.0270	-	-	-
[NI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise)	0.1744	-0.1576	-0.0168	-	-	-	-	-	-
[MI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise)	-0.0702	0.0717	-0.0015	0.0872	-0.0888	0.0016	0.0522	-0.0534	0.0012
[NI] Gender indicator (1 if driver was female, 0 otherwise)	-0.0408	0.0358	0.0050	-	-	-	-	-	-
[MI] Gender indicator (1 if driver was female, 0 otherwise)	-	-	-	-0.0349	0.0356	-0.0007	-0.0327	0.0333	-0.0006
[NI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise)	-0.0164	0.0128	0.0036	-	-	-	-0.0077	0.0071	0.0006
[MI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise)	-	-	-	-0.0076	0.0080	-0.0004	-	-	-
Temporal characteristics									
[MI] Early morning indicator (1 if time of day is between 12 AM to 5:59 AM, 0 otherwise)	-	-	-	-	-	-	0.0067	-0.0069	0.0002
[NI] Spring indicator (1 if crash occurred during the spring, 0 otherwise)	-0.0055	0.0047	0.0008	-	-	-	-0.0066	0.0061	0.0005
[MI] Spring indicator (1 if crash occurred during the spring, 0 otherwise)	-	-	-	-0.0078	0.0080	-0.0002	-	-	-
[MI] Summer indicator (1 if crash occurred during the summer, 0 otherwise)	-0.0049	0.0051	-0.0002	-0.0049	0.0050	-0.0001	-	-	-
[MI] Autumn indicator (1 if crash occurred during the autumn, 0 otherwise)	-	-	-	0.0001	0.0056	-0.0057	-	-	-
Vehicle characteristics									
[MI] Passenger car involvement indicator (1 if passenger car being involved in the crash, 0 otherwise)	-	-	-	0.0235	-0.0240	0.0005	-	-	-
[NI] Insurance indicator (1 if vehicle was insured, 0 otherwise)	-	-	-	-	-	-	0.0221	-0.0208	-0.0013
[SI] Insurance indicator (1 if vehicle was insured, 0 otherwise)	0.0065	0.0016	-0.0081	0.0032	0.0012	-0.0044	-	-	-
[MI] Vehicle age indicator (1 if the vehicle age is less than 5 years, 0 otherwise)	-	-	-	-	-	-	0.0057	-0.0059	0.0002
[NI] Vehicle age indicator (1 if the vehicle age is between 5 and 10 years, 0 otherwise)	-	-	-	-	-	-	0.0094	-0.0089	-0.0005
Roadway characteristics									
[MI] Traffic controls indicator (1 if traffic control functioned, 0 otherwise)	-	-	-	-	-	-	-0.0330	0.0337	-0.0007
[MI] The number of lanes indicator (1 if the number of lanes is 4–6, 0 otherwise)	-	-	-	-0.0160	0.0163	-0.0003	-	-	-

Variable	Center			Left			Right		
	NI	MI	SI	NI	MI	SI	NI	MI	SI
[MI] The number of lanes indicator (1 if the number of lanes is greater than 6, 0 otherwise)	-0.0089	0.0092	-0.0003	-	-	-	-	-	-
[NI] Speed limit 30-60 mph indicator (1 if speed limit is between 30 and 60 mph, 0 otherwise)	-0.0228	0.0199	0.0029	-	-	-	-	-	-
[MI] Speed limit 30-60 mph indicator (1 if speed limit is between 30 and 60 mph, 0 otherwise)	-	-	-	-0.0326	0.0333	-0.0007	-	-	-
[NI] Municipal street indicator (1 if crash occurred on the municipal street, 0 otherwise)	-	-	-	-	-	-	0.0076	-0.0071	-0.0005
[NI] Intersection indicator (1 if crash occurred on the intersection, 0 otherwise)	-	-	-	-	-	-	0.0050	-0.0049	-0.0001
[MI] Intersection indicator (1 if crash occurred on the intersection, 0 otherwise)	-	-	-	-	-	-	-0.0165	0.0171	-0.0007
Environment characteristics									
[MI] Dark-unlighted indicator (1 if lighting condition is dark-unlighted, 0 otherwise)	-	-	-	0.0068	-0.0069	0.0001	-	-	-
2016									
Crash characteristics									
[NI] Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise)	-0.0032	0.0030	0.0002	-	-	-	-0.0047	0.0040	0.0007
[NI] Animal indicator (1 if animal involved in the crash, 0 otherwise)	0.0083	-0.0077	-0.0005	0.0069	-0.0066	-0.0003	0.0045	-0.0043	-0.0002
[MI] Functional damage indicator (1 if damage to vehicle is functional, 0 otherwise)	-0.0222	0.0225	-0.0003	-0.0207	0.0210	-0.0002	-	-	-
[NI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise)	-0.1977	0.1846	0.0131	-0.0962	0.0903	0.0059	-0.0888	0.0772	0.0116
[NI] Straight driving indicator (1 if the vehicle was going straight preceding the crash, 0 otherwise)	-0.0283	0.0265	0.0018	-	-	-	-	-	-
Driver characteristics									
[NI] Old driver indicator (1 if driver age over 50, 0 otherwise)	-0.0287	0.0258	0.0029	-0.0082	0.0078	0.0004	-	-	-
[MI] Old driver indicator (1 if driver age over 50, 0 otherwise)	0.0167	-0.0180	0.0013	-	-	-	-0.0074	0.0076	-0.0002
[NI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise)	0.3257	-0.3103	-0.0155	0.2242	-0.2142	-0.0100	0.1487	-0.1334	-0.0153
[MI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise)	-0.1898	0.1941	-0.0043	-0.1650	0.1716	-0.0066	-	-	-
[NI] Gender indicator (1 if driver was female, 0 otherwise)	-0.0318	0.0302	0.0016	-0.0370	0.0350	0.0020	-0.0220	0.0198	0.0022
[NI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise)	-0.0113	0.0105	0.0008	-0.0118	0.0092	0.0026	-0.0049	0.0041	0.0008
[MI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise)	-	-	-	0.0052	-0.0069	0.0017	-	-	-
Temporal characteristics									
[SI] Weekday indicator (1 if crash occurred during the weekday, 0 otherwise)	-	-	-	0.0026	0.0024	-0.0050	-	-	-
[NI] Afternoon indicator (1 if time of day is between 12 PM to 6:59 PM, 0 otherwise)	-	-	-	-0.0131	0.0124	0.0007	-	-	-
[NI] Spring indicator (1 if crash occurred during the spring, 0 otherwise)	-	-	-	-	-	-	-0.0114	0.0098	0.0016
[NI] Summer indicator (1 if crash occurred during the summer, 0 otherwise)	-	-	-	-	-	-	-0.0078	0.0069	0.0009
Vehicle characteristics									
[SI] Passenger car involvement indicator (1 if passenger car being involved in the crash, 0 otherwise)	0.0024	0.0019	-0.0043	-	-	-	-	-	-
[NI] Insurance indicator (1 if vehicle was insured, 0 otherwise)	0.0471	-0.0444	-0.0027	0.0571	-0.0540	-0.0031	-	-	-
[NI] Vehicle age indicator (1 if the vehicle age is between 5 and 10 years, 0 otherwise)	-0.0086	0.0081	0.0005	-	-	-	-	-	-
[NI] Vehicle age indicator (1 if the vehicle age is older than 10 years, 0 otherwise)	-	-	-	-	-	-	-0.0887	0.0696	0.0191
[MI] Vehicle age indicator (1 if the vehicle age is older than 10 years, 0 otherwise)	-	-	-	-	-	-	0.0397	-0.0428	0.0031
Roadway characteristics									
[NI] Freeway indicator (1 if crash occurred on the freeway, 0 otherwise)	0.0606	-0.0584	-0.0022	-	-	-	-	-	-
[MI] Freeway indicator (1 if crash occurred on the freeway, 0 otherwise)	-0.0451	0.0460	-0.0009	-	-	-	-	-	-

Variable	Center			Left			Right		
	NI	MI	SI	NI	MI	SI	NI	MI	SI
[NI] Municipal street indicator (1 if crash occurred on the municipal street, 0 otherwise)	-	-	-	0.0119	-0.0110	-0.0008	0.0114	-0.0101	-0.0013
Environment characteristics									
[NI] Adverse weather condition indicator (1 if weather condition is adverse, 0 otherwise)	0.0206	-0.0193	-0.0012	0.0355	-0.0334	-0.0021	0.0243	-0.0216	-0.0027
2017									
Crash characteristics									
[MI] Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise)	-	-	-	-0.1383	0.1446	-0.0063	-0.1422	0.1452	-0.0030
[SI] Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise)	-	-	-	-0.0237	-0.0075	0.0312	-	-	-
[NI] Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise)	-	-	-	-0.0115	0.0103	0.0012	-	-	-
[MI] Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise)	-	-	-	-	-	-	-0.0103	0.0105	-0.0002
[NI] Animal indicator (1 if animal involved in the crash, 0 otherwise)	0.0113	-0.0106	-0.0007	-	-	-	-	-	-
[NI] Non-functional damage indicator (1 if damage to vehicle is non-functional, 0 otherwise)	0.0149	-0.0148	-0.0001	-	-	-	-	-	-
[MI] Non-functional damage indicator (1 if damage to vehicle is non-functional, 0 otherwise)	-	-	-	-	-	-	0.0154	-0.0154	0.0001
[MI] Functional damage indicator (1 if damage to vehicle is functional, 0 otherwise)	0.0207	-0.0208	0.0001	-0.0260	0.0262	-0.0002	0.0219	-0.0221	0.0002
[NI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise)	-	-	-	-0.1938	0.1655	0.0283	-	-	-
[SI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise)	-0.0318	-0.0124	0.0442	-	-	-	-0.0075	-0.0019	0.0094
[NI] Straight driving indicator (1 if the vehicle was going straight preceding the crash, 0 otherwise)	-	-	-	-0.0199	0.0174	0.0025	-	-	-
Driver characteristics									
[NI] Young driver indicator (1 if driver age below 30 years, 0 otherwise)	-	-	-	0.0174	-0.0154	-0.0020	-	-	-
[NI] Middle-aged driver indicator (1 if driver age between 30–50 years, 0 otherwise)	-	-	-	-	-	-	0.0308	-0.0293	-0.0015
[MI] Middle-aged driver indicator (1 if driver age between 30–50 years, 0 otherwise)	-0.0083	0.0086	-0.0003	-	-	-	-	-	-
[NI] Old driver indicator (1 if driver age over 50, 0 otherwise)	-0.0237	0.0193	0.0044	-0.0114	0.0093	0.0021	-0.0086	0.0073	0.0013
[MI] Old driver indicator (1 if driver age over 50, 0 otherwise)	0.0137	-0.0149	0.0012	0.0114	-0.0122	0.0008	-	-	-
[NI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise)	0.1564	-0.1413	-0.0151	-	-	-	-	-	-
[MI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise)	-0.0631	0.0651	-0.0020	-	-	-	0.0115	-0.0124	0.0009
[MI] Gender indicator (1 if driver was female, 0 otherwise)	-0.0318	0.0284	0.0034	-0.0438	0.0452	-0.0013	-0.0327	0.0334	-0.0007
[NI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise)	-0.0188	0.0151	0.0037	-	-	-	-0.0228	0.0187	0.0041
[MI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise)	-	-	-	-0.0061	0.0065	-0.0004	0.0120	-0.0129	0.0009
Temporal characteristics									
[SI] Early morning indicator (1 if time of day is between 12 AM to 5:59 AM, 0 otherwise)	-	-	-	-	-	-	0.0008	0.0002	-0.0010
[MI] Spring indicator (1 if crash occurred during the spring, 0 otherwise)	-	-	-	-	-	-	-0.0089	0.0091	-0.0002
[MI] Summer indicator (1 if crash occurred during the summer, 0 otherwise)	-	-	-	-	-	-	-0.0055	0.0057	-0.0001
Vehicle characteristics									
[NI] Insurance indicator (1 if vehicle was insured, 0 otherwise)	0.0768	-0.0696	-0.0072	0.1030	-0.0923	-0.0107	0.0323	-0.0294	-0.0029
[MI] Insurance indicator (1 if vehicle was insured, 0 otherwise)	-	-	-	-0.0488	0.0501	-0.0013	-	-	-
[SI] Vehicle age indicator (1 if the vehicle age is less than 5 years, 0 otherwise)	-0.0023	-0.0008	0.0032	-	-	-	-	-	-
Roadway characteristics									

Variable	Center			Left			Right		
	NI	MI	SI	NI	MI	SI	NI	MI	SI
[NI] Traffic controls indicator (1 if traffic control functioned, 0 otherwise)	-0.0963	0.1088	-0.0125	-	-	-	-	-	-
[MI] Traffic controls indicator (1 if traffic control functioned, 0 otherwise)	0.0482	-0.0432	-0.0050	-	-	-	-	-	-
[SI] The number of lanes indicator (1 if the number of lanes is 1–3, 0 otherwise)	-0.0055	-0.0021	0.0076	-0.0078	-0.0024	0.0102	-	-	-
[NI] The number of lanes indicator (1 if the number of lanes is greater than 6, 0 otherwise)	-	-	-	-0.0109	0.0088	0.0021	-	-	-
[MI] The number of lanes indicator (1 if the number of lanes is greater than 6, 0 otherwise)	-	-	-	0.0096	-0.0103	0.0007	-	-	-
[SI] Speed limit 30–60 mph indicator (1 if speed limit is between 30 and 60 mph, 0 otherwise)	-	-	-	-	-	-	-0.0070	-0.0014	0.0084

3.7 Concluding remarks

Using a three-year single-vehicle crash dataset under adverse road surface conditions in Ohio from 2015 to 2017, this study investigated the heterogeneous impacts, temporal instability, and non-transferability of various determinants on driver injury severities across different vehicle impact locations. Three groups of random parameters logit models with the heterogeneity in the means (and variances) corresponding to center, left-side, and right-side crashes were employed. A wide range of contributing factors was considered, including crash characteristics, driver characteristics, temporal characteristics, vehicle characteristics, roadway characteristics, and environment characteristics. Three crash injury severity categories were determined as discrete outcome variables: no injury, minor injury, and severe injury. The results of likelihood ratio tests indicated an overall temporal instability and locational non-transferability while some indicators, such as hitting animals, old drivers, safety restraint usage, female drivers, physically impaired drivers, and vehicles with insurance, were observed to be of temporal stability and impact location transferability. This study also examined the impact of year-to-year and location-to-location shifts by comparing the probability differences between out-of-sample predictions and within-sample observations. The results showed varying magnitudes and inconsistent directions of distribution characteristics, including mean, skewness, kurtosis, and prediction accuracy, across different locations and periods. Furthermore, this study suggested that the net effects of aggregate location-to-location shifts were greater than the net effects of year-to-year shifts. Consequently, the non-transferability of impact location had a higher influence on the prediction accuracy than the temporal instability. This highlights the importance of appropriately addressing the temporal instability and impact location variations in crash prediction.

Based on the locational variation and temporal instability of contributing factors on driver injury severities in adverse-road-involved crashes, a series of proactive countermeasures could be formulated to effectively prevent and mitigate crashes

associated with adverse road conditions. Regarding the non-transferability of impact locations, the current study reveals that dark-unlighted conditions pose a higher risk of severe injuries for left-side crashes instead of its center and right-side counterparts on adverse road surfaces. As a result, installing enough lighting is recommended. Furthermore, the implementation of advanced warning systems, such as variable message signs, can effectively notify drivers of potential hazards on the left front side, especially in areas with limited lighting conditions. Concerning the movement type preceding crashes, the finding deserves considerable attention that probabilities of severe injuries increase for center and left-side collisions even when the vehicle is driving straight on adverse road surfaces. This suggests that targeted education programs should be implemented to enhance drivers' safety awareness and remind them to avoid dangerous driving behaviours, such as aggressive driving, improper turns, and speeding. Considering the direct lateral force sustained by drivers and the associated high possibility of fatal injuries in left-side crashes, protective measures such as side airbags and active damping systems could be equipped on vehicles to mitigate the severity of driver injury, along with infrastructure improvements like the installation of crash barriers on the left side of roads. Additionally, the early morning indicator is found to be more likely to result in severe injuries in right-side crashes. Therefore, it is recommended to utilize technology channels to provide time-specific dynamic information reminders to drivers. This can involve utilizing broadcast media to deliver real-time updates on road conditions and driving tips to drivers, enabling them to take more appropriate precautions to reduce the likelihood of severe injuries in the early morning. In terms of the insights obtained from temporal instability, taking the vehicle aged 0–5 years as an example, it is observed to be associated with smaller probabilities of severe injuries in 2015, whereas showing greater effects in 2017. This result underscores the importance of advancing driving technologies to mitigate the heterogeneous impact of brand-new automobiles on drivers' adaptation to new features.

Chapter 4 Injury severity modelling and predictive analysis for undivided two-way highway-rail grade crossing crashes

4.1 Introduction

Highway-rail grade crossing (HRGC) crashes are a significant public safety concern as they are responsible for numerous fatalities and injuries each year. According to the Federal Railroad Administration, in 2021, there were 2,146 accidents at HRGCs, resulting in 122 fatalities and 419 injuries in the United States (Federal Railroad Administration, 2021). Highway-rail grade crossings (HRGCs) are intersections where roadways cross railroads at the same level, and the interaction between non-divided two-way traffic highways and railways can be particularly dangerous. These types of road entities are characterized by their lack of a physical barrier between opposing lanes of traffic. The Federal Railroad Administration reports that around 95% of HRGC accidents occurred at non-divided two-way traffic HRGCs, indicating the necessity to further analyse accidents at these crossings (Federal Railroad Administration, 2021).

Despite being critical for the smooth operation and safety of multimodal transportation systems, non-divided two-way traffic HRGCs are rarely explored specifically in previous studies. Most of them focused on the crashes that occurred on the non-divided two-way highway and highway crossings only. For instance, Lombardi et al. (2017) investigated the factors contributing to age-related risks and involvement rates in fatal vehicle crashes that occurred at intersections in the United States. The findings revealed that a significant proportion of fatal crashes occurred at four-way intersections and non-divided two-way traffic ways were equally distributed between daylight and night-time conditions. Liu and Fan (2021) proposed a partial proportional odds model for examining the factors contributing to the severity of head-on crashes. Their analysis also revealed that head-on collisions occurring on two-way non-divided roadways were associated with more severe injuries than those on one-way roads. In a

recent study conducted by Mahmud et al. (2022), the authors examined the safety risks associated with overtaking maneuvers on a bi-directional undivided two-lane highway in a heterogeneous traffic environment. The findings revealed that the speed difference between the overtaking and overtaken vehicles was a significant factor influencing the probability of severe conflicts. As indicated by Calvi et al. (2023), different types of median separation on two-lane rural roads can significantly affect driving behaviour (lateral positions and trajectories) and associated risks. Moreover, crashes are found to more commonly occur on non-divided two-way roads compared to other road types due to mixed traffic environments (Mahmud et al., 2022). Combining all road types (i.e., two-way traffic, divided traffic, and one-way traffic) when analyzing the injury severity of HRGC crashes can result in erroneous conclusions and improper countermeasures. Therefore, it is necessary to conduct separate studies focusing at non-divided two-way traffic HRGCs and investigate the factors affecting crashes in the context of this predominant traffic type.

Compared to statistical or econometric models, machine learning approaches have the advantage of being capable of processing big data and capturing intricate relationships between input variables and outcome predictions (Goswamy et al., 2023; Mannering et al., 2020a). Although machine learning models have been extensively studied for real-time risk prediction (Arvin et al., 2021; Khan and Ahmed, 2020; Sun et al., 2020), the application of these models to analyse injury severities at undivided two-way traffic HRGCs has not been investigated to the best of our knowledge. As a typical technique in the domain of machine learning, the XGBoost model has gained recognition as a powerful algorithm for classification and regression tasks. In traffic safety research, XGBoost has been utilized for its efficiency and accuracy in predicting road accident severity and identifying critical incident-related features (He et al., 2023; Ma et al., 2023). Additionally, it is worth noting that some previous studies have utilized the XGBoost model to evaluate highway crash injury severities, although these studies may not specifically focus on non-divided two-way highway and railway crashes. For

example, Soleimani et al., (2019) proposed a data-driven consolidation model for highway–rail grade crossings in the United States utilizing the XGBoost algorithm and incorporating various engineering variables. The developed model achieved an overall accuracy of 0.991 and provided insights into the relative importance of the input variables. Through a 10-fold empirical analysis of various performance metrics, Jamal et al., (2021) found that the XGBoost technique had superior collective predictive performance and individual class accuracies for injury severity compared to other machine learning models. The XGBoost feature importance analysis identified collision type, weather status, road surface conditions, on-site damage type, lighting conditions, and vehicle type as sensitive variables for predicting crash injury severity outcomes. Numerous studies have compared the performance of machine learning techniques with statistical models, finding that machine learning approaches have comparable predictive accuracy metrics (Goswamy et al., 2023; Islam et al., 2022; Yuan et al., 2022). Given that the XGBoost model could provide useful insights into crash severity analysis, this study specifically focuses on the application of this algorithm to investigate the influence of various determinants on injury severity outcomes at undivided two-way traffic HRGCs.

Previous studies in HRGC crash severity analysis only focused on analysing crash data before the outbreak of COVID-19, which may not accurately unveil the inherent mechanism of the injury severity in HRGC crashes during the pandemic. Meanwhile, it should be noted that the unobserved heterogeneity arising from various factors has not been fully considered as mentioned before. As such, further investigation is necessary to better understand the issue of unobserved heterogeneity when unveiling the relationship between injury severities and potential contributing factors in HRGC crashes after the outbreak of COVID-19 pandemic. To this end, the present study attempts to: (a) identify and compare the factors affecting the injury severity during and before the COVID-19 pandemic, and (b) address the issue of unobserved heterogeneity effectively by incorporating heterogeneity in the means in the random parameters logit

modelling framework.

It is important to acknowledge that while attempts are made to ensure the update and comprehensiveness of HRGC crash data, the collection of all pertinent information that could impact the occurrence of crashes is often limited by constraints related to costs and resources. In the case of HRGC, several crash-specific features, including the traffic density, average speed, and unexpected pedestrian or animal trespassing may pose challenges to record. Similarly, collecting human factors such as distraction, fatigue, the level of anxiety during the pandemic, or impairment of the driver may also bring considerable difficulties. Additionally, owing to different physical abilities, perceptions of risk, and reactions to external stimuli, there are considerable variations in HRGC crash injury severities among individuals as well. This may unavoidably give rise to the unobserved heterogeneity, and failing to account for unobserved variables or treating explanatory variables as fixed can lead to model misspecification, biased parameter estimates, and erroneous inferences (Alnawmasi and Mannering, 2019; Pervez et al., 2022).

4.2 Data description

This study utilizes the data collected from the Federal Railroad Administration's (FRA) Office of Safety Analysis System, which contains the HRGC crash records during the COVID-19 pandemic (2020-2021) and before the pandemic (2018-2019) in the United States (Federal Railroad Administration, 2022). The research data is derived from two sources: (1) the FRA's Office of HRGC accident data and (2) the FRA's Office of current crossing inventory data. The accident database contains comprehensive information on factors such as time, weather, visibility, vehicle, and demographic characteristics of highway users, while the current highway-rail crossing inventory database provides details on each crossing's location, type, illumination, signals, and traffic conditions.

In this study, injury severity outcomes are coded using a three-point ordinal scale,

with options for 1-Uninjured, 2-Injured, or 3-Killed. This discrete variable is designated as the dependent variable for the subsequent econometric analysis. The information in the current crossing inventory database is matched to the extracted crash database using the corresponding identification number assigned to each crossing to comprehensively identify factors influencing the crash injury severity. Furthermore, the integrated data is thoroughly verified and cleaned up to remove any crash observations with missing data in variables. The key determinants retrieved from the augmented database are then classified into crossing characteristics, crash characteristics, driver characteristics, vehicle characteristics, and environmental characteristics. Table 4.1 shows the detailed classification and descriptive statistics of independent variables. The final dataset used for analysis consists of 1503 crash records from 2020 to 2021, in which 1,009 individuals were uninjured (67.13%), 384 individuals were injured (25.55%), and 110 individuals were killed (7.32%). Meanwhile, the pre-pandemic dataset from 2018 to 2019 includes 2,154 crash records, with 1,350 individuals uninjured, 605 individuals injured, and 199 individuals killed. Figure 4.1 presents the spatial distribution of HRGC crashes that occurred during the study period.

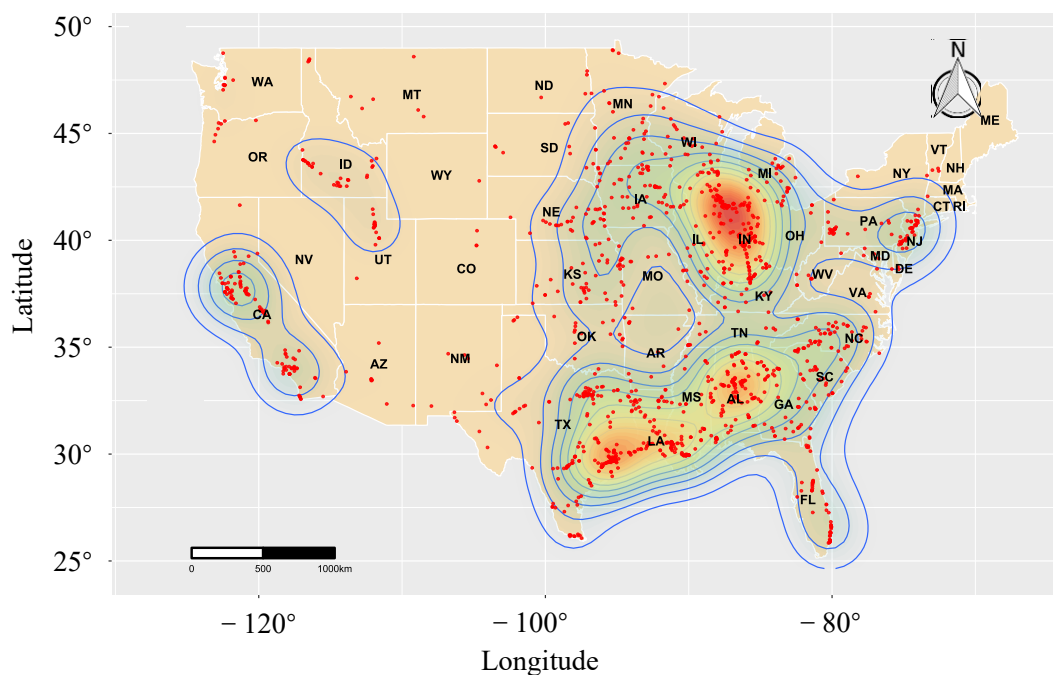


Figure 4.1. The spatial distribution of highway–rail grade crossings crashes.

Table 4.1. Descriptive statistics of independent variables.

Category	Variables	Frequency	Percentage
Crash characteristics	Train speed ≤ 45 MPH	1256	83.57
	Train speed > 45 MPH	247	16.43
	Unobstructed view	1444	96.10
	Obstructed view*	59	3.90
	Estimated vehicle speed ≤ 25 MPH	1374	91.40
	Estimated vehicle speed > 25 MPH	129	8.60
	Did not stop	574	38.19
	Stopped and then proceeded	333	22.16
	Stopped on the crossing	214	14.24
	Went around the gate	290	19.29
Crossing characteristics	Other actions	92	6.12
	Private crossing type	32	2.13
	Public crossing type	1471	97.87
	Highway speed limit ≤ 25 MPH	405	26.95
	Highway speed limit > 25 MPH	1098	73.05
	Annual average daily traffic (AADT) $\leq 5,000$	1047	69.66
	Annual average daily traffic (AADT) $> 5,000$	456	30.34
	Estimated percent of trucks $\leq 10\%$	1093	72.72
	Estimated percent of trucks $> 10\%$	410	27.28
	Crossing without signs or signals	32	2.10
	Crossing with signs or signals	1471	97.90
	Unpaved Highway	148	9.85
	Paved Highway	1355	90.15
	Land without commercial power	144	9.58
	Land with commercial power	1359	90.42
	Both-side crossing warning	1423	94.68
	Single-side crossing warning	80	5.32
	Crossing without illumination	928	61.74
	Crossing with illumination	575	38.26
	Dry crossing surface	1290	85.83
	Adverse crossing surface*	213	14.17
	Industry track	82	5.46
	Main track	1328	88.36
	Siding track	9	0.60
	Yard track	84	5.59
Vehicle characteristics	Auto	790	52.56
	Bus	2	0.13
	Motorcycle	9	0.60
	Truck	32	2.13
	Van	1374	91.40
	Other vehicles	527	35.06
Driver characteristics	Middle driver	643	42.78
	Old driver	483	32.14
	Young driver	377	25.08
	Female driver	392	26.08
	Male driver	1111	73.92
	Driver was not in vehicle	236	15.70
	Driver was in vehicle	1267	84.30
Environmental characteristics	Day	847	56.35
	Dusk	167	11.11
	Dark	360	23.95
	Dawn	129	8.58
	Clear	1060	70.53
	Cloudy	313	20.83
	Fog	13	0.86
	Rain	90	5.99
	Sleet	3	0.20
	Snow	24	1.60

*Adverse crossing surface encompasses conditions such as moisture, ice, snow, slush, sand, mud, or oil on roadways. Obstructed view arises from factors including vehicles, trains, railroad apparatus, infrastructure, terrain, flora, or similar obstructions.

4.3 Methods

The XGBoost model, an ensemble method that aggregates the forecasts from numerous decision trees, is applied in assessing the severity of injuries from HRGC accidents in this study (Goswamy et al., 2023; Yan et al., 2021b; Yuan et al., 2022). The objective function of XGBoost is defined as (Chen and Guestrin, 2016):

$$L(\theta) = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{t=1}^K \Omega(h_t) \quad (4.1)$$

where $l(y_i, \hat{y}_i)$ is the loss function that measures the difference between the predicted value $\hat{y}_i$ and the actual injury severity label y_i , K is the number of weak learners in the ensemble. The regularization term that penalizes the models' complexity is:

$$\Omega(h_t) = \gamma J + \frac{1}{2} \lambda \sum_{j=1}^J w_{tj}^2 \quad (4.2)$$

where J represents the total leaf count; γ is the parameter that controls the leaf quantity; The coefficient for the L2 regularization term, represented by λ , increases the model's conservatism with each increment; w_{tj} signifies the j -th leaf node's optimum value in the t -th decision tree. By minimizing the sum of the regularization term and the loss function, the objective function is optimized. The objective function changes to the following form when the second-order Taylor expansion is applied to it:

$$Obj = \sum_{j=1}^J \left[\frac{1}{2} (H_{tj} + \lambda) w_{tj}^2 + G_{tj} w_{tj} \right] + \gamma J \quad (4.3)$$

where H_{tj} represents the sum of the second-order derivatives for each leaf node, and G_{tj} denotes the total of the first-order derivatives for each individual leaf node. The optimal value for w_{tj} equals to $-\frac{G_{tj}}{H_{tj} + \lambda}$ at the point when the derivative of the objective function is 0. Subsequently, the optimal w_{tj} is used to split the tree. This process of branching continues until the depth of the node matches the predetermined maximum depth.

In this study, three dichotomous crash severity levels are further split and determined as:

$$y_i = \begin{cases} 1, & \text{if the sample belongs to } i, i = \text{Uninjured, Injured, or Killed} \\ 0, & \text{otherwise} \end{cases} \quad (4.4)$$

To evaluate the model's performance, the five-fold cross-validation method is used (Yan et al., 2021b). The accuracy is also calculated to measure the performance of the model:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (4.5)$$

where TP represents a correct prediction of the specific injury severity and FP represents a false classification of an injury severity case, being predicted as a non-injury-severity case, TN denotes a correct prediction of a non-injury-severity case and FN indicates a non-injury-severity case incorrectly predicted as an injury case.

Additionally, the performance of the model can be assessed by the Area Under the Receiver Operating Characteristic Curve (AUC), which evaluates the model's capacity to discern between instances that are positive and negative. A higher AUC indicates better performance (Yuan et al., 2022).

SHAP is a unified measure of feature importance that leverages cooperative game theory to allocate contribution of each feature towards the final prediction in a fair and computationally efficient manner (Lundberg and Lee, 2017). Each feature's SHAP value can be interpreted as the average marginal contribution of that feature across all possible feature subsets (Lundberg and Lee, 2017). It provides a powerful tool to interpret machine learning models such as XGBoost and deliver transparent and trustworthy predictions. Therefore, SHAP was utilized in this study to better interpret the results of the XGBoost models:

$$\phi_i = \sum_{S \subseteq N(i)} \frac{|S|!(k-|S|-1)!}{k!} (v(S \cup \{i\}) - v(S)) \quad (4.6)$$

where k represents the total number of features; ϕ_i denotes the influence of feature i ; S signifies a subset of features; and $|S|$ is the total feature number.

The Shapley value is an additive attribution-assignment approach, with the prediction from the model equating to the aggregate of these attributed values for every feature. This results in a representative linear model:

$$\zeta(z') = \phi_0 + \sum_{i=1}^M \phi_i z'_i \quad (4.7)$$

where ϕ_0 indicates the average prediction across all training samples; M is the total feature count; and z_i is a binary indicator that equals 1 if the feature is present, and 0 if not.

To ascertain the relative significance of each feature, the absolute values of the feature attributions across all samples is summed. Given n in the total sample count, the cumulative influence of feature i is encapsulated by:

$$I_i = \sum_{j=1}^n |\phi_{i,j}| \quad (4.8)$$

where $\phi_{i,j}$ denotes the attribution value of the i^{th} attribute for the j^{th} sample.

This paper also employed the random parameters logit model with heterogeneity in means to identify contributing factors to injury severities and investigate the heterogeneous impacts across two time periods: pre-pandemic and during the COVID-19 pandemic.

4.4 Results and discussions

4.4.1 Results of the XGBoost model

4.4.1.1 χ^2 test

Table 4.2. Test results of explanatory variables and the injury severity.

Variables	χ^2	p-value
Driver was in vehicle	112.657	< 0.01
Train speed > 45 MPH	73.143	< 0.01
Went around the gate	45.152	< 0.01
Stopped on the crossing	28.614	< 0.01
Did not stop	24.230	< 0.01
Estimated vehicle speed > 25 MPH	16.451	< 0.01
Truck	16.424	< 0.01
Main track	15.913	< 0.01
Motorcycle	12.358	< 0.01
Land with commercial power	10.242	< 0.01
Old driver	9.721	< 0.01
Yard track	9.608	< 0.01
Dark	9.288	< 0.01
Unpaved Highway	8.216	0.016
Went through the gate	7.754	0.021
Middle driver	7.422	0.024

Day	7.288	0.026
Female driver	7.215	0.027
Adverse crossing surface	6.785	0.034
Crossing without illumination	5.996	0.050

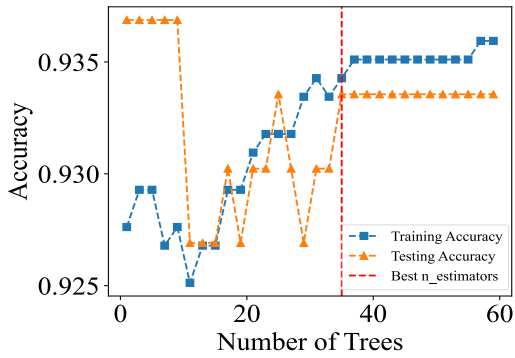
Table 4.2 presents the results of the χ^2 test to examine the association between each explanatory variable and the injury severity. A small p-value suggests that the observed categorical data is unlikely to occur by chance. The variables with a significant association with injury severity are listed in descending order based on the magnitude of the χ^2 value and the corresponding p-value. Variables such as driver was in vehicle, train speed > 45 MPH, and went around the gate show a strong correlation with injury severity outcomes, as evidenced by their high χ^2 values and negligible p-values. Only these indicators less than the chosen significance level of 0.05 are selected to predict the severity of the injury outcome in the XGBoost model.

4.4.1.2 The model performance in the hyper-tuning process for XGBoost

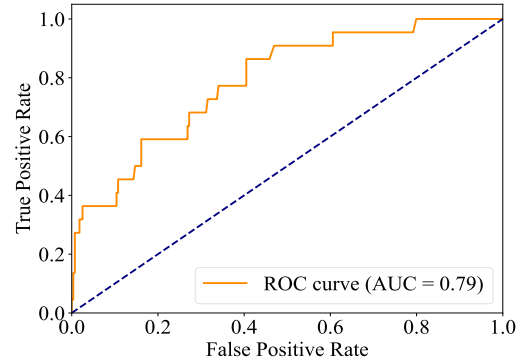
Modeling injury severities in HRGC crashes is approached as a binary classification problem in this study, encompassing a range of categorical variables and dichotomous outcomes (1 for Yes, 0 for No) corresponding to three distinct injury severity levels. Selection and refinement of hyperparameters within the XGBoost framework, specifically max_depth set to [3, 5, 7] and n_estimators within the range of 1 to 61 in steps of 2, were conducted to enhance model accuracy. These selected parameters and their corresponding searching ranges were subjected to preliminary tests to ascertain their influence on model sensitivity. Additionally, to balance computational efficiency and predictive accuracy, the grid search technique with selected parameters was adopted. The strategy includes a 5-fold cross-validation method to ensure the robustness of the optimized model. Each dataset was split into training and testing sets by an 80:20 ratio. This process involves training and comparing the model with different parameter combinations to find the optimal configuration. The validation set was used to measure the accuracy of the model for each parameter combination. The parameter combination that yielded the highest accuracy on the

validation set was selected as the best set of parameters.

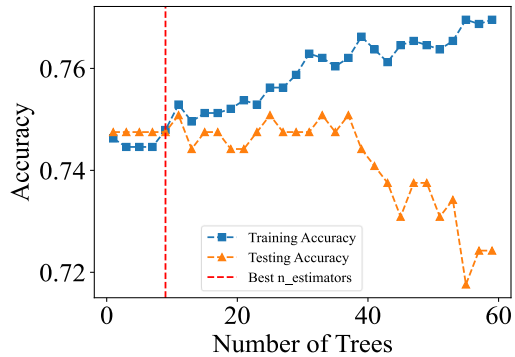
Figure 4.2 presents the model performance of the hyper-tuning process for the killed, injured, and uninjured datasets. Each row contains two subplots corresponding to the hyperparameter tuning curve and the ROC curve for each dataset. Subplots Figure 4.2 (a, c, e) show the variation of the chosen hyperparameters' performance with respect to the respective dataset. The best max_depth (3, 3, 3 for the killed, injured, and uninjured category, respectively) and n_estimators (35, 9, 35 for the killed, injured, and uninjured category, respectively) were utilized for the subsequent analysis. The trade-off between the true positive rate and the false positive rate at various classification thresholds is displayed by the ROC curves in subplots Figure 4.2 (b, d, f). It can be seen that the XGBoost model achieved the best performance in predicting the killed category, with an accuracy of 93.36% and an AUC of 0.79. However, the performance of the models in predicting the injured and uninjured datasets was less impressive, with accuracy values of 74.75% and 69.10%, respectively.



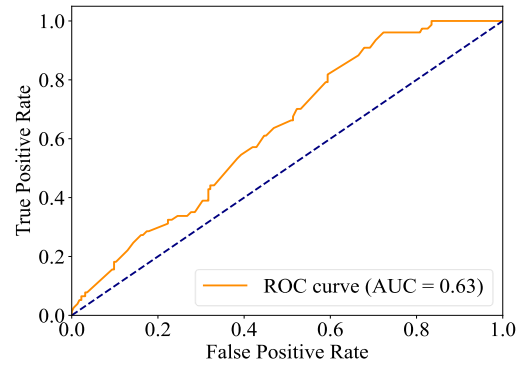
(a) Hyperparamter tuning in XGBoost: Killed



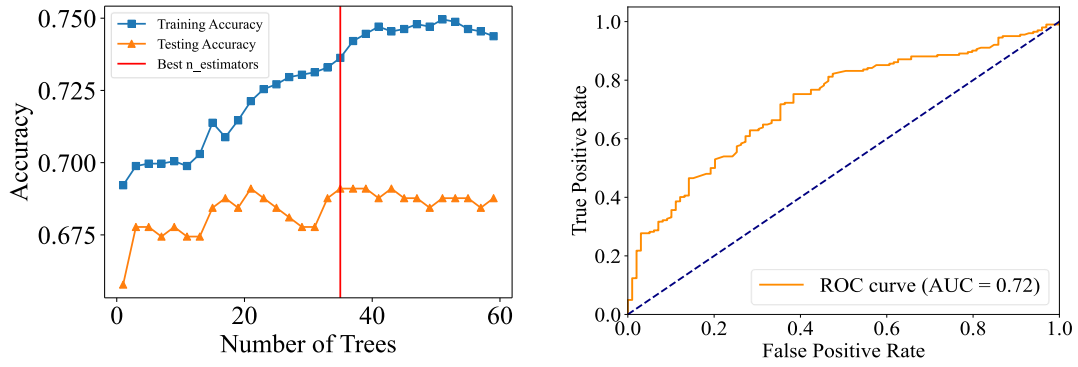
(b) ROC curve: Killed



(c) Hyperparamter tuning in XGBoost: Injured



(d) ROC curve: Injured



(e) Hyperparameter tuning in XGBoost: Uninjured (f) ROC curve: Uninjured
Figure 4.2. Model performance for killed, injured, and uninjured dataset.

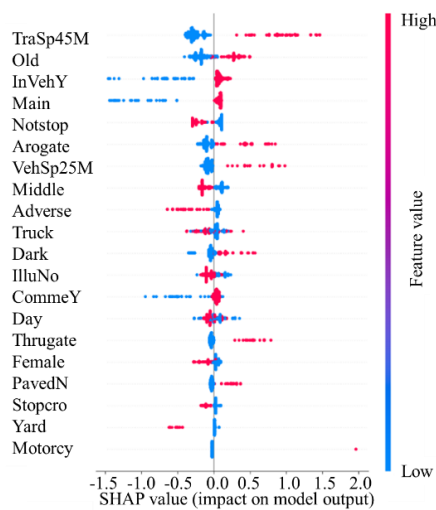
4.4.1.3 SHAP values of input features

The impact of each feature variable on the predictions made by the XGBoost model is shown in Figure 4.3. The beeswarm plot was employed to show each feature's distribution of SHAP values, with individual dots representing an undivided two-way traffic HRGC crash. The respective features are delineated along the vertical axis of subplots Figure 4.3 (a, c, e), and the SHAP values pertaining to each feature for three datasets are plotted along the horizontal axis. The sign of the SHAP value—be it positive or negative—denotes a positive or negative impact on the predicted injury severity outcome. The feature value's magnitude is illustrated through different colors where blue denotes lower values (interpreted as 0 for each variable) and red signifies higher values (interpreted as 1 for each variable). For example, it can be seen that the train speed > 45 MPH indicator was the most crucial impact factor and was positively associated with killed crashes.

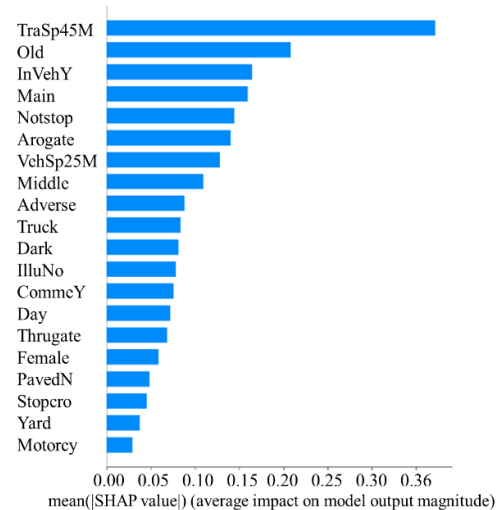
The subplots in Figure 4.3 (b, d, f) list the features by their importance for each injury severity dataset. According to the SHAP values, the top ten important feature indicators in the killed model are as follows: train speed > 45 MPH, old driver, driver was in vehicle, main track, did not stop, went around the gate, estimated vehicle speed > 25 MPH, middle driver, adverse crossing surface, and truck. The top ten important feature indicators in the injured model include driver was in vehicle, female driver, truck, main track, crossing without illumination, unpaved highway, land with

commercial power, went around the gate, adverse crossing surface, and old driver. The corresponding top ten important feature indicators in the uninjured model are driver was in vehicle, truck, train speed > 45 MPH, went around the gate, old driver, main track, female driver, dark, crossing without illumination, and did not stop.

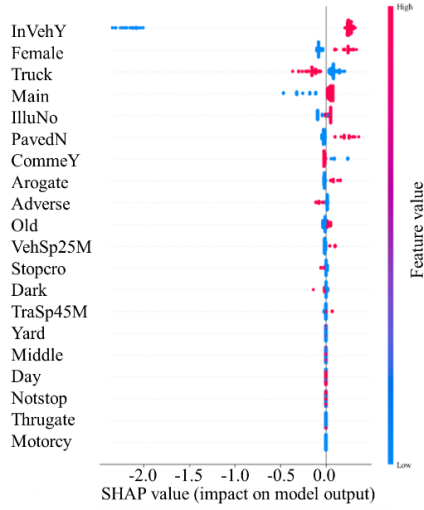
Comparing the important features between the killed and injured models, it can be seen that some important features overlapped, such as old driver, driver was in vehicle, main track, went around the gate, adverse crossing surface, and truck. However, there are also some differences, such as train speed > 45 MPH, did not stop, middle driver, and estimated vehicle speed > 25 MPH were identified as important features in the killed model but not in the injured model, while female driver, crossing without illumination, unpaved highway, and land with commercial power were significant features in the injured model but not in the killed model. The results also indicated that the XGBoost model could distinguish between different severity levels.



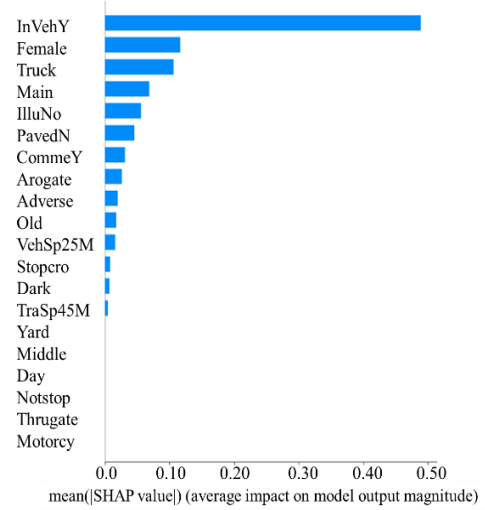
(a) Impact of the feature on Killed crashes.



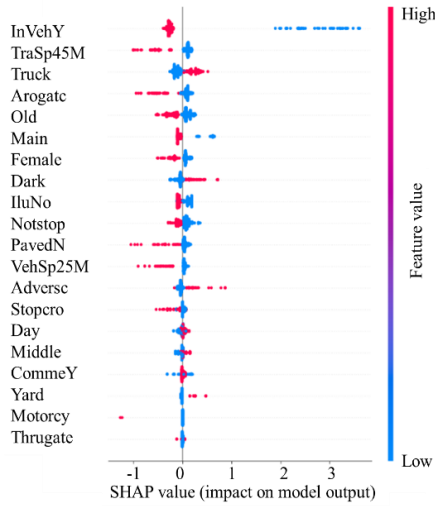
(b) Feature importance in Killed crashes.



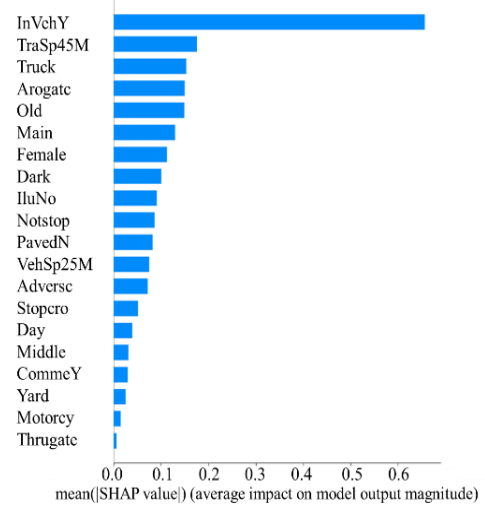
(c) Impact of the feature on Injured crashes.



(d) Feature importance in Injured crashes.



(e) Impact of the feature on Uninjured crashes.



(f) Feature importance in Uninjured crashes.

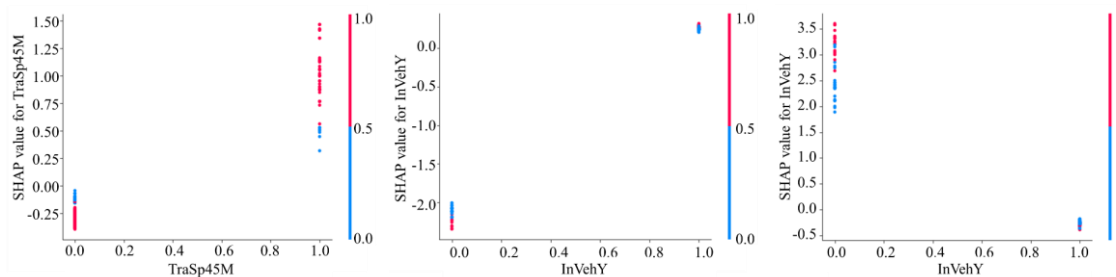
Figure 4.3. SHAP summary plot of input features.

4.4.1.4 SHAP dependency plots for top three features

More detailed information regarding the relationships between determinants and injury severity outcomes can be extracted by investigating the dependency plots of the SHAP values. It can not only be used to understand the overall importance of a feature but also to explore the detailed distribution and the context-dependent nature of feature influences on model predictions, thereby ensuring more reliable predictions and informing potential interventions based on the predictive factors. Figure 4.4 displays SHAP dependency plots for the three most influential features in killed, injured, and

uninjured crashes, respectively. If the SHAP values are highly concentrated within a certain range, this may indicate that the model has a high sensitivity to the feature values within that range. In contrast, a sparse distribution of SHAP values across a wide range of variables may suggest that there is a significant variation in the model's predictive influence for this feature. For example, the driver was in vehicle indicator exhibited a very consistent and concentrated distribution of SHAP values across three datasets representing varying levels of injury severity. This observation implies that the influence of this particular feature on the model's prediction is rather stable and reliable across different injury severity outcomes.

For killed crashes, the partial levitation observed in Figure 4.4 (a) suggests that there were specific values of train speed > 45 MPH that led to higher SHAP values, indicating a stronger impact on the prediction outcome. In addition, the SHAP values for certain values of the old driver fluctuate throughout the subplot, it could indicate the presence of interactions with other features, such as time of day (which might affect visibility) or the type of area (urban vs. rural, which impacts driving speed and emergency medical service response time). For injured crashes, a sparse distribution of SHAP values can also be observed in Figure 4.4 (b) for the female driver and truck, reflecting the variability in the impact of these factors. Notably, the partial levitation can only be seen for the truck indicator in injured crashes, suggesting that this feature may have a heterogeneous impact on predicting uninjured outcomes. Meanwhile, the train speed > 45 MPH indicator was negatively associated with no injuries in Figure 4.4 (c), implying that higher train speeds were less likely to be related to no-injury scenarios.



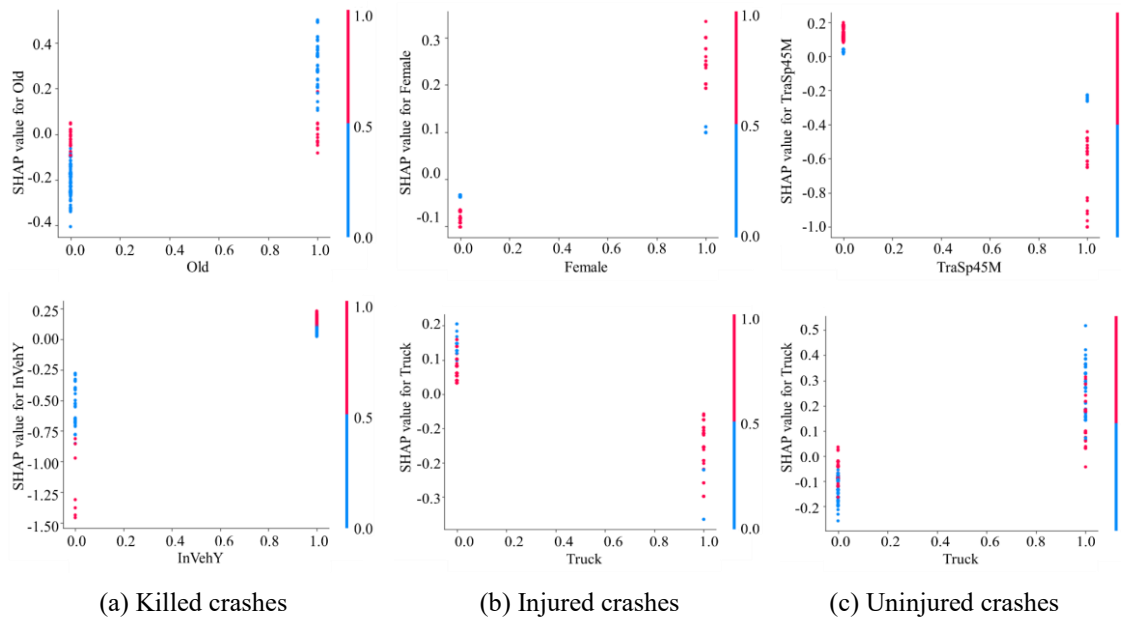


Figure 4.4. SHAP dependency plots for top three features.

4.4.2 Results of the random parameter logit models for COVID-19 effects

This section presents the estimation results and discussions, commencing with the correlation analysis among explanatory variables, followed by the estimates of the random parameters logit model with heterogeneity in means and the multinomial logit model. To evaluate the relationship among the explanatory discrete variables and identify highly correlated variables that may need to be excluded from the model, the Pearson correlation coefficient analysis is carried out first (Pearson, 1895). As indicated in previous studies (Apronti et al., 2016; Cabral et al., 2015), a threshold of 0.5 is considered high for the correlation coefficient. The results of the correlation analysis for the pandemic period are shown in Figure 4.5, indicating that the all variables have relatively lower correlation coefficients. Besides, this analysis was also conducted for the pre-pandemic period to mitigate the multicollinearity among incorporated variables.

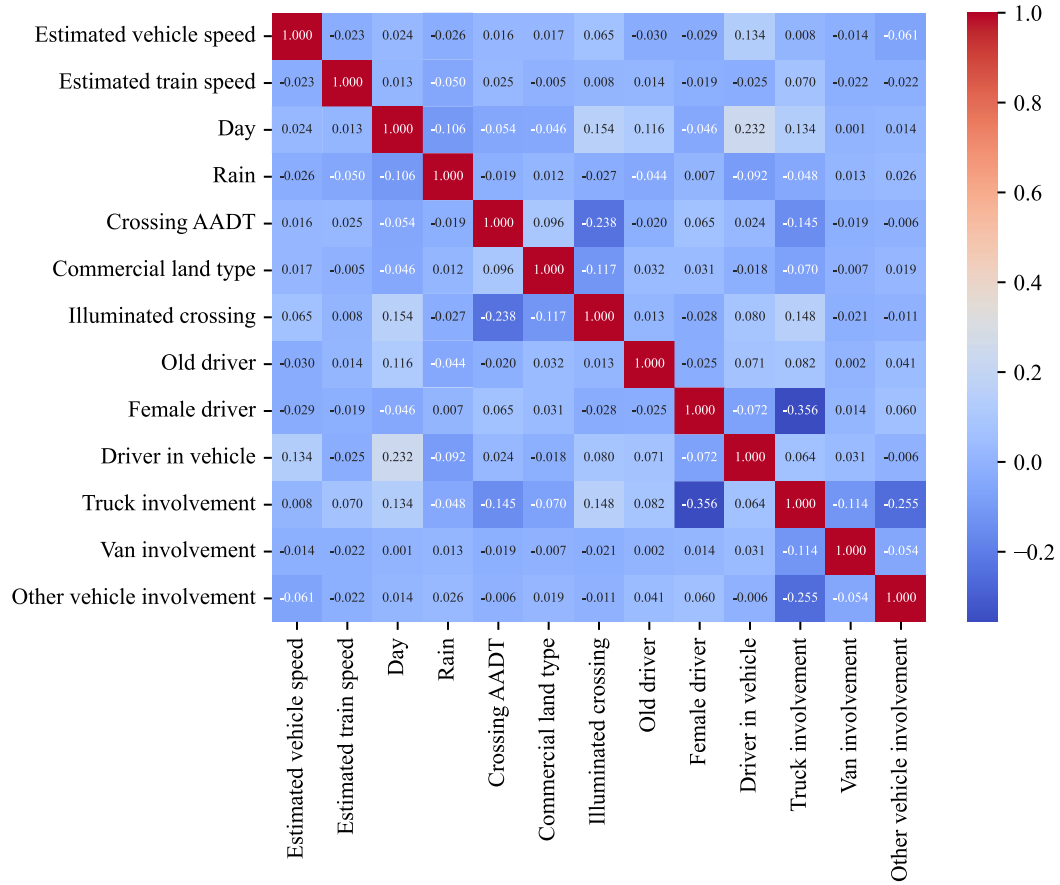


Figure 4.5 Explanatory variables' correlation coefficients for the pandemic data.

Table 4.3 presents the measure-of-fit of the estimated competitive models. As for the pandemic period (2020-2021), results indicate that no heterogeneity in variances was found, and the RPL_HM presents lower AIC and BIC values than RPL and OL, thus indicating a better model fit. With confidence level higher than 99%, the χ^2 likelihood ratio test also proves that the RPL_HM is the best. By considering the variability in the random parameters' means, this model can provide more accurate parameter estimates (Pervez et al., 2022). Regarding the pre-pandemic period (2018-2019), it should be noted that no significant random parameters were found in the RPL. That is to say, considering the unobserved heterogeneity cannot improve the model performance. As such, only MNL and OL were used to model the crash injury severities. Similarly, the results indicate that the MNL is superior than the OL. Therefore, the subsequent discussions and findings in this study are based on the RPL_HM for the

Table 4.3 Measure-of-fit of the estimated models.

Model metrics	Pandemic period (2020-2021)			Pre-pandemic period (2018-2019)	
	OL	RPL	RPL_HM	OL	MNL
Number of estimated parameters (K)	12	15	20	10	11
Log-likelihood at zero, $LL(0)$	-1853.888	-2453.201	-2453.201	-1872.985	-1872.985
Log-likelihood at convergence, $LL(\beta)$	-1686.934	-1709.515	-1622.849	-1863.409	-1847.793
AIC	3397.9	3449.0	3287.7	3746.8	3717.6
BIC	3466.4	3534.7	3407.6	3803.6	3780.0
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.090	0.303	0.338	0.050	0.134
Number of observations (N)	2233	2233	2233	2154	2154
$\chi^2 = -2 [LL(RPL) - LL(RPL_HM)]$	128.170	173.332			31.232
Degree of freedom	8	5		1	
Confidence level	>99.99%	>99.99%		>99.99%	

Table 4.4 Model estimation results of the random parameters logit model with heterogeneity in means for pandemic period (2020-2021).

Variables	Coeff.	t-stat	Marginal Effects		
			Uninjured [UI]	Injured [I]	Killed [K]
Constant [I]	-0.708	-2.80			
Constant [K]	-4.511	-10.74			
Random parameter (normally distributed)					
Old driver indicator (1 if driver age over 55, 0 otherwise) [UI]	4.591	1.88	-0.0149	0.0082	0.0066
Standard deviation of parameter distribution	4.505	2.79			
Illuminated crossing indicator (1 if crossing was illuminated, 0 otherwise) [I]	-4.461	-4.91	-0.0462	0.0536	-0.0074
Standard deviation of parameter distribution	1.650	3.54			
Heterogeneity in the means of random parameter					
Old driver indicator: Driver-in-vehicle indicator (1 if driver was in the vehicle, 0 otherwise) [UI]	-4.467	-2.08			
Old driver indicator: Estimated train speed indicator (1 if train was traveling at 45 MPH speed or greater, 0 otherwise) [UI]	-2.265	-1.77			
Illuminated crossing indicator: Driver-in-vehicle indicator (1 if driver was in the vehicle, 0 otherwise) [I]	4.742	5.61			
Illuminated crossing indicator: Crossing AADT indicator (1 if AADT was 10,000 vehicles per day or greater, 0 otherwise) [I]	-0.876	-2.08			
Illuminated crossing indicator: Estimated train speed indicator (1 if train was traveling at 45 MPH speed or greater, 0 otherwise) [I]	0.886	3.28			

Variables	Coeff.	t-stat	Marginal Effects		
			Uninjured [UI]	Injured [I]	Killed [K]
Crash characteristics					
Estimated vehicle speed indicator (1 if vehicle was traveling at 25 MPH speed or greater, 0 otherwise) [UI]	−0.811	−3.61	−0.0107	0.0080	0.0027
Estimated train speed indicator (1 if train was traveling at 45 MPH speed or greater, 0 otherwise) [K]	2.338	11.19	−0.0318	−0.0224	0.0542
Rain indicator (1 if crash occurred on rainy weather, 0 otherwise) [UI]	0.737	2.59	0.0055	−0.0044	−0.0011
Crossing characteristics					
Commercial land type (1 if land use type was commercial, 0 otherwise) [I]	−0.640	−2.73	0.0562	−0.0705	0.0142
Driver characteristics					
Female driver indicator (1 if driver was female, 0 otherwise) [I]	0.404	2.55	−0.0119	0.0145	−0.0026
Driver-in-vehicle indicator (1 if driver was in the vehicle, 0 otherwise) [K]	1.822	4.41	−0.0549	−0.0432	0.0981
Vehicle characteristics					
Truck involvement indicator (1 if truck was involved in the crash, 0 otherwise) [UI]	0.859	4.99	0.0325	−0.0239	−0.0086
Van involvement indicator (1 if van was involved in the crash, 0 otherwise) [UI]	−0.825	−2.10	−0.0031	0.0023	0.0008
Other vehicle involvement indicator (1 if other motor vehicles was involved in the crash, 0 otherwise) [UI]	−0.871	−4.07	−0.0136	0.0103	0.0034

Table 4.5 Model estimation results of the multinomial logit model for pre-pandemic period (2018-2019).

Variables	Coeff.	t-stat	Marginal Effects		
			Uninjured [UI]	Injured [I]	Killed [K]
Constant [I]	−0.572	−8.66			
Constant [K]	−1.589	−5.27			
Crash characteristics					
Dark (1 if lighting condition is dark, 0 otherwise) [UI]	0.318	2.97	0.0731	−0.0552	−0.0180
Dawn (1 if lighting condition is dawn, 0 otherwise) [UI]	0.615	3.51	0.1415	−0.1068	−0.0348
Dawn (1 if lighting condition is dawn, 0 otherwise) [K]	0.562	2.40	−0.0318	−0.0148	0.0466
Dusk (1 if lighting condition is dusk, 0 otherwise) [UI]	0.542	3.57	0.1248	−0.0941	−0.0307
Adverse crossing surface indicator (1 if crash occurred on adverse roadway surfaces, 0 otherwise) [UI]	0.365	2.43	0.0840	−0.0633	−0.0206
Rain indicator (1 if crash occurred on rainy weather, 0 otherwise) [UI]	−0.391	−1.84	−0.0900	0.0679	0.0221
Clear indicator (1 if crash occurred on clear weather, 0 otherwise) [K]	−0.362	−2.11	0.0205	0.0095	−0.0300
Crossing characteristic					
Commercial land type (1 if land use type was commercial, 0 otherwise) [K]	0.411	2.59	−0.0232	−0.0108	0.0340
Both-side crossing warning indicator (1 if crossing warning was located on both sides, 0 otherwise) [K]	−0.580	−2.10	0.0328	0.0152	−0.0480

pandemic period and MNL for the pre-pandemic period. Estimation results of the models during the COVID-19 pandemic and before the pandemic are presented in Table 4.4 and Table 4.5, which indicate overall satisfactory statistical fits with ρ^2 values being 0.338 and 0.134, respectively. Besides, the marginal effects of the significant explanatory factors (arranged by variable classification) affecting crash severities are shown in Figure 4.6 and Figure 4.7. The following parts will compare and discuss these results in detail.

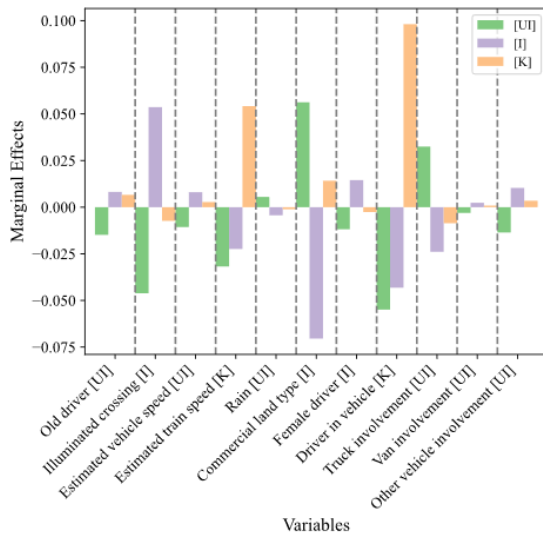


Figure 4.6 Marginal effects of significant variables in 2020-2021.

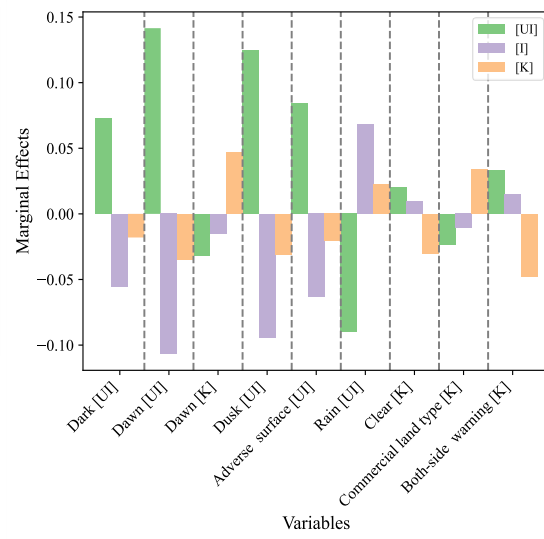


Figure 4.7 Marginal effects of significant variables in 2018-2019.

4.4.2.1 Heterogeneity in the means of random parameters

Table 4.4 shows that two variables are identified as random parameters with normal distributions during the COVID-19 pandemic: the old driver indicator specific to uninjured category and the illuminated crossing indicator defined for injury category. In contrast, no significant random parameters and unobserved heterogeneity are found for the pre-pandemic period in Table 4.5. The findings indicate that a significant varying influence of the unobserved characteristics on the injury severities is captured by these random parameters after the outbreak of the pandemic. The probability density diagrams of these random parameters are depicted in Figure 4.8. The impact of all explanatory variables on the means and variances of the random parameters is

thoroughly assessed to determine the presence of heterogeneity. The results reveal that the random parameters associated with the presence of the old driver indicator and illuminated crossing indicator only exhibit heterogeneity in means.

Regarding the heterogeneity in means during the COVID-19 pandemic, the driver-in-vehicle indicator and the estimated train speed indicator are observed to decrease the means of parameter estimate in the old driver indicator for uninjured outcomes, suggesting an increase in severe injuries relative to young and middle-aged drivers during the pandemic. In the context of HRGC crashes during the COVID-19 pandemic, this result is intuitive since these unique driving conditions of the crossings may substantially affect the elderly drivers' driving performance. Particularly, the declined perception and reaction ability of old drivers further bring serious obstacles in dealing with complicated traffic driving scenarios (e.g., the high train speed, obstructed view, or improper post-accident treatment), especially when the elderly drivers are infected with the virus.

Concerning the other random parameter during the COVID-19 pandemic, illuminated crossing indicator defined for the injured category, it is found that its means increase in the existence of the driver-in-vehicle indicator and the estimated train speed indicator. The reason is similar to the aforementioned interpretation that the unexpectedly higher train speed and in-vehicle status tended to cause severe injury severities. By contrast, the means of the illuminated crossing indicator decrease when the crossing AADT indicator is involved in HRGC crashes. This phenomenon could be attributed to the fact that compensatory driving behaviours, such as reducing the driving speed and merging more cautiously, may be adopted by drivers during the COVID-19 pandemic in response to high traffic volumes, which could lessen the frequency and severity of crashes. However, it is important to note that these compensatory behaviours may not always be effective in reducing the crash severity. For example, if drivers are not paying attention or are engaging in risky behaviours such as distracted driving, the compensatory effects may be negated (Ren and Xu, 2023b).

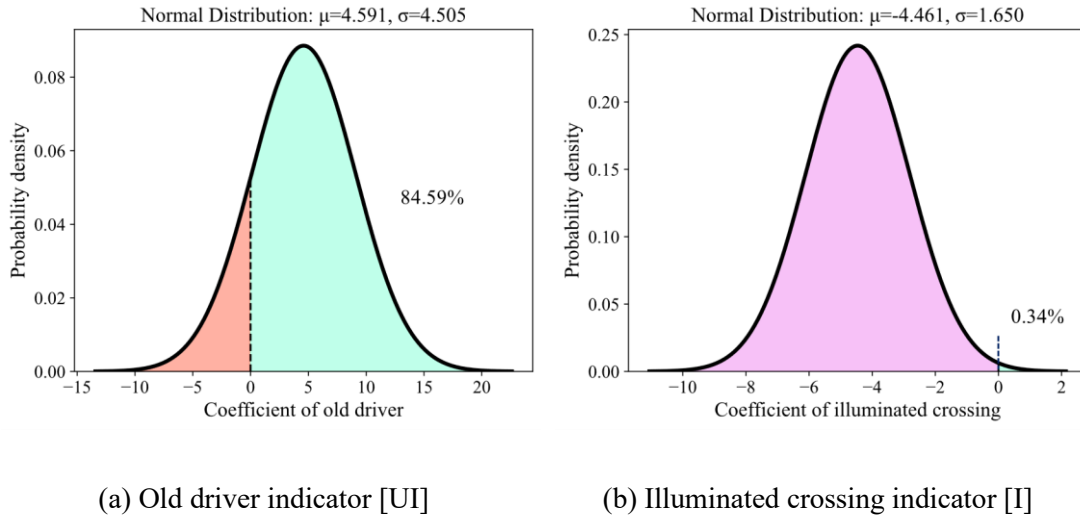


Figure 4.8 Distribution of random parameters in 2020-2021.

4.4.2.2 Crash characteristics

During the COVID-19 pandemic period, two types of crash characteristics are found to be significant in the estimated model: speed-related variables and weather-related variables. The estimated vehicle speed indicator, with a coefficient of -0.811 in the uninjured utility model, resulting in an increase in the likelihood of being injured and killed by 0.0080 and 0.0027 in HRGC crashes. This relationship is consistent with common sense and previous research (Ahmed et al., 2023; Keramati et al., 2020), which has found that higher speeds increase the force of impact and reduce the time available for drivers to react to hazards. Likewise, the estimated train speed indicator has a coefficient of 2.338 corresponding to the killed category, indicating that crashes involving trains traveling at high speeds are more likely to result in fatalities (by 0.0542). This result is plausible as faster trains are more likely to cause significant damage to any vehicles they collide with, leading to more severe outcomes.

Weather conditions are also important predictors of the crash severity during the pandemic and pre-pandemic period. The rain indicator, featured with a coefficient of 0.737 in the uninjured model from 2020 to 2021, it is observed to have a lower probability of injured (by -0.0044) and killed outcomes (by -0.0011). This might

be due to the fact that rainy conditions can lead to decreased driving speeds and increased caution among drivers, which in turn reduces the likelihood of severe accidents. This explanation is also applicable to the adverse crossing surface indicator included in the pre-pandemic model, where less severe injuries are observed. As for the pre-pandemic period, contradictory results that rainy conditions are more likely to get involved in more severe injury severities are reported. One possible reason for this difference is that driving in unfavorable circumstances could dramatically increase the frequency of driving errors and dangerous driving behaviours (Alnawmasi and Mannering, 2022a; Billah et al., 2022; Wang et al., 2022). This discrepancy indicates that the driver compensation mechanism may be enhanced after the outbreak of COVID-19 pandemic. Considering the possible heterogeneity and inherent temporal instability, more attention should be given to understand the crash generating mechanism and driver compensation mechanism in HRGC crashes. Moreover, it can be expected that the clear weather indicator is positively associated with the uninjured and injured outcomes, and negatively correlated with the killed crashes before the pandemic.

Numerous factors regarding lighting conditions are also found to significantly affect crash severity outcomes before the COVID-19 pandemic period. Specifically, the dark, dawn, and dusk indicators specific to the uninjured category would decrease the likelihood of injured and killed crashes, while increasing the likelihood of uninjured crashes. This also suggests that the compensation mechanism functions under these temporal characteristics. In contrast, the dawn variable defined for the killed category is observed to have a higher probability of killed outcomes. This disparity indicates that dawn, being a transitional period between night and day, might still involve low visibility conditions that can complicate the perception and reaction times of drivers, thus increasing the risk of severe accidents. Nevertheless, these lighting indicators are not found to be significant during the pandemic period, which can be attributed to several factors related to the unique circumstances brought about by the pandemic. One

of the most immediate impacts of the pandemic was the significant reduction in traffic volumes due to lockdowns, stay-at-home orders, and the general decrease in economic and social activities. With reduced traffic volume and congestion, the influence of lighting conditions on crash severity may be lessened. Additionally, the heightened awareness and caution among drivers during the pandemic might have mitigated the risks associated with poor lighting conditions.

4.4.2.3 Crossing characteristics

The commercial land type is a significant factor affecting injury severities in both the pandemic and pre-pandemic model. The marginal effects imply that accidents occurring at crossings located in commercial areas may be more likely to result in fatalities. This result can be explained from two perspectives. Firstly, in commercial areas, the mix of vehicular and pedestrian traffic often leads to situations where fatal accidents occur due to the vulnerability of pedestrians in cases of high-speed impacts. Secondly, the design and usage patterns of commercial lands typically involve numerous access points, parking lots, and intersections where vehicles are often involved in more dangerous movements (such as vehicles rushing to enter or exit the commercial areas), thus causing higher fatality possibilities.

The present study also reveals that the illuminated crossing indicator defined to injured category produces a random parameter that is normally distributed with a mean of -4.461 and a standard deviation of 1.650 in the pandemic model. This implies that this variable decreases the likelihood of injured outcomes for 99.66% of the HRGC crashes while only increasing the likelihood of that for 0.34% of these observations during this period. The result could stem from the fact that the good lighting condition and the additional lights provide warning signals can alert drivers and pedestrians to the presence of a train. This increased awareness could lead to drivers slowing down and being more cautious when approaching the crossing, thus giving them more time to react and avoid a collision. As such, the present study suggests that the illuminated

crossing indicator is an effective safety device that can help to reduce the severity of injuries in pandemic HRGC crashes.

Another significant factor before the COVID-19 pandemic is the presence of both-side crossing warnings, which has a negative coefficient of -0.580 in the killed model. Meanwhile, the marginal effect of this variable is associated with a lower probability of fatality crashes (by 0.0480). This finding suggests that the presence of warning signs prompts drivers to comply with traffic regulations, thereby reducing the probability of severe accidents (Ren et al., 2024b).

4.4.2.4 Driver characteristics

No significant driver-related variables are found during the pre-pandemic period. As for the pandemic model, female drivers have a positive coefficient of 0.404 for injured category. The marginal effects also indicate that female drivers are more likely to be involved in injured crashes (by 0.0145) due to their susceptibility to traffic accidents. One possible explanation is that female drivers may be less experienced and drive fewer miles than their male counterparts, which could result in the mishandling of risky driving situations, especially in the context of HRGC during the epidemic.

Moving on to the old driver indicator, it is observed to follow a normal distribution with a mean of 4.591 and a standard deviation of 4.505 . It can be concluded that the parameter of old driver is negative with a probability of 15.41% and positive with a probability of 84.59% for each observation. The marginal effects suggest that this variable would increase the possibility of injury and fatality (by 0.0082 and 0.0066 , respectively) during the epidemic. These findings are in line with previous studies (Alnawmasi and Mannering, 2022a; Chen et al., 2016). It can be attributed to the fact that aging may lead to a decline in physical and cognitive abilities, which may affect their driving skills and reaction time. Consequently, older drivers may face difficulty in avoiding accidents at railway crossings, particularly when the elderly drivers are infected with the virus. Furthermore, older adults are more likely to have underlying

medical conditions that may impact their driving ability, such as vision and hearing impairments. These conditions could further increase their vulnerability to accidents at HRGCs, making injury severities more severe.

The positive coefficient of 1.822 for the driver-in-vehicle indicator in the killed effect function and the corresponding marginal effect suggest that the probability of being killed increases by 0.0981 during the epidemic. One possible explanation is that the pandemic has led to changes in traffic patterns, with more people opting to travel by private vehicles in order to avoid exposure to the virus on public transit. This increase may lead to a higher incidence of HRGC accidents involving vehicles. Meanwhile, the reduction in traffic volumes during the pandemic may have unintended consequences, such as an increase in speeding or reckless driving, or a decrease in the use of seat belts or other safety features. Moreover, it is worth noting that the change in emergency response times or the availability of medical care in the aftermath of an in-vehicle accident during the COVID-19 pandemic increase the risk of being killed.

4.4.2.5 Vehicle characteristics

No vehicle-related variables are found to be significant from 2018 to 2019. As for the pandemic model, the type of the vehicle involved in a crash can significantly impact the severity of the injuries sustained by the individuals involved in railway crossing accidents. Note that the truck involvement indicator is found to be positively correlated with uninjured outcomes and associated with a lower risk of injuries and fatalities (by -0.0239 and -0.0086 , respectively). This may be due to the fact that trucks are generally larger and heavier than other types of vehicles, which could provide greater protection to their occupants in the event of a HRGC crash. Another factor could be that trucks are typically driven by professional drivers who are trained to drive defensively and follow safety protocols before crossing the tracks, which may result in a lower likelihood of being injured in a HRGC crash. It is crucial to take these coefficients into account in relation to other pertinent factors like impact speed and angle, as well as the

use of safety equipment like seatbelts and airbags. For example, the risk of fatal injuries is still high if the impact is severe enough or the occupants are not wearing seatbelts. Therefore, drivers should exercise caution and adhere to safety protocols when crossing railway tracks to minimize the risk of accidents and injuries. The coefficients for the van and other involvement indicators in the uninjured category are negative and their estimated marginal effects also indicate that being involved in a crash with these types of vehicles is associated with a higher risk of severe injuries.

The discrepancy in driver-related and vehicle-related variables' significance between pandemic and pre-pandemic periods indicates that the onset of the pandemic could have altered the factors influencing HRGC accidents and their outcomes.

4.5 Concluding remarks

Highway-rail grade crossing crashes in non-divided two-way traffic scenarios are a significant public concern and have caused numerous fatalities and injuries over the years. The injury outcomes were divided into three categories: Uninjured, Injured, and Killed. Given the advantage of machine learning methods in capturing intricate relationships between input variables and outcome predictions, the XGBoost model was used to compare the prediction accuracy between different injury severity categories and extract critical features. The relationship between each explanatory factor and the injury severity was first examined using the χ^2 test, and only the factors with a significant association with injury severities were chosen to predict the outcomes. The XGBoost model, optimized through hyperparameter tuning and validated by five-fold cross-validation, demonstrated proficiency in distinguishing different injury severities, particularly in predicting fatal outcomes with a highest degree of accuracy of 93.36% and an AUC of 0.79. The model's performance in predicting the injured and uninjured datasets was less impressive, with accuracy values of 74.75% and 69.10%, respectively. Furthermore, the top ten most important feature indicators for the killed, injured, and uninjured datasets were identified. It was found that some of them

overlapped, such as old driver, driver was in vehicle, main track, went around the gate, adverse crossing surface, and truck, while there were also some differences. The diverse feature highlights the nuanced nature of risk factors across different severity levels. The application of SHAP values further enhanced the interpretability of XGBoost models, offering a granular perspective on the influence of individual features. The detailed distributions of the respective top three significant variables that emerged from the analysis were presented, including train speed > 45 MPH, driver was in vehicle, truck, old driver, and female driver.

The present study found that the did not stop behaviour produced varying effects on injury severity outcomes. Therefore, there is a great necessity for targeted programs to educate drivers about avoiding risky or improper driving behaviours at HRGCs. Besides, clear signage, visible traffic signals, and proper lane markings should be incorporated into the crossing to enhance visibility and provide clear instructions, thus reducing the likelihood of non-stop behaviour. Installing adequate lights in roadways and crossings is necessary to improve visibility and reduce the risk of accidents. And encouraging the use of reflective materials on vehicles during nighttime travel can also be helpful. To enhance HRGC safety in commercial areas, it is crucial to promote the installation of warning signs that provide drivers with important information and alerts, including speed limits, pedestrian crossings, and potential hazards. This study further identified several factors that increase the likelihood of severe injuries in HRGC crashes, including estimated vehicle speed > 25 MPH, train speed > 45 MPH, going around the gate, old driver, female driver, motorcycle, and the driver was in vehicle indicators. Based on the results, countermeasures such as implementing lower speed limits at crossings, strengthening gate enforcement, and developing targeted initiatives for vulnerable road users could be taken to reduce the likelihood of injuries. Notably, the adverse crossing surface and truck indicators exhibited unexpected marginal effects and decreased the possibility of severe injury outcomes at non-divided two-way traffic HRGCs. Nevertheless, it is essential to enhance the maintenance of HRGCs, including

repairing potholes, improving road surfaces, and ensuring proper drainage to minimize the risk under adverse crossing surface conditions. Additionally, educational programs should be implemented to raise awareness among truck drivers about the importance of following traffic rules, yielding to trains, and exercising caution at crossings.

Using a HRGC crash dataset in the United States from 2020 to 2021, this paper further employed the random parameters logit model with heterogeneity in means to identify contributing factors to injury severities and investigate the heterogeneous impacts. Additionally, to illustrate the distinctive findings observed during the COVID-19 pandemic period, a multinomial logit model was also developed using pre-pandemic HRGC crashes from 2018 to 2019. The present study suggests that accounting for the heterogeneity in means of random parameters can enhance the model fit and provide new insights into injury severity concerning HRGC crashes during the pandemic. Specifically, the presence of old drivers and illuminated crossing were found to have varying effects on injury severity outcomes. Additionally, the unobserved heterogeneity of random parameters' means was found to be associated with the driver in vehicle, estimated train speed, and crossing AADT indicators. The study further identified several factors that increase the likelihood of severe injuries in HRGC crashes during the pandemic, including estimated vehicle speed, estimated train speed, commercial land type, female driver, driver in vehicle, van, and other vehicles. Notably, the truck and rain indicators exhibited unexpected marginal effects and decreased the possibility of severe injury outcomes during the COVID-19 pandemic.

Additionally, the significant variables varied remarkably between these two periods. Notably, no significant indicators related to drivers or vehicles were identified from 2018 to 2019, contrasting with the pandemic model. For example, prior to the COVID-19 pandemic, the indicators for dark, dawn, and dusk typically reduced the probability of crashes resulting in injuries or fatalities. However, these lighting indicators did not exhibit significant effects during the pandemic. As for the rain indicator, contradictory results were observed. In the pre-pandemic period, the presence

of rain was associated with a higher probability of incidents involving severe injuries. Conversely, during the pandemic, this probability decreased. This variation hints at a possible improvement in the driver compensation mechanism after the outbreak of the COVID-19 pandemic. Other significant indicators include the adverse crossing surface, clear weather, and both-side crossing warning signal. Considering that the COVID-19 pandemic introduced a multitude of changes to transportation patterns and driver behaviours, it is conceivable that this has made more factors sensitive to the injury severity outcome.

These findings have important implications for policymakers and transportation authorities in developing tailored interventions to mitigate the risk of severe injuries at HRGCs during the pandemic and beyond. As for the pre-pandemic period, no significant random parameters and unobserved heterogeneity were identified. The results reveal a notable fluctuating impact of unobserved characteristics on crash injury severities after the outbreak of the pandemic, as evidenced by the old driver indicator and the illuminated crossing indicator. Therefore, to mitigate the risks associated with vulnerable populations such as old drivers during the pandemic, it is necessary to carry out tailored driving training and education programs. By providing them with the knowledge and skills needed to safely pass through these high-risk areas, including slowing down when approaching a crossing, avoiding distracted driving, and obeying traffic laws, the likelihood of accidents and severe injuries can be reduced. Besides, it is recommended that these vulnerable drivers reduce their travel frequency especially when they are infected with the virus, as their declined perception and reaction abilities can pose significant challenges in handling complex HRGC driving situations. The present study also reveals that the illuminated crossing indicator have been effective in reducing the severity of injuries in HRGC crashes from 2020 to 2021. Thus, regular maintenance and inspection of the crossing infrastructure, including lighting, warning signs, road markings, and gates, can help reduce the risk of severe injury in HRGC crashes. Meanwhile, considering the association between high speeds and serious injury

outcomes during the pandemic, another potential intervention is to implement speed reduction measures, such as reducing speed limits, installing speeding cameras, and increasing enforcement of speeding. Infrastructure improvements such as the use of traffic calming measures (e.g., speed humps and chicanes) can also help to slow down the traffic and encourage drivers to be more cautious. Moreover, given that the commercial area will increase the severity of HRGC crashes during both the pre-pandemic and pandemic periods, comprehensive measures could be taken to reduce the incidence of HRGC accidents in proximity to commercial areas, such as reinforcing traffic management, augmenting extra traffic signals, and enhancing the awareness of traffic safety among drivers.

Chapter 5 Heterogeneity in crash patterns of autonomous vehicles: The latent class analysis coupled with multinomial logit model

5.1 Introduction

In the rapidly evolving landscape of transportation technology, autonomous vehicles (AVs) have emerged as a transformative force, promising reduced traffic congestion, enhanced road safety, and increased accessibility (Liu et al., 2024; Zhu and Meng, 2022). However, the transition from conventional human-driven vehicles to AVs is fraught with complexities that necessitate a thorough understanding of crash patterns and the identification of underlying causal factors. The urgency to dissect these crash patterns stems from multiple considerations. Firstly, AVs operate on principles fundamentally different from human-driven vehicles, necessitating a tailored safety assessment due to the reduction of human error—a leading cause of conventional road accidents globally (World Health Organization, 2022). Secondly, despite the integration of advanced technologies, such as sophisticated sensors and artificial intelligence, AVs are not immune to accidents (California Department of Motor Vehicles, 2024; NHTSA, 2024). These vehicles may introduce new factors that can influence crash occurrences, such as sensor malfunction, miscommunications between vehicle components, and algorithm misinterpretation. Thirdly, the public acceptance and regulatory approval of AVs hinge on their demonstrated safety, making it critical to identify and mitigate potential risks proactively.

As AV testing becomes more prevalent after the COVID-19 pandemic, the volume of data from AV collision reports has increased a lot. For example, the California Department of Motor Vehicles (CA DMV) records on AV collisions and disengagements are the predominant source of road test data for numerous contemporary studies (California Department of Motor Vehicles, 2024). As of the latest update, these reports encompass 702 documents in PDF format, detailing incidents involving AVs. Furthermore, the National Highway Traffic Safety

Administration has implemented a Standing General Order mandating that manufacturers and operators should submit reports to the agency concerning crashes involving vehicles equipped with automated driving systems or SAE Level 2 advanced driver assistance systems (NHTSA, 2024). To date, this dataset has 1,142 pertinent crash records. Meanwhile, leading AV manufacturers, such as Tesla and Google, have released general descriptive statistics that characterize the safety performance of their AV technologies (Tesla, 2024; Waymo, 2024). This presents unprecedented opportunities for further in-depth safety analysis from empirical evidence.

Nevertheless, a notable deficiency in existing research is that they predominantly focused on holistic dataset analysis, overlooking the heterogeneity embedded within the AV crash data (Mannering et al., 2016b). The heterogeneity in AV crash patterns is a critical research area that requires special attention, given the multifaceted nature of AV operations and the diverse range of scenarios in which these vehicles may encounter challenges. Conducting AV accident analysis on a heterogeneous dataset can obscure significant relations (Mannering et al., 2016b; Ren and Xu, 2023b). It can mask underlying patterns and significant relationships that are crucial for understanding the dynamics of AV accidents, thus resulting in biased parameter estimates and erroneous inferences (Mannering et al., 2016b). Some previous research efforts have been invested in a particular attribute of conventional vehicle accidents to mitigate heterogeneity within the data, such as distinct categories of crashes, certain age demographics, different periods, specific crash locations, and lighting conditions (Fountas et al., 2020; Ren et al., 2024a). Nonetheless, it is important to recognize that those pre-specified segmentations may not ensure homogeneity within each subgroup and heterogeneity across different subgroups (Kim and Mokhtarian, 2023).

Based on the expanding AV crash data pool, a systematic data extraction framework was first employed in this study to extract key variables from the CA DMV crash records. The dataset was then augmented by the road infrastructure characteristic and precise geographical coordinates. Subsequently, a two-step method that combines

the latent class analysis and multinomial logit model was used to examine the heterogeneity and investigate contributing factors that significantly impact the damage severity of AV crashes in specific subsets. This dual approach not only enhances the reliability of crash models but also facilitates a comprehensive understanding of AV safety.

5.2 Data description

The AV collision reports used in this study were collected from the Department of Motor Vehicles, State of California. The CA DMV initiated the Autonomous Vehicle Deployment Program in 2014, setting forth the standards for the deployment of AVs on California's public roads. This program requests manufacturers conducting on-road AV trials to submit reports of any resultant collisions causing damage, bodily injury, or fatality within a ten-day incident window (California Department of Motor Vehicles, 2024). As of April 12, 2024, there have been 702 collision reports in PDF format involving AVs submitted to the CA DMV.

Notably, in 2017, the CA DMV made a significant update to the OL 316 form, Report of Traffic Collision Involving an Autonomous Vehicle (California Department of Motor Vehicles, 2024). The updated form offers a more comprehensive insight into various aspects of AV-involved crashes that were not captured previously in the original 2013 version. Specifically, more details regarding vehicle damage location, severity of the collision, road surface, movement preceding the collision, type of collision, weather, lighting, and other related elements are provided. Later on, those AV-involved crashes that occurred after April 2018 were documented by the revised forms. Therefore, to ensure the structural integrity of variables underpinning the subsequent analytical procedures, this study adopted the research time window encompassing records with updated forms from April 1, 2018 to April 12, 2024. Figure 5.1 shows the detailed distribution of AV crash numbers by year.

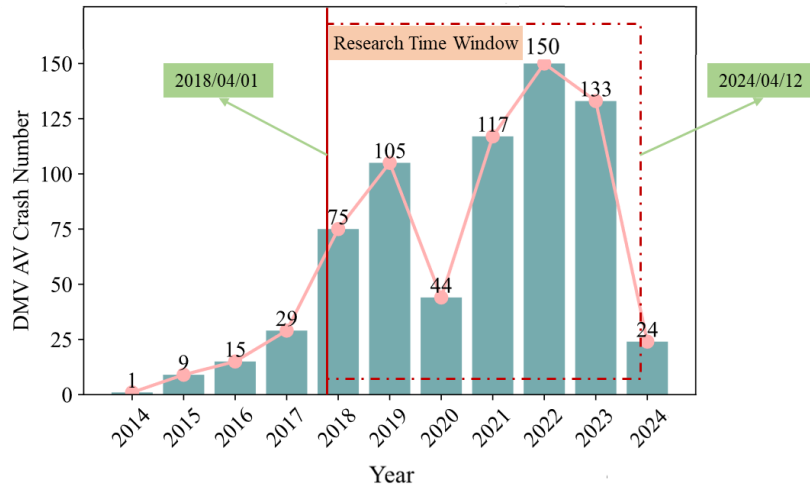


Figure 5.1 CA DMV AV crash number by year.

A systematic data extraction framework was developed to facilitate the conversion of PDF format crash records into excel and comma-separated formats, thereby enabling their compatibility with statistical software and scripting languages for subsequent in-depth analysis. Figure 5.2 presents the flowchart of CA DMV AV crash data extraction and augmentation. To be specific, 61 scanned hand-written records in 2018 were manually scrutinized and extracted. As for data that was documented in the uniform digital reports from 2019 onward, a highly automatic and fast PDF extractor based on Python was deployed to specifically obtain the variables from these retrieved reports. The OCR program was set up with a pipeline that includes pre-processing steps (such as image conversion and variable region designation), text and marking detection, and post-processing steps (such as variable saving). Each individual report in PDF format was first converted into an image file to enable the Python library to read the text contained therein. Subsequently, the Optical Character Recognition (OCR) and computer vision techniques were employed to extract the text and markings from specific regions. Once the texts and checkmarks had been extracted, they were transcribed into a CSV file, with predefined columns representing crash-related variables. The pipeline is fine-tuned to handle the PDF format and content of CA DMV collision reports, thus allowing for automatic labelling by identifying and extracting relevant information with minimal human intervention. The data was also scrutinized

and validated to ensure the detection accuracy. Specifically, a portion ($10\% \times 573 \approx 57$) of the automatically extracted crash data was randomly selected and manually reviewed to cross-check the accuracy of the OCR extraction results. We found that the accuracy of the OCR program is as high as 100% on these randomly selected digital crash records. Therefore, the effectiveness and accuracy of this data extraction framework can be ensured simultaneously.

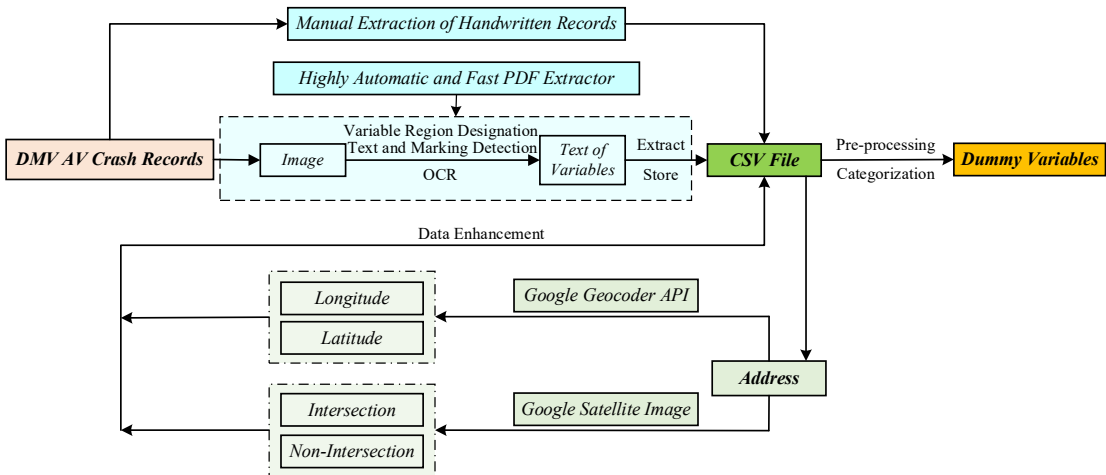


Figure 5.2 Flowchart of CA DMV AV crash data extraction and augmentation.

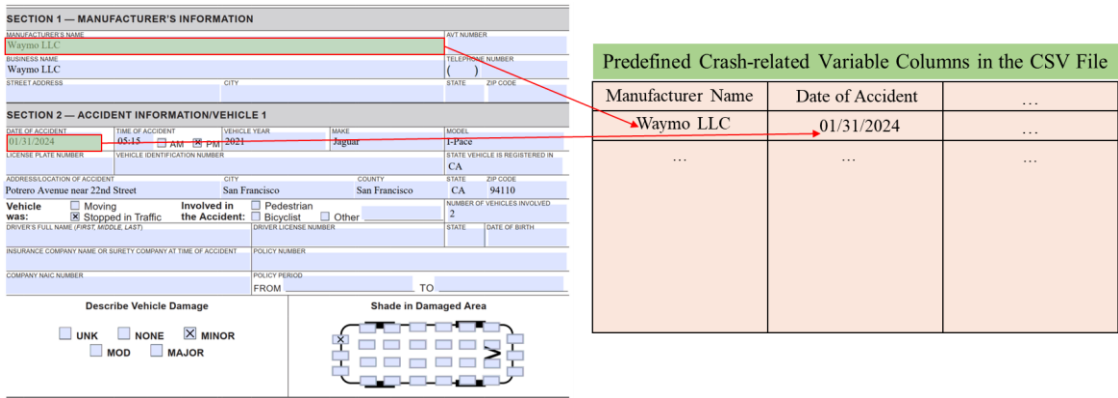


Figure 5.3 An example of extraction results in the form of pictures-to-text.

The extraction process involves using a CPU (Intel i9-13900K) and a GPU (GeForce RTX 3080) to process a total of 573 digital reports. The total extraction time taken for this task was 1250 seconds. On average, it took approximately 2.18 seconds to process each PDF report. Figure 5.3 illustrates an example of extraction results in the form of pictures-to-text. As such, it greatly reduces the manpower and time traditionally required for data extraction processes from CA DMV collision reports, while manual

data entry and analysis are both time-consuming and prone to human error (Liu et al., 2024; Sinha et al., 2021; Shafique et al., 2024). This not only streamlines the workflow but also facilitates instant data updates, particularly as the volume of data continues to increase.

In addition to the AV collision report, the characteristic of the road infrastructure, especially whether a crash occurred at an intersection, was also collected using Google Satellite Image based on the extracted address. This augmentation is crucial, given the findings from previous studies that suggested intersections play a significant role in increasing the likelihood of accidents (Liu et al., 2024; Ren et al., 2024b). Additionally, the CA DMV AV crash reports do not provide precise geographical coordinates, specifically latitude and longitude, for each collision site. To ascertain these locations, the Google Geocoder Application Programming Interface was utilized in this study. Figure 5.4 illustrates the spatial distribution patterns of AV collisions within the specified research timeframe, with each dot symbolizing an individual AV collision event. It can be seen that the majority of the collisions were concentrated in the San Francisco and Mountain View areas.

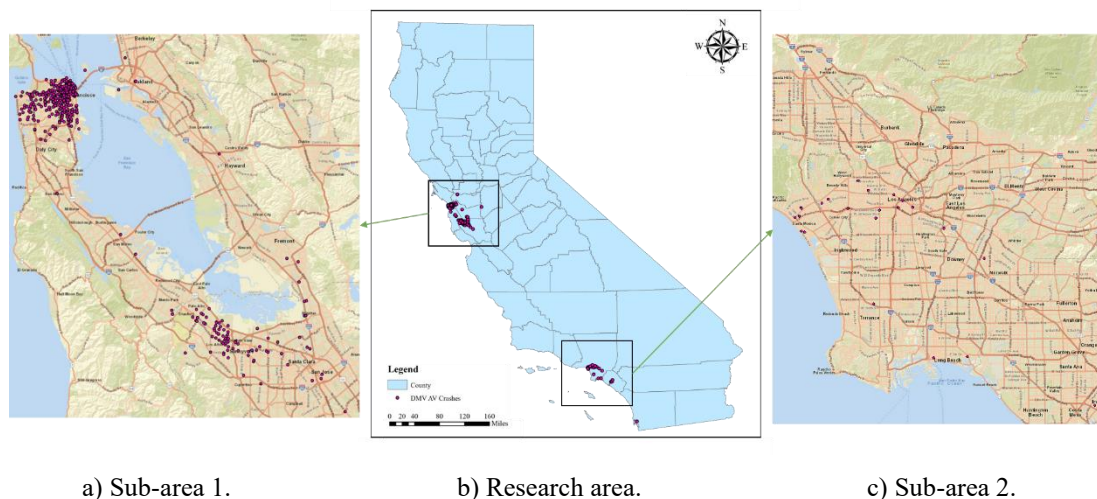


Figure 5.4 The spatial distribution of AV crashes in California.

To further analyse the geographical coordinates of AV crashes and identify corresponding accident blackspots, the spatial clustering was conducted (Fan et al.,

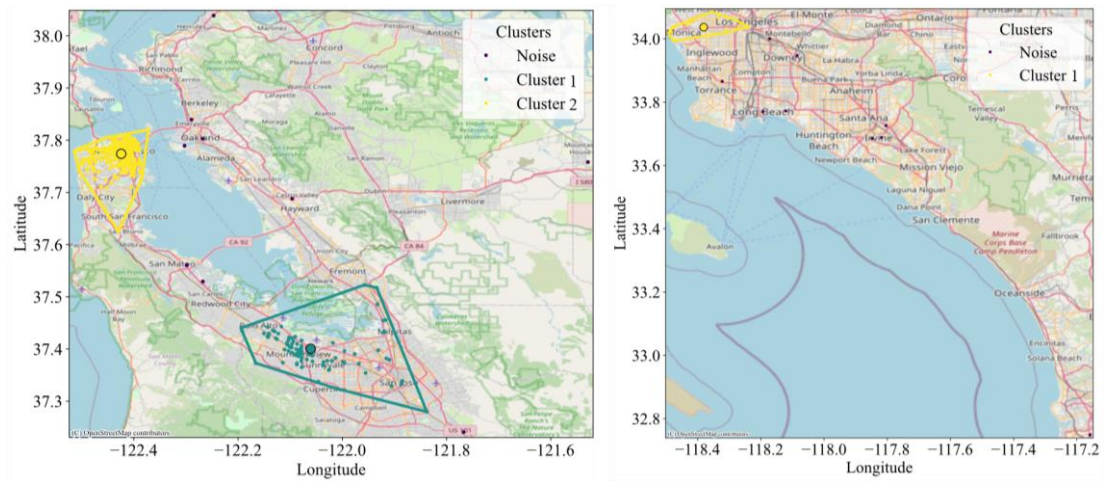
2022; Jia et al., 2018). The DBSCAN algorithm was utilized for this analysis due to its effectiveness in discovering clusters of arbitrary shapes and handling spatial data with noise (Ester et al., 1996). Note that the spatial clustering analysis on the AV crash points was performed separately for two sub-areas due to the considerable spatial distance between these two regions. Subsequently, the visualization of the spatial clustering results was achieved through a scatter plot overlaying on the OpenStreetMap. The spatial clustering of AV crashes in California is detailed in Table 5.1 and illustrated in Figure 5.5. Unique colors represent different clusters and noise points distinctly identified. Noise points in the context of our study refer to AV crash data points that do not belong to any cluster and are considered outliers due to the low crash point density (Ester et al., 1996). For each cluster, the convex hull was plotted and the centroid was calculated, providing a clear representation of crash cluster boundaries and average crash central points. The geographical and built environment characteristics of each centroid clustered were then carefully scrutinized. For sub-area 1, the cluster 1's centroid is near major highways and intersections, indicating potential high-speed and complex traffic flow interactions. The cluster 2's centroid in sub-area 1 is situated in a densely built urban area, suggesting that this cluster may be simultaneously influenced by high pedestrian activity, non-motorized traffic, and motorized traffic. Meanwhile, the centroid of cluster 1 in sub-area 2 is located near residential and commercial borders, indicating potential needs for traffic management and safety improvements.

Table 5.1 The spatial clustering results of AV crashes in California.

	Sub-area 1			Sub-area 2	
	Cluster 1	Cluster 2	Noise	Cluster 1	Noise
Crash numbers	445	103	10	17	9
Centroid	(-122.061, 37.400)	(-122.424, 37.773)		(-118.381, 34.037)	

The spatial clustering analysis was further conducted from intersection and road segment aspects using kernel density estimation (Jia et al., 2018; Jiang et al., 2013; Lu et al., 2013; Silverman, 2018). Figure 5.6 and Figure 5.7 show the spatial clustering of AV crashes in sub-area 1 from intersection and road segment aspects (It is noteworthy that sub-area 2 includes 11 crashes that occurred at intersections and 15 crashes that

occurred on road segments. The scarcity of data points results in the absence of multiple incident locations belonging to the same road segment or intersection. Thus, further clustering analysis in this region is not feasible.). Larger circles stand for locations where more AV crashes occurred.



a) Sub-area 1. b) Sub-area 2.

Figure 5.5 The spatial clustering of AV crashes in California.

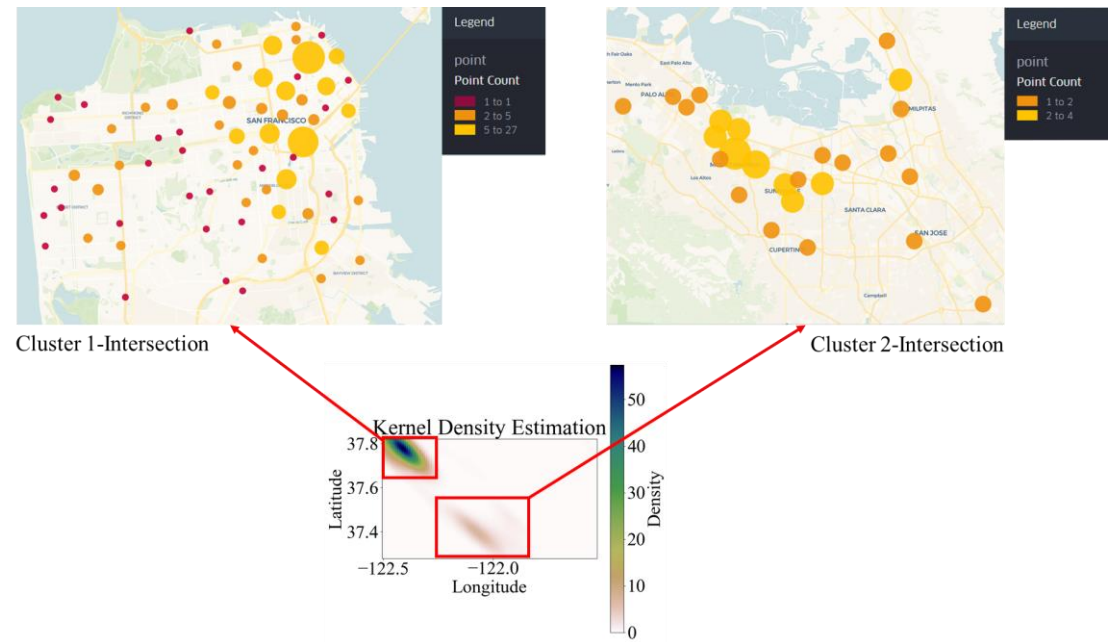


Figure 5.6 The spatial clustering of AV crashes in sub-area 1 from intersection aspect.

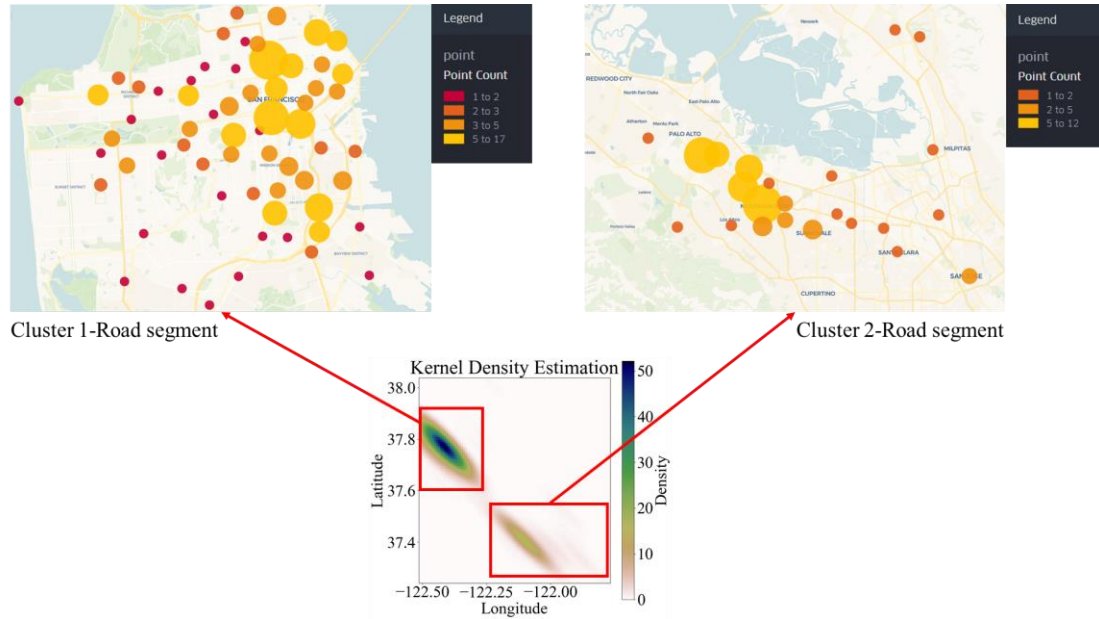


Figure 5.7 The spatial clustering of AV crashes in sub-area 1 from road segment aspect.

Based on the spatial clustering analysis, the top 5 intersections and road segments with the highest number of AV crashes were identified in sub-area 1, as shown in Table 5.2. These results highlight specific intersections and road segments within sub-area 1 that are particularly prone to AV incidents, which could be priority areas for targeted safety improvements. The overlap for both the intersection (Van Ness Avenue and Market Street) and associated road segment (Van Ness Avenue) suggests a potentially high-risk zone.

Additionally, it can be observed that the crash locations are quite geographically scattered, with only a few crashes concentrated at specific intersections or road segments. This scattering suggests that there are very few accident blackspots within the study area, providing positive evidence for the safety of automated vehicles. Unlike human drivers, who are constrained by limited sensing capabilities and often encounter unreasonable traffic infrastructure such as poorly designed road segments or chaotic intersections (Ashraf et al., 2021), AVs appear to operate more safely across a wider geographical area. This observation underscores the value of spatial clustering analysis in understanding the AV safety performance (Fan et al., 2022; Jia et al., 2018; Jiang et al., 2013; Lu et al., 2013), which may significantly inform future transportation

planning and policy decisions.

Table 5.2 The top 5 intersections and road segments in sub-area 1.

Top 5	Sub-area 1			
	Intersection	Count	Road segment	Count
1	Folsom Street and 19th Street (-122.415, 37.760)	8	Alma Street	6
2	Bryant Street and Kate Street (-122.406, 37.773)	7	Van Ness Avenue	5
3	Lombard Street and Hyde Street (-122.420, 37.802)	7	Shoreline Blvd	4
4	Van Ness Avenue and Market Street (-122.419, 37.775)	4	Sacramento Street	3
5	Pacific Avenue and Montgomery Street (-122.404, 37.797)	3	Bayshore Blvd	2

After the elimination of irrelevant variables and records with missing variables, a total of 584 AV crash observations with clearly defined vehicle damage and detailed crash information were utilized for this analysis. To discern the factors contributing to AV incidents, the crash damage outcomes were classified into four categories: none damage, minor damage, moderate damage, and major damage. Meanwhile, the independent variables under consideration were grouped into five categories, including crash characteristics, road characteristics, temporal characteristics, vehicle characteristics, and environment characteristics. These multi-source determinants were subsequently transformed into categorical variables for in-depth analysis. The detailed descriptive statistics on the explanatory variables are provided in Table 5.3. Notably, to reduce modelling bias caused by an insufficient number of samples, variables with small sample sizes and similar characteristics were combined according to the rules mentioned in the notes section of Table 5.3. As such, a total of 43 candidate variables were identified for the subsequent model development.

An interesting aspect observed in the descriptive analysis is that, unlike traditional human-driven vehicle accidents where the distribution of damages typically decreases with the severity of injury (Mannering et al., 2016b; Ren and Xu, 2023b), accidents involving AVs predominantly result in minor damage (73.97%). This is followed by moderate damage (15.24%), none damage (8.22%), and major damage (2.57%),

respectively.

Table 5.3 Descriptive statistics of explanatory variables.

Categories	Variables	Dummy variables	Description	Frequency	Percentage
	Vehicle Damage	None	1 = True; 0 = False	48	8.22%
		Minor	1 = True; 0 = False	432	73.97%
		Moderate	1 = True; 0 = False	89	15.24%
		Major	1 = True; 0 = False	15	2.57%
Crash characteristics	Vulnerable Road User (VRU)	No VRU involved	1 = True; 0 = False	550	94.18%
		VRU involved ¹	1 = True; 0 = False	34	5.82%
	AV movement	Stopped	1 = True; 0 = False	248	42.47%
		Proceeding straight	1 = True; 0 = False	168	28.77%
		Making turns ²	1 = True; 0 = False	56	9.59%
		Backing	1 = True; 0 = False	20	3.42%
		Slowing/Stopping	1 = True; 0 = False	47	8.05%
		Parked/Parking	1 = True; 0 = False	22	3.77%
		Other movements ³	1 = True; 0 = False	23	3.93%
	Type of collision	Head-on	1 = True; 0 = False	47	8.05%
		Side swipe	1 = True; 0 = False	145	24.83%
		Rear end	1 = True; 0 = False	282	48.29%
		Broadside	1 = True; 0 = False	46	7.88%
		Hit object	1 = True; 0 = False	39	6.68%
		Other collision categories	1 = True; 0 = False	25	4.27%
Road characteristics	Intersection	Non-intersection	1 = True; 0 = False	297	50.86%
		Intersection	1 = True; 0 = False	287	49.14%
	Roadway surface	Dry	1 = True; 0 = False	543	92.98%
		Adverse roadway surface ⁴	1 = True; 0 = False	41	7.02%
	Roadway condition	Unusual conditions ⁵	1 = True; 0 = False	28	4.79%
		No unusual conditions	1 = True; 0 = False	556	95.21%
Vehicle characteristics	Vehicle status	Moving	1 = True; 0 = False	318	54.45%
		Stopped in traffic	1 = True; 0 = False	266	45.55%
	Vehicle number	Single	1 = True; 0 = False	502	85.96%
		Multiple	1 = True; 0 = False	82	14.04%
	Driving mode	Autonomous mode	1 = True; 0 = False	316	54.11%
		Conventional mode	1 = True; 0 = False	268	45.89%
Environment characteristics	Weather	Clear	1 = True; 0 = False	496	84.93%
		Cloudy	1 = True; 0 = False	61	10.45%
		Raining/Foggy	1 = True; 0 = False	27	4.62%
	Lighting	Daylight	1 = True; 0 = False	399	68.33%
		Dark without street lights ⁶	1 = True; 0 = False	20	3.42%
		Dark with street lights	1 = True; 0 = False	165	28.25%
Temporal characteristics	Week	Weekday	1 = True; 0 = False	448	76.71%
		Weekend	1 = True; 0 = False	136	23.29%
	Time of day	Early morning (0:00 - 5:59)	1 = True; 0 = False	52	8.90%
		Morning (6:00 - 11:59)	1 = True; 0 = False	174	29.79%
		Afternoon (12:00 - 18:59)	1 = True; 0 = False	261	44.69%
		Evening (19:00 - 23:59)	1 = True; 0 = False	97	16.61%
	Quarter	Quarter I	1 = True; 0 = False	146	25.00%
		Quarter II	1 = True; 0 = False	144	24.66%
		Quarter III	1 = True; 0 = False	155	26.54%
		Quarter IV	1 = True; 0 = False	139	23.80%

¹Vulnerable Road User: Pedestrian/Bicyclist/Scooter.

²Making turns: Making right turn/Making left turn/Making U turn.

³Other movements: Passing other vehicle/Changing lanes/Entering traffic/Crossing into opposing lane/Merging.

⁴Adverse roadway surface: Wet and snowy-icy surfaces.

⁵Unusual conditions: Holes and deep rut/Loose material on roadway/Obstruction on roadway/Construction-repair zone/Reduced roadway width/Other unusual conditions.

⁶Dark without street lights: Dusk/Dawn/Dark without street light category.

5.3 Methods

In an effort to investigate the unobserved heterogeneity within AV crashes, the latent class logit model and the random parameter logit model were initially used to explore and model the data. However, these models failed to meet the significance criteria, which is plausibly attributable to the limited sample size available in the AV crash dataset. In light of these problems, we pivoted to a hybrid research methodology that integrates the latent class analysis with the multinomial logit model. The combined methodology represents a well-established research framework to explore the unobserved heterogeneity in the field of traffic safety analysis (Kim, 2023; Kim and Mokhtarian, 2023; Labbo et al., 2024; Sivasankaran and Balasubramanian, 2020).

Firstly, the latent class analysis was used to identify the patterns in AV crash incidents. On the one hand, the latent class analysis effectively manages the heterogeneity in two significant ways: (1) It eliminates the need for parametric assumptions about the distribution of the heterogeneity underlying the data (Mannering et al., 2016), and (2) It acknowledges the existence of common parameters across unobserved clusters. This relaxation is particularly beneficial in the contextual small sample size data where the true underlying distribution of unobserved factors is uncertain or may not follow a known parametric form. On the other hand, as a probability-based partitioning approach, the latent class analysis approach offers distinct advantages over other similarity-based techniques such as K-means (Sun et al., 2019; Zhu et al., 2023): (1) It does not require a predetermined number of clusters. Statistical criteria can be employed to retrospectively determine the optimal model and corresponding number of clusters. (2) It can probabilistically assign each crash to a specific cluster, leveraging membership probabilities that are estimated through a rigorous maximum likelihood procedure. (3) It can accommodate a wide array of variable types, encompassing numerical, nominal, or mixed formats, without the need for pre-analysis standardization. This feature streamlines the data preparation process and broadens the applicability of latent class analysis to datasets with heterogeneous

variable characteristics.

Secondly, the multinomial logit model was employed to examine the relative contributions of various determinants—including crash characteristics, road characteristics, vehicle characteristics, environment characteristics, and temporal characteristics—to the AV crash damage severity. Finally, the marginal effects of the significant factors were calculated to interpret their specific impacts on different crash patterns. This combined approach enabled us to identify latent classifications within the small sample data while simultaneously providing an interpretable analysis of the correlation between crash factors and damage severity outcomes.

5.3.1 Latent class analysis

Latent class analysis is a statistical technique commonly utilized in the field of traffic safety to uncover underlying patterns in crash data with inherent diversity (Sun et al., 2019). The core principle of latent class analysis is to classify multivariate categorical observations into a finite number of unobserved subgroups or latent classes based on their characteristics and the outcome. Observations that display comparable response patterns on explicit variables are often grouped together within identical latent class structures. As such, the homogeneity within the sub-classes and the heterogeneity between sub-classes are maximized.

Consider a data sample with I AV crashes and J categorical indicators. The probability of a particular response pattern for crash i can be given by the formula:

$$P(\mathbf{X}_i = \mathbf{x}_i) = \sum_{n=1}^N P(C_n) \prod_{j=1}^J P(X_{ij} = x_{ij} | C_n) \quad (5.1)$$

where $\mathbf{X}_i$ is the set of observed variables for AV crash i , $\mathbf{x}_i$ is a specific response pattern observed for AV crash i , N is the number of latent classes, C_n represents the n -th latent class, $P(C_n)$ is the membership probability of latent class C_n , $P(X_{ij} = x_{ij} | C_n)$ is the conditional probability of crash i providing response j in latent

class C_n .

Based on this probability model, latent class analysis tries to estimate the parameters that best fit the observed data through maximum likelihood estimation. This involves iterative computation, often using the Expectation-Maximization algorithm, to find the latent class structure that most likely produced the observed response patterns (Linzer and Lewis, 2011; Sun et al., 2019). Once the model has been estimated, the classification of specific AV crash cases into distinct categories is achieved through the computation of posterior probabilities using Bayes formula:

$$P(C_n | X_{ij} = x_{ij}) = \frac{P(C_n)P(X_{ij} = x_{ij} | C_n)}{P(X_i = x_i)} \quad (5.2)$$

In the absence of explicit criteria for ascertaining the ideal sample size for latent class analysis, a heuristic often recommended with a minimum of 500 observations to ensure the validity and reliability of the results (Finch and Bronk, 2011). Notably, empirical evidence from various latent class analysis investigations indicates that valid results can be obtained with a small sample size. For example, Nylund-Gibson and Choi (2018) posited that a sample of at least 300 individuals is generally sufficient to conduct latent class analysis effectively. Taking into account these benchmarks and the specific context of our research, the inclusion of 584 AV crash samples is considered to be an appropriate and sufficient sample size for the application of latent class analysis. The R-package *poLCA* (Polytomous Variable Latent Class Analysis) was employed to identify the complex interplay of various factors contributing to AV crashes (Linzer and Lewis, 2011).

5.3.2 Multinomial logit model

The multinomial logit model is a robust econometric approach widely used in the analysis of categorical dependent variables, making it particularly suitable for modelling the damage severity of accidents involving AVs (Behnood and Mannering, 2015; Islam and Mannering, 2020; Fred L. Mannering et al., 2016b; Washington et al.,

2020). This model allows for the estimation of the probability of each category of accident severity (e.g., none, minor, moderate, severe) based on a set of predictors.

The basic framework adopted for determining the specific damage severity level k in AV crash i initiates by formulating a linear function, as follow:

$$U_{ki} = \beta_k X_{ki} + \varepsilon_{ki} \quad (5.3)$$

where β_k is the vector of estimated parameters for damage severity level k , X_{ki} is the vector of explanatory variables influencing the damage severity k in AV crash i , ε_{ki} is the stochastic error term, and U_{ki} represents the probability of damage severity k in AV crash i .

Under the presumption that the disturbance terms adhere to a distribution that is both independently and identically generalized extreme value, the framework can be represented as a standard multinomial logit model (McFadden, 1981b):

$$P_{ki} = \int \frac{\exp(\beta_k X_{ki})}{\sum \exp(\beta_k X_{ki})} f(\beta|\varphi) d\beta \quad (5.4)$$

where P_{ki} signifies the probability of the k -th categorical damage severity arising from the i -th incident involving an AV, $f(\beta|\varphi)$ constitutes the probability density function corresponding to the vector of parameters β , while φ denotes a parameter vector that defines the density function's characteristics.

Estimation of the model parameters was implemented through the simulation-driven maximum likelihood method (Washington et al., 2020b). In the multinomial logit model, the coefficient corresponding to a specific variable does not straightforwardly indicate its causal impact. Therefore, the marginal effects are essential to quantify how changes in predictor variables can influence the likelihood of different AV accident severities, providing valuable safety insights in AV context (Washington et al., 2020b). Specifically, the marginal effect denotes the alteration in the probability of the k -th category of damage severity in crashes involving AVs,

attributable to a one-unit escalation in the explanatory variable X_{ki} . In instances where X_{ki} assumes the form of an indicator variable, as observed in our study, the marginal effects can be calculated directly by comparing the probabilities when the variable alters from 0 to 1 (Washington et al., 2020). This computation entails the averaging of the marginal effects over the entirety of observed AV crashes as follows:

$$ME_{X_{ki}} = \bar{P}[\text{given } X_{ki} = 1] - \bar{P}[\text{given } X_{ki} = 0] \quad (5.5)$$

5.4 Results and discussions

5.4.1 Latent class analysis

The selection of an appropriate number of latent classes is crucial for the latent class analysis. To identify the most representative model structure, various statistical criteria, such as the Akaike Information Criterion (AIC) (Hirotugu Akaike, 1974), Bayesian Information Criterion (BIC) (Schwarz, 1978), likelihood ratio chi-square (G^2), and maximum log-likelihood are commonly used. The AIC and BIC are comparative indices in latent class analysis for assessing the model fit with the given AV crash data. Models with lower values on these criteria are considered to have a superior fit and indicate more homogeneous groups (Rafiq and McNally, 2021; Schwarz, 1978). G^2 refers to the likelihood ratio chi-square statistic for the observed versus predicted cluster counts, which is another method used to assess the goodness-of-fit of the model (Goodman, 1970). A lower G^2 suggests a more precise model fit (Goodman, 1970). Furthermore, the maximum log-likelihood values provide quantitative assessments of how well the estimated model fits the observed crash data, with larger values indicating better fits.

Previous research has indicated BIC is a more reliable metric in determining the optimal number of clusters compared to other criteria (Nylund et al., 2007). Therefore, this study primarily employs BIC to ascertain the most appropriate number of classes. Meanwhile, it should be noted that an increase in cluster quantity does not perpetually

correspond to a minimized BIC value (Liu and Fan, 2020). Besides, given the small sample sizes in the context of AV crash data, an excessive number of clusters can result in minimal differences among segmented groups. This situation potentially diminishes the informational value of each cluster and increases the complexity of analysis. According to previous studies, the current research posits that the optimal number of clusters is determined when the relative percentage reduction in BIC value among competing models is below 1 percent threshold (Lin and Fan, 2021; Samerei and Aghabayk, 2024). As such, the heterogeneity can be accurately captured and the interpretability of the results can be significantly enhanced.

Incorporating the full set of explanatory variables, class sizes ranging from 1 to 6 were explored respectively to assess their fit metrics and the interpretability of the derived classes. The comparative model statistics for competing models, specifically AIC, BIC, G^2 , and the maximum log-likelihood, are detailed in Table 5.4. An overall declining trend in the metrics was observed except for the maximum log-likelihood with the increment of cluster sizes until to class size of six. Notably, the decreasing rate of these indices was inconsistent from one class to six classes, with a pronounced sharp reduction rate post the first base group and a subsequent plateau after two clusters. Particularly, the percentage change of BIC was -4.18% from 1 cluster to 2 clusters, while decreasing less than one percentage from 2 to 6 clusters. Therefore, the two-cluster model was selected as the optimal model for subsequent crash pattern identification and interpretation analysis.

Table 5.4 Model fit metrics for different number of clusters.

Number of clusters	1	2	3	4	5	6
AIC	13,260.86	12,556.81	12,389.53	12,165.13	12,043.40	12,064.71
BIC	13,400.70	12,840.85	12,817.78	12,737.58	12,760.06	12,925.58
Percentage change of BIC	-	-4.18%	-0.18%	-0.63%	0.18%	1.30%
G^2	5,994.09	5,224.04	4,990.76	4,700.36	4,512.63	4,467.94
Maximum log-likelihood	$-6,598.43$	$-6,213.41$	$-6,096.77$	$-5,951.56$	$-5,857.70$	$-5,835.36$

The class-conditional response probabilities associated with the explanatory variables are presented in Table 5.5. Class-conditional response probabilities represent the probability of observing a particular response given membership in a specific latent class (Lanza et al., 2013). Due to the assumption of conditional independence, the within-class probabilities sum to 1. These probabilities are crucial as they help in distinguishing between the different latent classes by indicating the characteristic patterns of responses within each class. The class population shares reveal that cluster 1 constitutes 46.4% of the crash dataset, while cluster 2 accounts for 53.6%. The allocation of crashes to these clusters was predicated on the modal assignment principle, whereby each crash was attributed to the cluster with the highest probability of membership (Rafiq and McNally, 2021). Summary statistics have been derived by employing a probability-weighted approach to compute mean values across the entirety of incidents. Each identified latent class signifies a distinct subgroup of AV crashes that were characterized by a particular crash pattern.

Subsequently, a detailed description of the damage severity patterns of the two clusters of AV crashes was provided in Figure 5.8. The probability (vertical axis) of the variable (horizontal axis) outcome refers to the probability of a specific value of a variable in the overall sample. This is the result of considering both the class-conditional response probabilities and the class probabilities. The class numbers 1 to 7 on the right-hand axis indicate different dummy variables considered in our analysis, and the details can be found in Table 5.5. According to the clustering results, two distinct groups based on the skewed distributions of vehicle status and driving mode were determined. The first class encompasses incidents where the AV was in motion at the time of the crash (accounting for 99.1% of observations), with crashes predominantly occurring in conventional driving mode (58.5%). Conversely, the second class is featured by crashes where the AV stopped in traffic, representing 97.1% of such incidents. These accidents predominantly occurred when the vehicle was operating in autonomous mode (68.7%).

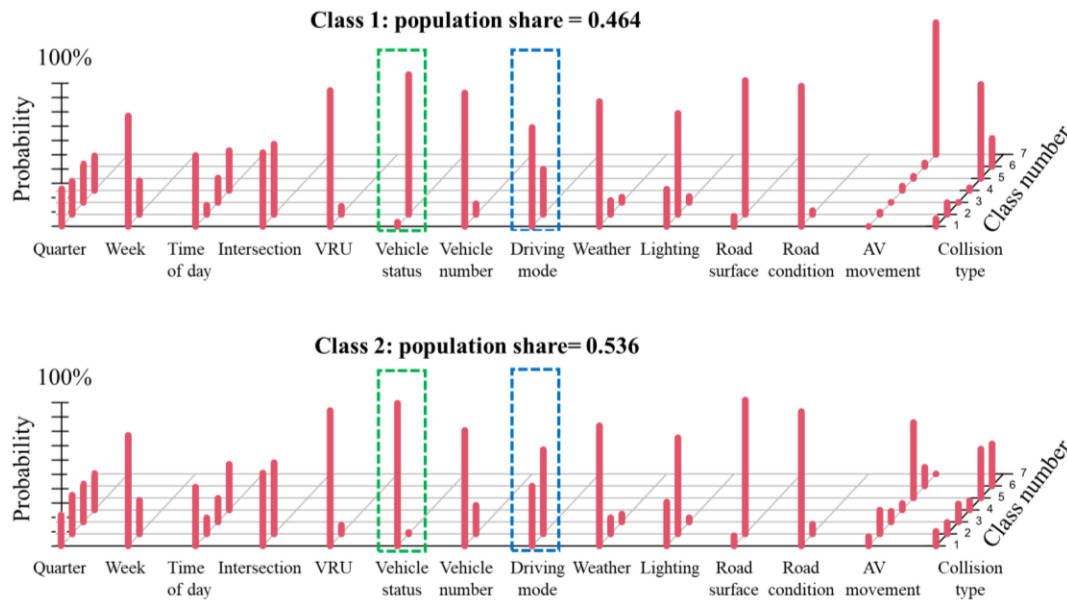


Figure 5.8 Clustering results for AV crashes in California.

The “natural breaks” embedded in the dataset represent and highlight identifiable patterns in AV accident occurrences relative to vehicle operational states. The first class indicates that a majority of crashes involving AVs happened while the vehicles were in motion. This could be attributed to the complex dynamic interactions with other moving vehicles and road users, sensor detection limitations, or decision-making algorithms underestimating certain risks in real-time dynamic traffic scenarios (Zhang et al., 2023). The second class, where AVs stopped in traffic during the crash event, points to potential vulnerabilities in how these vehicles respond to sudden changes in their surrounding environment, such as the behaviours of other vehicles. It is noteworthy that a significant proportion of these incidents occurred when the autonomous system was engaged, which could indicate difficulties in predicting and reacting to the actions of other road users (Selvaraj et al., 2023).

The higher incidence of crashes in autonomous mode, identified in both classes, could also be linked to a transitional technology phase where human drivers and autonomous systems coexist and interact on public roads. This coexistence may lead to unpredictable situations, as human drivers may not always anticipate or understand the behaviour of AVs. Moreover, the “natural breaks” suggest that different traffic conditions may necessitate distinct approaches to prevent AV accidents. For instance,

strategies that are effective for moving vehicles, such as advanced predictive algorithms and enhanced sensor systems, may differ from those needed when vehicles are controlled to stop, like robust fail-safes for sudden traffic halts.

Table 5.5 Conditional response probabilities of explanatory variables for each class.

Dummy variables		Class number	Cluster 1	Cluster 2
<i>Class population shares</i>			0.464	0.536
Crash characteristics				
Vulnerable Road	No VRU involved	1	0.940	0.944
User (VRU)	VRU involved	2	0.060	0.056
AV movement	Stopped	7	0.000	0.916
	Proceeding straight	5	0.524	0.015
	Making turns	2	0.165	0.016
	Backing	1	0.064	0.000
	Slowing/Stopping	6	0.130	0.024
	Parked/Parking	4	0.045	0.030
	Other movements	3	0.073	0.000
Type of collision	Head-on	2	0.080	0.081
	Side swipe	6	0.292	0.195
	Rear end	5	0.339	0.653
	Broadside	1	0.101	0.053
	Hit object	3	0.125	0.000
	Other collision categories above	4	0.064	0.019
Road characteristics				
Intersection	Non-intersection	1	0.506	0.512
	Intersection	2	0.494	0.488
Roadway surface	Dry	2	0.930	0.930
	Adverse roadway surface	1	0.070	0.070
Roadway condition	Unusual conditions	2	0.067	0.026
	No unusual conditions	1	0.933	0.974
Vehicle characteristics				
Vehicle status	Moving	1	0.991	0.029
	Stopped in traffic	2	0.010	0.971
Vehicle number	Single	2	0.198	0.073
	Multiple	1	0.802	0.927
Driving mode	Autonomous mode	1	0.415	0.687
	Conventional mode	2	0.585	0.313
Environment characteristics				
Weather	Clear	1	0.834	0.867
	Cloudy	2	0.112	0.096
	Raining/Foggy	3	0.054	0.037
Lighting	Daylight	2	0.668	0.701
	Dark without street lights	3	0.029	0.041
	Dark with street lights	1	0.304	0.258
Temporal characteristics				
Week	Weekday	1	0.768	0.767
	Weekend	2	0.232	0.233
Time of day	Early morning (0:00 -5:59)	2	0.112	0.063
	Morning (6:00 - 11:59)	4	0.317	0.276
	Afternoon (12:00 - 18:59)	1	0.408	0.492
	Evening (19:00 - 23:59)	3	0.164	0.169
Quarter	Quarter I (	2	0.269	0.228
	Quarter II	4	0.253	0.240
	Quarter III	3	0.264	0.268
	Quarter IV	1	0.215	0.265

5.4.2 Multinomial logit model

To mine informative insights regarding determinants influencing the AV crash damage severity embedded in the pooled data and two identified clusters, three separate models were developed and estimated respectively. Note that the pooled data refers to the entire AV crash dataset without clustering. To check the Independence of Irrelevant Alternatives assumption entailed by the multinomial logit model, the Hausman-McFadden test was conducted on the pooled data (Hausman and McFadden, 1984). Specifically, the restricted model was specified and estimated based on a smaller set of choices excluding the major damage severity outcome and parameters in the major damage severity utility functions. Thus, the number of estimated parameters in the restricted model was $n = 16 - 5 = 11$. Table 5.6 presents the results of the Hausman-McFadden test. With the Hausman-McFadden statistic value of 2.847 and a p-value of 0.993, the test results suggest that the Independence of Irrelevant Alternatives assumption should be accepted in our study.

Table 5.6 Results of the Hausman-McFadden test.

Number of estimated parameters in the restricted model (n)	Hausman-McFadden statistic value	p-value
11	2.847	0.993

All explanatory variables listed in Table 5.3 were utilized to develop three distinct models, which aimed to investigate their variations across different datasets and highlight the special findings under the framework of latent class analysis. Additionally, it is worth noting that the Pearson correlation coefficient analysis, with a predefined threshold of 0.5, was performed to pinpoint highly correlated variables that need to be excluded from the model to avoid multicollinearity (Pearson, 1895). Figure 5.9 shows the results of the correlation analysis, which indicates that all significant variables included in the final model specification have reasonable correlation coefficients.

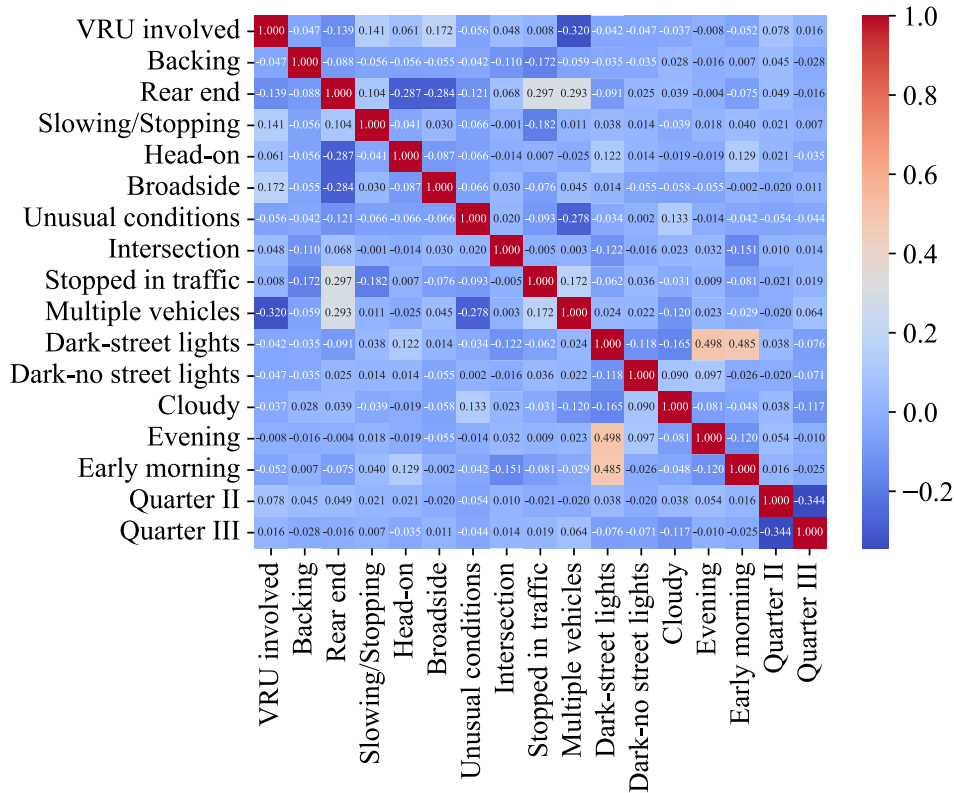


Figure 5.9 Significant variables' correlation coefficients.

Note that before determining the final analytical model, a comparative evaluation encompassing four distinct model frameworks was conducted. This comparison included the multinomial logit model (MNL), the ordered logit model (OL), the ordered probit model (OP), and the random parameters logit model (RPL). Table 5.7 shows the detailed model metrics for these three models in the pooled data. Specifically, the log-likelihood value at convergence measures the degree to which the model accurately represents the observed crash data. A higher log-likelihood value indicates a superior fit between the model and the data. The AIC and BIC are indicators of model complexity, where lower values signify a more favorable balance between model complexity and fit (Akaike, 1974; Schwarz, 1978a). It can be seen that the MNL has the highest log-likelihood value at convergence. Besides, the AIC and BIC metrics for the MNL are the lowest. With the confidence level higher than 99%, the likelihood ratio tests indicate that the MNL outperformed the OL and OP alternatives. Therefore, the comparative analysis reveals that the MNL outperforms the other two models.

Subsequently, the random parameter logit model (RPL) was selected as the potential candidate to model the AV crash data. During our preliminary analysis, we conducted extensive tests attempting to identify significant random parameters. However, we found that the inclusion of any random parameters did not significantly improve the model's performance. This result was based on the quantitative evidence that all random parameters were not significant at the 90% confidence level. As such, only the MNL was used to model the crash damage severities and present the subsequent findings.

Table 5.7 Estimated model metrics for preliminary models in the pooled data.

Model metrics	OL	OP	MNL
Number of estimated parameters (K)	15	13	16
Log-likelihood at zero, $LL(0)$	-472.535	-472.535	-472.535
Log-likelihood at convergence, $LL(\beta)$	-452.232	-456.312	-437.841
Akaike information criterion (AIC)	934.5	938.6	907.7
Bayesian Information Criterion (BIC)	1000.0	995.4	977.6
Number of observations (N)	584	584	584
	MNL vs OL	MNL vs OP	
χ^2	28.781	36.943	
Degree of freedom	1	3	
Confidence level	>99.99%	>99.99%	

Table 5.8 displays the results of the estimated models that assess the severity of crash damage for AVs within the pooled data, cluster 1, and cluster 2. Specifically, the pooled data model uses the entire dataset without any clustering, providing a general overview of the AV crash patterns for all data points, while the cluster 1 model focuses on a specific subset of the data identified as cluster 1 and the cluster 2 model analyses another subset identified as cluster 2. Note that the variables' names followed by crash types inside square brackets represent their inclusion in the different damage severity utility functions (Washington et al., 2020). In the pooled data model, 16 variables and constant terms emerged as significant in determining the crash damage severity. In cluster 1, the model identified 10 significant variables and constant terms, whereas the model pertaining to cluster 2 discerned 13 variables and constant terms as significant ones. ***, **, and * are utilized to represent variables' significance at the 99%, 95%, and 90% confidence level. The corresponding thresholds for t-stat are $|t\text{-stat}| \geq 2.57$, $|t\text{-stat}| \geq 1.96$, and $|t\text{-stat}| \geq 1.64$.

$stat \geq 1.96$, and $|t-stat| \geq 1.645$, respectively. It can be seen that the factors that influence crash damage outcomes are remarkably different between cluster 1 and cluster 2. Furthermore, Table 5.8 reveals a substantial disparity in the impacts of variables between the analysis of the pooled dataset and that of individual clusters. That is to say, the crash patterns behind them are different.

Table 5.9 presents each significant variable's marginal effects over the pooled data, cluster 1, and cluster 2. As readers may find, the marginal effects must contain at least a negative or a positive element. This is because the sum of one variable's marginal effects for NO, MI, MO, and MA is zero, which is both empirically verified and theoretically proven (Ben-Akiva and Lerman, 1985; Train, 2009; Washington et al., 2020c). To enhance the comparative analysis of the accident causes identified within each dataset, a graphical representation was provided in Figure 5.10. For ease of interpretation, the variables belonging to the same characteristics are rearranged. Subsequent sections will interpret the results derived from these three models in detail.

5.4.2.1 Crash characteristics

Vulnerable road users defined for no damage can significantly decrease the likelihood of minor damage (by 0.2336 in pooled data, 0.1330 in cluster 1, and 0.1238 in cluster 2), moderate damage (by 0.0412 in pooled data, 0.0243 in cluster 1, and 0.0310 in cluster 2), and major damage (by 0.0054 in pooled data, 0.0035 in cluster 1, and 0.0040 in cluster 2), while consistently increasing the likelihood of no damage (by 0.2802 in pooled data, 0.1608 in cluster 1, and 0.1588 in cluster 2). Meanwhile, the effect function of minor damage in the aggregate model also showed a significant association with the presence of a vulnerable road user. These marginal effects suggest that when AV accidents involve vulnerable road users, the resulting damage to vehicles is less severe. Specifically, the probabilities of moderate and major damage would be decreased by 0.2282 and 0.0377, respectively. However, it is crucial to point out that the inequity in such incidents warrants special attention. Firstly, it is imperative to

Table 5.8 Results of multinomial logit models for the pooled data, cluster 1, and cluster 2.

Variables [#]	Pooled data		Cluster 1		Cluster 2	
	Parameter Estimates	t-stat	Parameter Estimates	t-stat	Parameter Estimates	t-stat
Constant [NO]			3.222***	3.06		
VRU involved [NO]	4.009***	3.70	2.040***	2.87	2.840***	4.73
Backing [NO]	1.275*	1.92			1.380**	1.97
Rear end [NO]	0.634*	1.95	0.923*	1.71		
Unusual conditions [NO]			1.936**	2.11		
Stopped in traffic [NO]			-2.189***	-2.65		
Dark with street lights [NO]					-2.256**	-2.34
Evening [NO]					-1.546*	-1.80
Constant [MI]	3.127***	10.97	4.251***	7.23	3.558***	8.40
VRU involved [MI]	2.080**	1.99				
Head-on [MI]	-0.615*	-1.86			-0.800*	-1.78
Intersection [MI]	-0.441**	-2.19				
Multiple vehicles [MI]					-0.741**	-1.97
Evening [MI]			-0.635*	-1.78		
Quarter II [MI]					-0.692**	-2.35
Constant [MO]	1.228***	4.05	2.390***	3.97	1.255***	3.80
Slowing/Stopping [MO]					-1.530**	-2.04
Broadside [MO]	0.818**	2.04			0.746*	1.69
Dark with street lights [MO]	0.439*	1.74				
Quarter III [MO]	-0.545*	-1.83				
Broadside [MA]	2.189***	3.25				
Intersection [MA]	-2.094***	-2.71				
Multiple vehicles [MA]	-0.978*	-1.91			-1.231**	-2.26
Cloudy [MA]	1.244*	1.84				
Dark without street lights [MA]			2.079*	1.73		
Dark with street lights [MA]	1.359***	2.74				
Early morning [MA]			2.441**	2.56	1.620**	2.50
Model statistics						
Number of observations (<i>N</i>)		584		273		311
Number of estimated parameters (<i>K</i>)		16		10		13
Log-likelihood at zero, <i>LL</i> (0)		-472.535		-215.701		-255.409
Log-likelihood at convergence, <i>LL</i> (β)		-437.841		-203.280		-228.747

[#]NO = None Damage; MI = Minor Damage; MO = Moderate Damage; MA = Major Damage.

***, **, and * represent significance at the 99%, 95%, and 90% confidence level.

Table 5.9 Estimated marginal effects of contributing factors in the pooled data, cluster 1, and cluster 2.

Variables [#]	Pooled data				Cluster 1				Cluster 2			
	NO	MI	MO	MA	NO	MI	MO	MA	NO	MI	MO	MA
Crash characteristics												
VRU involved [NO]	0.2802	-0.2336	-0.0412	-0.0054	0.1608	-0.1330	-0.0243	-0.0035	0.1588	-0.1238	-0.0310	-0.0040
VRU involved [MI]	-0.1212	0.3871	-0.2282	-0.0377								
Backing [NO]	0.0891	-0.0743	-0.0131	-0.0017					0.0773	-0.0602	-0.0151	-0.0020
Rear end [NO]	0.0443	-0.0370	-0.0065	-0.0008	0.0728	-0.0602	-0.0110	-0.0016				
Slowing/Stopping [MO]									0.0167	0.1811	-0.2053	0.0075
Head-on [MI]	0.0358	-0.1144	0.0675	0.0111					0.0349	-0.1461	0.0947	0.0165
Broadside [MO]	-0.0084	-0.0898	0.1018	-0.0036					-0.0082	-0.0883	0.1001	-0.0036
Broadside [MA]	-0.0029	-0.0396	-0.0098	0.0523								
Road characteristics												
Unusual conditions [NO]					0.1525	-0.1262	-0.0230	-0.0033				
Intersection [MI]	0.0257	-0.0821	0.0484	0.0080								
Intersection [MA]	0.0028	0.0379	0.0094	-0.0501								
Vehicle characteristics												
Stopped in traffic [NO]					-0.1725	0.1427	0.0261	0.0037				
Multiple vehicles [MI]									0.0323	-0.1353	0.0877	0.0153
Multiple vehicles [MA]	0.0013	0.0177	0.0044	-0.0234					0.0018	0.0253	0.0060	-0.0331
Environment characteristics												
Dark-street lights [NO]									-0.1263	0.0984	0.0247	0.0032
Dark-street lights [MO]	-0.0045	-0.0481	0.0546	-0.0020								
Dark-street lights [MA]	-0.0018	-0.0246	-0.0061	0.0325								
Dark-no street lights [MA]					-0.0035	-0.0335	-0.0059	0.0429				
Cloudy [MA]	-0.0017	-0.0225	-0.0056	0.0298								
Temporal characteristics												
Evening [NO]									-0.0865	0.0674	0.0169	0.0022
Evening [MI]					0.0414	-0.1143	0.0627	0.0102				
Early morning [MA]					-0.0041	-0.0393	-0.0069	0.0503	-0.0023	-0.0334	-0.0079	0.0436
Quarter II [MI]									0.0302	-0.1265	0.0820	0.0143
Quarter III [MO]	0.0056	0.0598	-0.0678	0.0024								

[#]NO = None Damage; MI = Minor Damage; MO = Moderate Damage; MA = Major Damage.

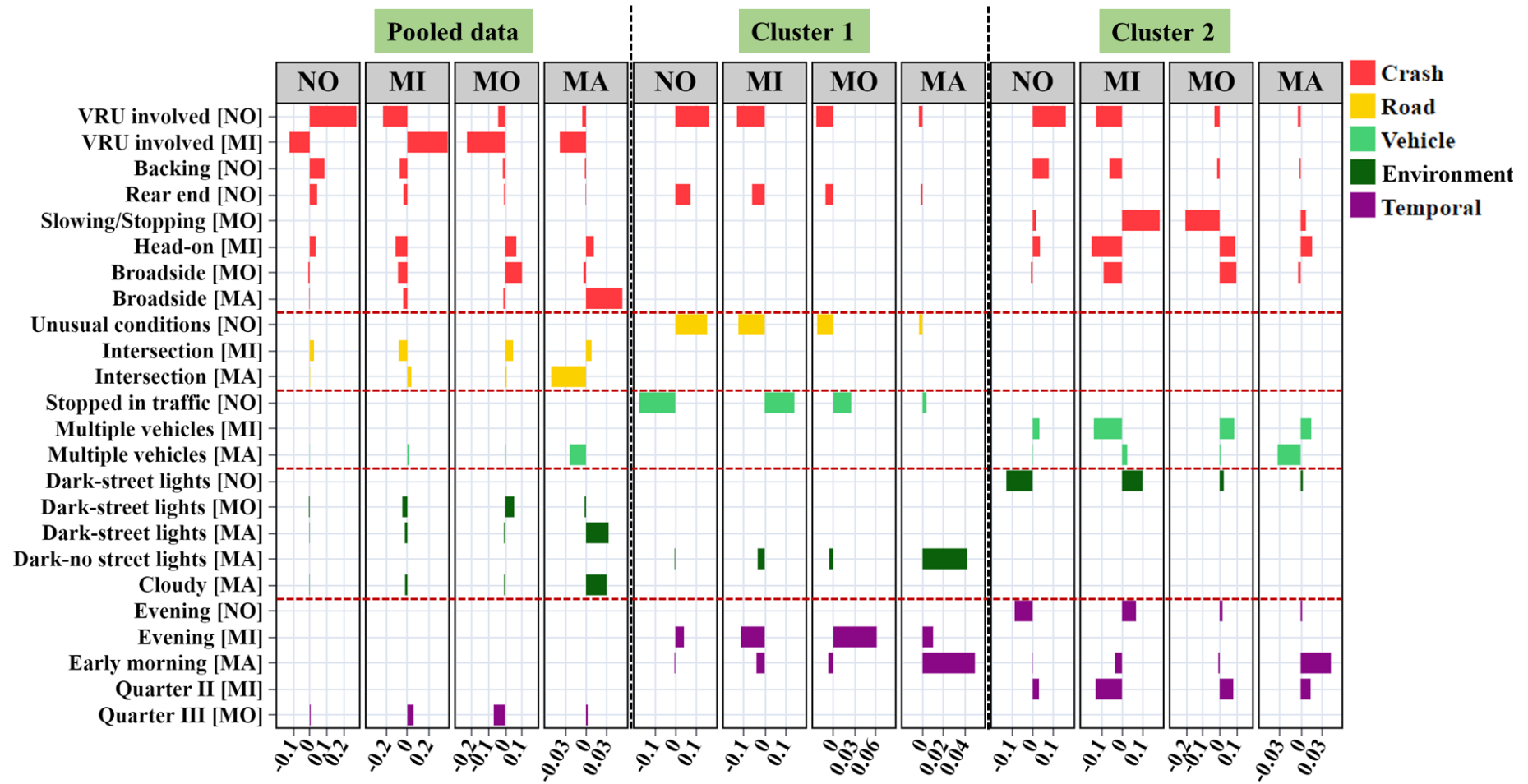


Figure 5.10 Comparison of variables' marginal effects over the pooled data, cluster 1, and cluster 2.

ensure that the benefits of AV technology, such as potential reduction in the injury severity, are equitably distributed across different road user groups (Rahman et al., 2023). This includes paying close attention to how these technologies perform across various demographic and socioeconomic groups, who may have different levels of exposure or vulnerability in traffic. Furthermore, the fact that the significance of this effect persists across both pooled data and individual clusters indicates that this is not an isolated phenomenon but rather a systematic feature of AV interactions with vulnerable road users. Given these concerns, ensuring that the development and deployment of AVs do not inadvertently increase vulnerabilities or inequities among vulnerable road users is essential in the future (Khogali and Mekid, 2023). To this end, incorporating a wide range of real-world scenarios and user behaviours in the testing and refinement of AV systems, along with continuous monitoring of their performance post-deployment, should be considered.

Turning to the movement preceding AV-involved crashes, backing defined for none damage category is more likely to produce significant decreases in the probability of minor damage (by 0.0743 in pooled data and 0.0602 in cluster 2), moderate damage (by 0.0131 in pooled data and 0.0151 in cluster 2), and major damage (by 0.0017 in pooled data and 0.0020 in cluster 2) in both the combined model and the cluster 2 model. However, this variable is not observed to be significant in cluster 1. Furthermore, the rear end indicator specific to none damage category exhibits marginal effects that are similar to those observed for backing maneuvers in AV incidents, although this similarity in impacts is confined to the cluster 1 model and the combined crash model. It is found that the probabilities of major damage would be decreased by 0.0008 for the pooled data and 0.0016 for cluster 1 when rear end crashes occurred. Meanwhile, for moderate damage, the likelihood decreases by 0.0065 in the pooled data and 0.0110 in cluster 1. The likelihood of minor damage also decreases by 0.0370 in the pooled data and 0.0602 in cluster 1. In contrast, the rear end indicator would increase the probabilities of none damage by 0.0443 in the pooled data and 0.0728 in cluster 1. This indicates that while the backing and rear end movements are associated with analogous outcomes, the significance of these variables is not uniformly distributed across all cluster-based models. This reinforces the notion that latent class clustering analysis is critical for uncovering the nuanced effects of specific variables within heterogeneous datasets (Kim and Mokhtarian, 2023), allowing for more informed conclusions about

the contributing factors.

As for cluster 2 which is predominantly characterized by scenarios involving AVs stopped in traffic, the variable related to slowing or stopping movement emerges as a significant factor. This variable's marginal effects demonstrate a negative correlation with the occurrence of moderate damage (-0.2053). However, the results also indicate that this variable's presence is associated with an increase in the probabilities of other damage categories. Specifically, the probabilities of minor and major damage increase by 0.1811 and 0.0075 , respectively. Meanwhile, the probability of no damage increases by 0.0167 . The dual impact of the slowing or stopping movement variable within cluster 2 highlights the complex relationship between AV behaviours and accident outcomes. On one hand, the ability to decelerate effectively may serve as a protective measure against moderate damage to AVs. This could be attributed to the vehicles' advanced sensors and control systems, which enable precise and timely responses to some traffic conditions (Sarker et al., 2020), thereby preventing or reducing the severity of collisions. On the other hand, the insufficient time to stop or the complex surrounding circumstances (e.g., the presence of obstacles or other vehicles) could lead to an escalation of damage severities (Chen et al., 2024a). This dichotomy highlights the necessity for a more granular understanding of the crash dynamics. The findings also reveal that the full-data model not only masked the existence of these disparities but also entirely concealed the pertinent variables. Conversely, the cluster-based models provided a more exhaustive and detailed interpretation of the AV crash scenarios.

The other two collision-related variables, including head-on and broadside, are found to significantly affect the damage severity in AV crashes among the combined model and cluster 2 model, which typically increase the probability of moderate or major damage and decrease the probability of none or minor damage. It is observed that the head-on indicator would increase the probability of none damage (by 0.0358 in pooled data and 0.0349 in cluster 2), moderate damage (by 0.0675 in pooled data and 0.0947 in cluster 2), and major damage (by 0.0111 in pooled data and 0.0165 in cluster 2), while decreasing the probability of minor damage (by 0.1144 in pooled data and 0.1461 in cluster 2). As for the broadside indicator specific to moderate damage, it would decrease the probability of none damage (by 0.0084 in pooled data and 0.0082 in cluster 2), minor damage (by 0.0898 in pooled data and 0.0883 in cluster 2), and major damage (by 0.0036 in pooled data and 0.0036 in cluster 2), while increasing the

probability of moderate damage (by 0.1018 in pooled data and 0.1001 in cluster 2). Additionally, the probabilities of none damage, minor damage, and moderate damage would be decreased by 0.0029, 0.0396, and 0.0098 in the pooled data, while the probabilities of major damage would be increased by 0.0523 when the broadside variable is included in the major damage utility function. This suggests that the latent class clustering analysis can effectively mitigate the corresponding heterogeneity specific to these variables. The underlying reasons for the observed effects can be attributed to several factors. Firstly, head-on collisions often involve vehicles colliding with each other at high speeds, resulting in a greater transfer of kinetic energy and subsequently causing more severe damage (Ren and Xu, 2023b). This is particularly true in the context of AVs and human-driven vehicles, where the insufficiency of driver reaction time and takeover time (Deng et al., 2024), and the potential failure of advanced collision avoidance systems may contribute to the increased likelihood of moderate and major damage. Similarly, broadside collisions, also known as T-bone accidents, occur when the front of one vehicle impacts the side of another vehicle at a perpendicular angle (Shang and Eskandarian, 2023). The impact forces from such collisions can pose a higher risk of serious vehicle damage.

5.4.2.2 Road characteristics

AV crashes that occurred on unusual road conditions tend to have low crash damage levels only in cluster 1, where the scenarios predominantly involve vehicles in motion, as indicated by an increased probability of none damage by 0.1525 and decreased probabilities of minor damage by 0.1262, moderate damage by 0.0230, and major damage by 0.0033. This pattern suggests that AVs may possess inherent capabilities that enable them to handle unexpected road conditions more effectively. This can be attributed to the vehicles' advanced sensor systems, which allow early detection and response to anomalies, and their sophisticated algorithms that facilitate real-time adjustments to maintain stability and safety (Sharara et al., 2023). These capabilities allow AVs to navigate challenging conditions, thus reducing the likelihood and severity of crashes by proactively adapting to the environment and mitigating potential hazards through precise control and decision-making processes. The findings further imply that the implementation of cluster-based modelling methodologies enriches the comprehension of AV crashes by providing additional analytical perspectives.

The intersection indicator specific to minor damage can significantly increase the probabilities of moderate damage by 0.0484 and major damage by 0.0080 in the combined model. Additionally, this variable specific to major damage would also increase the probabilities of moderate damage by 0.0094. However, this variable was not found to be significant in the cluster 1 and cluster 2 models. Intersections are inherently more hazardous due to the convergence of multiple traffic flows, the potential for conflicting movements, and a higher likelihood of unexpected maneuvers by other road users (Ashraf et al., 2021; Liu et al., 2024). To ensure safer and more reliable AV performance at intersections, it is necessary to use sensor fusion techniques to combine data from multiple sensors and roadside infrastructures to enhance the AV's situational awareness. Besides, intersection-specific operational protocols for AVs, including reduced speed limits and enhanced vigilance, can be developed and enforced. Moreover, it is crucial to train autonomous driving systems to prioritize safety at intersections, such as potentially overriding other commands if necessary and developing advanced navigation systems specifically designed for intersections, thereby effectively avoiding collisions and ensuring the overall safety of all road users in complex traffic environments. This variability also underscores the potential benefits of employing a joint modelling approach, which combines data from multiple clusters, thereby thoroughly improving the identification of significant predictors. Thus, the combination of combined and separate modelling strategies highlights the importance of considering both the heterogeneity of the data and the robustness of statistical inferences, especially in the context of small sample size AV crash data.

5.4.2.3 Vehicle characteristics

The identification of stopped in traffic indicator suggests a significant relationship between this condition and the crash damage severity. The marginal effects of this variable indicate that stopped in traffic increases the probabilities of minor, moderate, and major damage crashes by 0.1427, 0.0261, and 0.0037, respectively. This pattern implies that the risk of collision escalates as AVs are stationary within the traffic flow, potentially due to factors such as the incapability to respond to dynamic traffic situations and reduced reaction time for evasive maneuvers. It underscores the need for tailored safety interventions and motion planning algorithms that can adapt to the unique challenges posed by different traffic scenarios, particularly those would immobilize the AVs. This finding also emphasizes the value of cluster-based analysis

in identifying and addressing localized risk factors that may not be as significant in the aggregated model.

Multiple vehicles involved crashes are observed to significantly impact the likelihood of severe crash damage in cluster 2 and the combined model. Specifically, it is found to increase the likelihood of moderate and major damage crashes by 0.0877 and 0.0153 in the minor damage category of cluster 2, and it would increase the likelihood of moderate damage crashes by 0.0060 in the major damage category. Meanwhile, for the pooled data, the involvement of multiple vehicles increases the likelihood of no damage, minor damage, and moderate damage by 0.0013, 0.0177, and 0.0044, respectively, while decreasing the likelihood of major damage by 0.0234. The slight discrepancy in the impact of multiple vehicles on the crash severity between cluster 2 and the combined model could be attributed to the specific characteristics of traffic flow, vehicle dynamics, and driver behaviours. Nevertheless, the increased possibility of moderate or major damage in both groups suggests that when multiple vehicles are involved in an AV crash, the potential for more severe outcomes is heightened possibly due to the cumulative impact forces and complex collision dynamics (Zhang et al., 2024). The following safety improvement measures can be proposed to address the increased possibility of involving multiple vehicles. Firstly, conducting more rigorous crash testing and validation procedures on AVs in multi-vehicle collision scenarios is necessary. Secondly, more advanced collision avoidance systems capable of predicting and responding to such crash scenarios should be developed and implemented. Additionally, high-strength and lightweight materials can be designed and used to enhance AV crashworthiness and reduce the impact force during collisions.

5.4.2.4 Environment characteristics

With respect to the light condition, it is observed that the dark with street lights indicator in cluster 2 would increase the likelihood of minor damage by 0.0984, moderate damage by 0.0247, and major damage by 0.0032, while negatively correlating with none damage outcomes (-0.1263). As for the pooled data model, this variable would increase the likelihood of moderate damage by 0.0546 and major damage by 0.0325 for two damage categories, while showing a decrease of 0.0045 and 0.0481 for none and minor damage specific to moderate damage, and a decrease of 0.0018 and 0.0246 for none and minor damage specific to major damage. The unexpected finding

could be explained by the complex interplay between visual perception, lighting conditions, and the operational capabilities of AVs and human-driven vehicles. While street lights are generally beneficial for enhancing visibility and reducing accident risk during night-time driving, the contrast and glare created by street lights can challenge AV vision sensors and humans, potentially leading to misinterpretations of the driving environment (Yang et al., 2023). Furthermore, the specific design and performance of vehicle crash avoidance systems under varying lighting conditions may not be fully optimized (Moradloo et al., 2024), leading to increased vulnerability to moderate and major damage when street lights are present. This underscores the need for further research into how AV systems can adapt to different lighting scenarios to maintain safety and reduce crash damage severities.

Regarding the cloudy and dark without street light indicators, it is reasonable to expect that they are associated with an increased possibility of major damage outcomes by 0.0298 and 0.0429 respectively, while decreasing the possibility of none, minor, and moderate damage outcomes by 0.0017, 0.0225, and 0.0056 for cloudy, and 0.0035, 0.0335, and 0.0059 for dark without street lights. These results can be explained by the combined effects of reduced visibility and increased difficulty in perceiving the driving environment (Ren and Xu, 2023; Yan et al., 2021). Cloudy conditions can diffuse and scatter light, making it harder for human drivers and AV sensors to discern objects and road features clearly (Pandharipande et al., 2023). Similarly, under dusk, dawn or dark conditions without street lights, the absence of direct illumination can significantly impair visibility, posing a challenge for both the AV adopting a pure vision-based system and manually operated vehicles to detect and react to hazards promptly. These factors can lead to delayed response times and misjudgments, which are particularly critical in situations where rapid decision-making is required to avoid severe collisions.

5.4.2.5 Temporal characteristics

For the evening indicator, the likelihood of none damage outcome decreases by 0.0865, while minor damage, moderate damage, and major damage increase by 0.0674, 0.0169, and 0.0022 in cluster 2, respectively. In cluster 1, minor damage decreases by 0.1143, while moderate damage and major damage increase by 0.0627 and 0.0102, respectively. Crashes during the early morning decrease the likelihood of none damage by 0.0041, minor damage by 0.0393, and moderate damage by 0.0069 respectively, while major damage increases by 0.0503 in cluster 1. As for cluster 2, the possibilities

of none damage, minor damage, and moderate damage decrease by 0.0023, 0.0334, and 0.0079 respectively, while major damage increases by 0.0436. The positive correlation between AV crashes in the evening and early morning hours and more severe damage (i.e., moderate or major damage) in cluster 1 and cluster 2 can be attributed to the challenges posed by reduced visibility and adverse driving conditions during these times. As daylight diminishes, artificial lighting may not be sufficient to compensate for the loss of natural light, leading to a decrease in the ability of both human drivers and AV sensors to accurately perceive the environment (Pandharipande et al., 2023). This reduced visibility can exacerbate the detection of obstacles, pedestrians, and other vehicles. Consequently, these factors contribute to a higher frequency of driving errors and a greater propensity for severe damage during the evening and early morning hours.

The increased likelihood of more severe damage in Quarter II of cluster 2 (by 0.0820 and 0.0143 for moderate and major damage) and Quarter III of the pooled data (by 0.0024 for major damage) can be explained by the specific environmental and operational challenges associated with these periods. Quarter II typically corresponds to the late spring to early summer months, which may experience adverse weather conditions, such as heavy rainfall (Ren et al., 2024b). Similarly, Quarter III often includes the late summer to early fall months, which may also encounter weather-related challenges such as storms (Yan et al., 2021). These factors can complicate the operation of AVs, potentially leading to sensor malfunctions or misinterpretations of the driving environment. Therefore, it is crucial to upgrade the sensors used in AVs to ensure that they are more resilient and can function accurately in heavy rainfall, storms, and other adverse weather conditions. Besides, conducting extensive testing of AVs under various adverse weather conditions to identify potential challenges and improve vehicle decision-making capabilities is essential. This should include simulated environments and controlled outdoor testing to expose vehicles to a wide range of specific weather-related scenarios.

5.5 Conclusion remarks

Understanding the heterogeneity in crash patterns of AVs is of paramount importance for the development of safer autonomous transportation systems and public acceptance of AVs. To this end, a dataset comprising 702 AV collision reports in PDF format, dated by April 12, 2024, was collected from the CA DMV. To ensure the structural integrity of variables essential for detailed analytical processes, this study

integrated a time window encompassing 584 updated forms after April 2018 and excluded records utilizing the original 2013 crash form. A systematic framework for data extraction was first developed to streamline the transformation of PDF crash records into excel and comma-separated value formats, thus ensuring their compatibility with statistical software and scripting languages for subsequent analytical processes. The dataset was then augmented by the intersection characteristic and precise geographical coordinates.

Subsequently, the latent class analysis, coupled with the multinomial logit model, provided a robust framework for dissecting the heterogeneity and identifying the significant factors that impact the AV damage severity. Two distinct clusters were determined based on the statistical criteria. According to the class-conditional response probabilities associated with the explanatory variables for AV crashes, the embedded “natural breaks” based on skewed distributions of vehicle status and driving mode were identified. The first cluster comprises incidents wherein the AV was in motion at the time of the crash, constituting 99.1% of the total observations, with the majority of these crashes (58.5%) transpiring in conventional driving mode. Conversely, the second cluster predominantly includes crashes where the AV was stopped in traffic, representing 97.1% of these occurrences, with the majority of accidents (68.7%) taking place while the vehicle was in autonomous mode. This study further extends the current understanding of AV crash scenario studies.

To illustrate the significance of the latent class analysis and obtain informative insights into the factors that influence crash damage severities, three individual multinomial logit models were then constructed for the combined AV crash dataset and two identified clusters. The marginal effects were also computed to quantify each variable’s impacts. The findings reveal a significant correlation between moderate/major damage crashes and various risk factors, such as head-on, intersection, multiple vehicles, dark with street lights, dark without street lights, and early morning. The model estimation results further demonstrate that there were significant variations among the variables that contribute to the damage severity of AV crashes within two specific subclasses. Additionally, dividing the AV crash dataset into heterogeneous subsets aids in discerning key contributing factors that are not apparent when the dataset is considered as a combined entity, such as the evening indicator.

Chapter 6 Unveiling autonomous vehicle crash patterns with supplementary points of interest information: Insights from structural equation modelling

6.1 Introduction

The advent of autonomous vehicles (AVs) has been heralded as a transformative shift in modern transportation systems, promising enhanced road safety, reduced congestion, and increased mobility (Liu et al., 2019). However, despite these potential benefits, AVs continue to face persistent safety challenges, as evidenced by the fact that they are not immune to accidents (California Department of Motor Vehicles, 2024). Recent studies indicate that AV crashes, while distinct from conventional vehicle accidents predominantly caused by human error (World Health Organization, 2020), exhibit unique patterns influenced by external environmental factors, technological limitations, and behavioral responses of human drivers sharing the road (Chen et al., 2024; Liu et al., 2024b; Ren and Xu, 2025). Understanding the novel AV-involved crash pattern is imperative to ensure the safe deployment of AVs in increasingly dynamic urban environments and promote the integration of AVs into existing transportation systems.

A growing body of literature underscores the influence of the building environment on traffic safety (Amini et al., 2022), yet its impact on AV operations remains underexplored. Points of interest (POI) attributes—such as intersections, pedestrian zones, and nearby public fatalities—could introduce heterogeneous traffic conditions that challenge AV perception systems (Kuo et al., 2024). Prior studies have established correlations between POI characteristics and conventional human-driven vehicle crashes (Merlin et al., 2020; Soto et al., 2022), but whether these relationships persist in AV-involved collisions is still unclear. It can be speculated that building environment elements would influence AV performance in ways that diverge from human-driven vehicles. Bridging this knowledge gap through a holistic analysis of AV

crash determinants is essential for developing context-aware safety frameworks tailored to AV operations and safety.

Mediation analysis offers a rigorous framework to quantify indirect causal pathways (Wang et al., 2020), elucidating latent mechanisms through which mediation variables influence AV crash outcomes. In this regard, the structural equation modelling (SEM) approach is gaining traction for modelling traditional human-driven vehicle crash severity due to its ability to address complex interactions among multiple dependent and independent variables, including indirect or latent relationships (Najaf et al., 2017). For example, Xu et al. (2018a) utilized the SEM to convert traffic-related variables into independent latent factors, establishing interrelationships between key determinants and crash risks. Their findings highlighted that the path in SEM can effectively capture both direct and indirect effects of traffic variables on traffic crash risks. Dong et al. (2022) utilized the multigroup SEM to identify latent driving behaviour indicators and investigate their relationships with crash damage severities and other independent variables during the COVID-19 pandemic. The employed SEM approach also demonstrated superior model fit compared to traditional probit models. Failure to account for the aforementioned indirect relationships may result in Type I errors (false positives) in identifying risk factors or, more critically, Type II errors (false negatives) that overlook genuine safety threats for AV crashes (Washington et al., 2020). Therefore, the adoption of SEM in AV crash outcome analysis would hold substantial promise and can offer a robust framework to unravel the complex interdependencies that shape AV safety outcomes.

6.2 Data collection and processing

Figure 6.1 shows the flowchart of CA DMV AV crash data collection, key variable extraction, POI characteristic augmentation, and variable conversion processes. First of all, the AV crash records used in this study were collected from the CA DMV (California Department of Motor Vehicles, 2024). This study then developed a highly automatic

and fast data extraction framework to transform AV crash records from PDF format into comma-separated value (CSV) format. This transformation enables seamless integration with scripting languages and statistical software for advanced quantitative examination. Following feature selection and removal of records with missing values, the final analytical dataset comprised 584 AV collision cases with detailed crash determinants and outcomes. Given the absence of precise geospatial coordinates for each collision site in CA DMV records, we first extracted the specific crash addresses from each record and then utilized the Google Geocoding API to convert these addresses into exact latitude and longitude coordinates. Given the necessity for obtaining detailed building environment features, which are not fully provided in the AV collision records, we further collected the POI characteristics with the Overpass API (Olbricht, 2011). The details on traffic signals, zebra crossings, and the nearest distance and counts of various public facilities within a 500-meter radius of each accident site were collected. Specifically, public facilities, including entertainment venues, medical facilities, educational facilities, recreational areas, and bus stops along with their distances from the accident location were collected. We also gathered details about the number of lanes, the presence of bike paths, and the type of road where the accident occurred, such as rural streets, freeways, or urban arterial roads. This supplementary dataset is crucial for understanding how nearby traffic infrastructures and public facilities influence AV crash outcomes. By integrating these detailed POI characteristics into the dataset, we aim to provide a holistic understanding of the environmental context surrounding each AV-involved accident.

To effectively integrate POI characteristics and crash record data into the SEM framework, the included explanatory variables were meticulously defined. The categorical independent variables were divided into two categories, including crash characteristics and environment characteristics. To discern the determinants of AV crashes, crash damage severities (including major damage, moderate damage, minor damage, and none damage) were set as independent variables. Table 6.1 provides the

detailed descriptive statistics of these categorical explanatory variables.

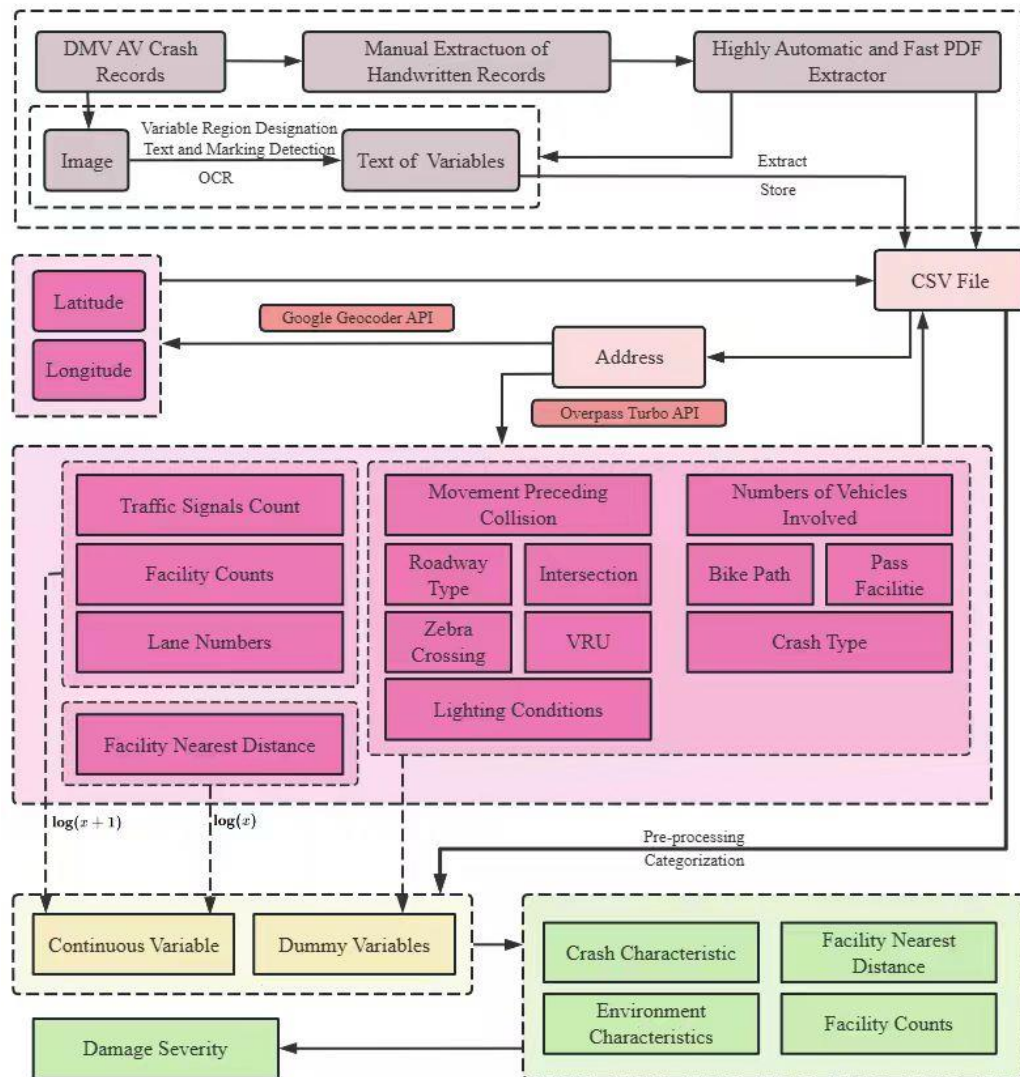


Figure 6.1 Flowchart of CA DMV AV crash data extraction and augmentation processes.

Additionally, continuous variables (such as facility nearest distance) and count variables (such as traffic signal count) were respectively transformed using $\log x$ and $\log(x+1)$ to mitigate long-tail distributions (Washington et al., 2020). Table 6.2 presents the descriptive statistics of the facility nearest distance and count before and after the data conversion. Apart from the mean and standard deviation, the skewness and kurtosis of these variables were also calculated to evaluate the normality assumption essential for the subsequent SEM analysis (Shirley and Smidts, 2018). The results reveal varying degrees of deviation from normal distribution across different variables. Specifically, variables with the absolute value of skewness less than 1 or kurtosis less than 3 were

considered to have minor deviations, causing negligible impact on SEM outcomes. Variables displaying moderate deviations (skewness between 1-2 or kurtosis between 3-7) potentially affected the model fit and parameter estimations. Moreover, variables with absolute skewness > 2 or kurtosis > 7 exhibit severe deviations and would substantially distort SEM results. It can be observed in Table 7.2 that all facility nearest distance and count variables meet the normality assumption essential for the analysis.

Table 6.1 Descriptive statistics of categorical explanatory variables (N=584 crashes).

Category	Variable	Variable type	Frequency	Percentage (%)
Dependent variables	Damage severity	Major	15	2.568
		Moderate	89	15.240
		Minor	432	73.973
		None	48	8.219
Crash characteristics	Crash type	Head on	47	8.048
		Side swipe	145	24.829
		Rear end	279	47.774
		Broadside	46	7.877
		Hit object	39	6.678
		Other collision categories	28	4.795
	Numbers of vehicles involved	Single	82	14.041
		Two	490	83.904
		Multiple	12	2.055
	Vulnerable Road User (VRU) ¹	VRU involved	35	5.993
		No VRU involved	549	94.007
	Movement preceding collision	Stopped	251	42.979
		Proceeding straight	168	28.767
		Making turns ²	56	9.589
		Backing	20	3.425
		Slowing/Stopping	47	8.048
		Parked/Parking	22	3.767
		Other movements	20	3.425
Environment characteristics	Lighting conditions	Daylight	399	68.322
		Dark with streetlights ³	165	28.253
		Dark without streetlights	20	3.425
	Intersection	At intersection	543	92.980
		Not at intersection	41	7.020
	Zebra crossing	With zebra crossing	121	20.719
		No zebra crossing	463	79.281
	Bike path	With bike path	203	34.760
		No bike path	381	65.240
	Pass facility	With pass facility	13	2.226
		No pass facility	571	97.774
	Roadway type	Urban	384	65.753
		Freeway	25	4.281
		Rural	170	29.110
		Other road types	5	0.856

¹Vulnerable Road User (VRU) refers to pedestrian, bicyclist, or scooter.

²Making turns includes making right turn, making left turn, and making U turn.

³Dark without street lights refers to dark without street light, dawn, and dusk categories.

Table 6.2 Descriptive statistics of facility nearest distance and count before and after the data conversion (N=584 crashes).

Categories	Variables	Before data conversion				After data conversion			
		Mean	S.D.	Skewness	Kurtosis	Mean	S.D.	Skewness	Kurtosis
Facility nearest distance	Entertainment nearest distance	193.476	17542.750	193.476	17542.750	3.396	5.845	-0.529	-1.453
	Medical facility nearest distance	253.457	16573.967	253.457	16573.967	2.981	7.356	-0.133	-1.891
	Education service nearest distance	319.865	13248.098	319.865	13248.098	1.748	6.953	0.866	-1.217
	Industrial land nearest distance	5.558	1939.432	5.558	1939.432	0.133	0.658	1.173	3.675
	Recreational facility nearest distance	296.373	13209.631	296.373	13209.631	0.594	3.005	0.600	4.845
	Living facility nearest distance	214.721	17420.156	214.721	17420.156	4.195	4.394	-1.234	0.012
	Food shopping nearest distance	130.756	14407.269	130.756	14407.269	3.998	2.630	-1.142	0.861
	Office area nearest distance	170.660	15788.524	170.660	15788.524	3.983	3.985	-1.167	0.005
	Bus stop nearest distance	98.256	8076.664	98.256	8076.664	4.106	1.253	-1.035	2.216
Facility count	Entertainment count	0.600	0.263	0.600	0.263	1.388	1.393	0.160	-1.399
	Medical facility count	1.320	2.962	1.320	2.962	0.621	0.410	0.544	-0.882
	Education service count	0.400	0.452	0.400	0.452	0.247	0.151	1.191	0.103
	Industrial land count	0.030	0.032	0.030	0.032	0.020	0.014	1.033	3.006
	Recreational facility count	0.110	0.109	0.110	0.109	0.076	0.049	0.670	5.525
	Living facility count	5.340	44.336	5.340	44.336	1.396	0.907	0.178	0.774
	Food shopping count	44.910	2551.967	44.910	2551.967	3.065	2.185	-0.685	-0.378
	Office area count	11.550	205.912	11.550	205.912	1.867	1.521	-0.079	-1.084
	Bus stop count	25.650	322.536	25.650	322.536	2.997	0.753	-1.100	1.421
	Traffic signal count	0.990	1.935	0.990	1.935	0.504	0.328	0.765	-0.485
	Lane numbers	2.260	1.610	2.260	1.610	1.087	0.223	-1.064	0.716

6.3 Methods

The SEM offers significant advantages in evaluating direct variables and mediation pathways. Its capability to model cascading effects overcomes three critical limitations of traditional regression approaches (Bowen and Guo, 2011): (1) testing hypothesized causal chains, (2) accounting for measurement error in explanatory variables, and (3) simultaneously estimating multiple pathways, including both direct and mediation effects of factors on AV crash outcomes. In our study, it is hypothesized that the AV crash severity outcomes are directly or indirectly influenced by different kinds of characteristics in Table 7.1 and Table 7.2. To this end, we construct two kinds of paths, i.e., direct paths (the crash damage severity affected by multiple characteristics) and indirect paths which are used to identify mediator variables. The structural model of the SEM is formulated as:

$$y_i^* = \sum_{q=1}^n \beta_q x_q + \sum_{k=1}^m \gamma_k z_k + \epsilon_{y_i} \quad (6.1)$$

$$z_k = \sum_{l=1}^p \alpha_l x_l + \epsilon_{z_k} \quad (6.2)$$

where i is the index for different AV crash damage severity outcomes (e.g., none, minor, moderate, and major); y_i^* is the probability of the crash severity for outcome i . If $y_i^* > \phi$, then $y_i = 1$ (indicating occurrence of the corresponding crash severity); otherwise, $y_i = 0$. A threshold value of $\phi = 0.5$ is used to determine the crash severity outcome. x_q represents independent variables for crash severity i . β_q is the coefficient corresponding to the independent variable x_q . z_k represents mediator variables. γ_k is the coefficient of the mediator variable z_k . α_l is the coefficient of the independent variable x_l that influences the mediator variable z_k . ϵ_{y_i} and ϵ_{z_k} are normally distributed error terms.

Maximum Likelihood Estimation (MLE) was used to estimate the parameters of the proposed SEM with mediation path in our study. It is robust and effective in estimating models with mixed continuous and categorical variables. Besides, it can yield accurate parameter estimates in small sample sizes, such as the 584 observations in our AV crash dataset, thus it is well-suited for modelling AV crash patterns.

To comprehensively evaluate the performance of the SEM, a series of assessment

indices were employed. The chi-square (χ^2) test was utilized to assess the goodness-of-fit of the SEM. The degree of freedom (df) constitutes an integral part of calculating the χ^2 statistic, reflecting the number of parameters that can freely vary in the model (Yuan, 2005). The χ^2 value should be as small as possible, and a p-value smaller than 0.05 indicates an adequate model fit. Besides, the Root Mean Square Error of Approximation (RMSEA) was also employed to measure the degree of discrepancy between the model and the AV crash data (Rigdon, 1996):

$$RMSEA = \sqrt{\frac{\chi^2 - df}{df(N - 1)}} \quad (6.3)$$

where N is the number of AV crash observations. A RMSEA less than 0.08 suggests a reasonable model fit.

The other two widely used fit indices for SEM, including comparative fit index (CFI) and Tucker Lewis index (TLI), were also employed (Kim, 2023). They can reveal the impacts of model complexity, thus providing a more nuanced evaluation of model performance (Shi et al., 2019). They range from 0 to 1, with values closer to 1 indicating a better fit. Additionally, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were also employed in our study to evaluate the goodness of the final SEM model (Dziak et al., 2012):

$$AIC = -2LL(\beta) + 2K \quad (6.4)$$

$$BIC = -2LL(\beta) + K * \ln(N) \quad (6.5)$$

where $LL(\beta)$ is the log-likelihood at convergence, K is the number of parameters in the estimated model.

In this study, the semopy package in Python was used to estimate the SEM model (Igolkina and Meshcheryakov, 2020). Figure 6.2 shows the flowchart of constructing SEM with mediation pathways. Firstly, a single SEM was developed in this study, which incorporated direct causal pathways from various influencing factors to AV crash damage severity outcomes. The influencing factors were also analysed to identify potential mediator variables. Subsequently, if any pathway within the model failed to demonstrate a statistically significant relationship, it was then removed and the model was re-estimated. Following this procedure, the model's goodness of fit was evaluated and compared against reasonable thresholds. Ultimately, this study retained the SEM model that demonstrates the best fit indices and reasonable interpretability

(Peng et al., 2023).

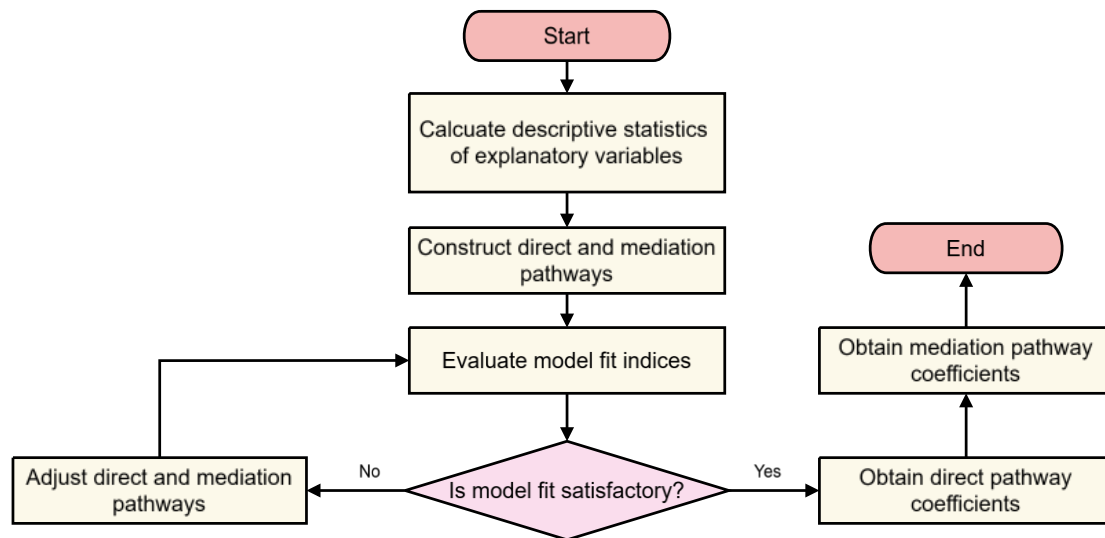


Figure 6.2 Flowchart of constructing the SEM with mediation pathways.

6.4 Results and discussions

6.4.1 Model assessment

Table 6.3 presents the goodness-of-fit statistics of the final SEM model. It can be seen that the constructed model demonstrates good performances across multiple fit indices. Both the CFI (0.794) and TLI (0.768) reflect a satisfactory model fit, while the RMSEA (0.076) also falls within the reasonable threshold (0.05-0.08). Furthermore, the final SEM framework demonstrates strong model performance and robustness, as evidenced by its competitive AIC (212.033) and BIC (698.547) values when compared to alternative intermediate models.

Table 6.3 The goodness-of-fit statistics of the SEM.

Goodness-of-fit metric	Value of the SEM framework
CFI	0.794
TLI	0.768
RMSEA	0.076
AIC	212.033
BIC	698.547

6.4.2 Direct and mediation pathway assessment

The SEM frameworks in Figure 6.3 and Figure 6.4 respectively illustrate the direct pathways and mediation pathways between determinants and AV crash outcomes. Table 6.4 and Table 6.5 further demonstrate the detailed estimation results of direct and mediation pathway estimations. The model parameters (coefficients and p-values) of

explanatory variables were used to assess the impacts of determinants on AV crash damage severities and types.

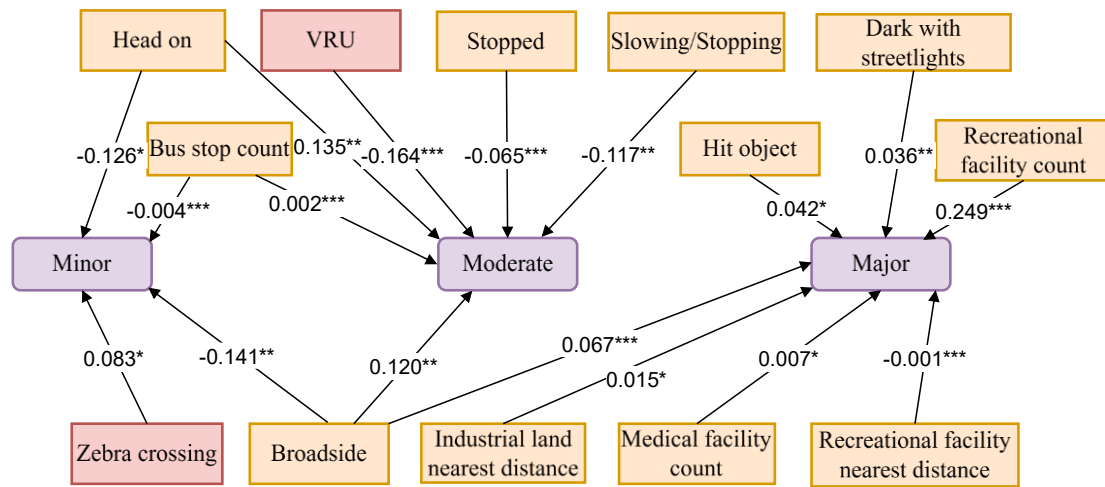


Figure 6.3 Direct pathways of the SEM framework.

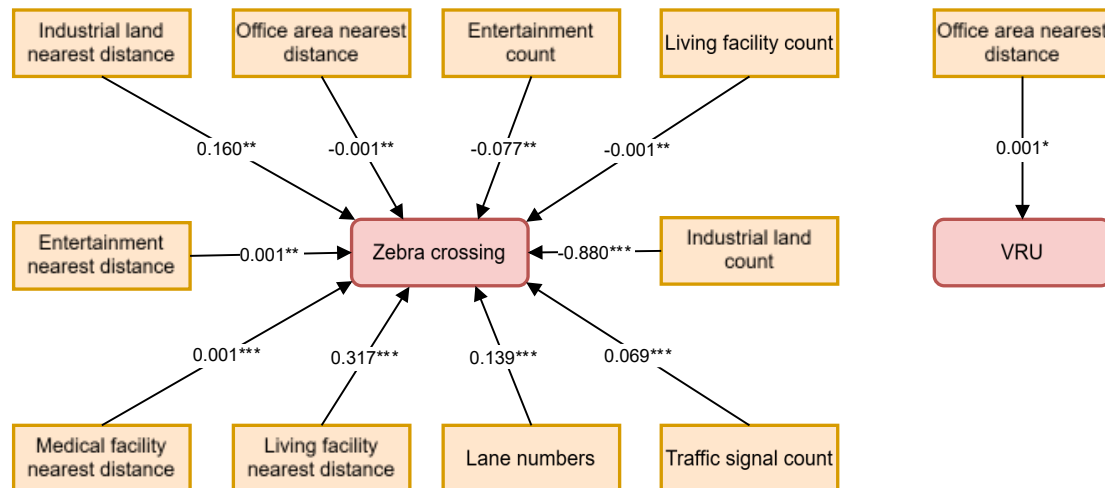


Figure 6.4 Mediation pathways of the SEM framework.

The SEM employed in this study provides a robust framework to disentangle the complex interdependencies among crash characteristics, environment characteristics, and supplementary POI characteristics in shaping AV-involved crash damage severities. The following parts will systematically interpret the mechanisms underlying both direct and mediation causal pathways. The direct effects of multiple characteristics on AV crash damage severities will be interpreted first. Subsequently, we will explore the mediation pathways, examining how mediator variables indirectly modulate final damage severity outcomes.

Table 6.4 Estimation results of direct pathways for AV crash damage severities.

No.	Independent variable	Direct pathway	β	p-value
1	Head on	Head on=>Minor	-0.126*	0.055
2		Head on=>Moderate	0.135**	0.011
3	Broadside	Broadside=>Minor	-0.141**	0.032
4		Broadside=>Moderate	0.120**	0.027
5		Broadside=>Major	0.067***	0.005
6	Hit object	Hit object=>Major	0.042*	0.096
7	VRU	VRU=>Moderate	-0.164***	0.009
8	Stopped	Stopped conditions=>Moderate	-0.065**	0.040
9	Slowing/Stopping	Slowing/Stopping=>Moderate	-0.117**	0.032
10	Dark with streetlights	Dark with streetlights=>Major	0.036**	0.013
11	Zebra crossing	Zebra crossing=>Minor	0.083*	0.069
12	Recreational facility nearest distance	Recreational facility nearest distance =>Major	-0.001***	0.002
13	Industrial land nearest distance	Industrial land nearest distance =>Major	0.015*	0.084
14	Medical facility count	Medical facility count=>Major	0.007*	0.052
15	Recreational facility count	Recreational facility count=>Major	0.249***	<0.001
16	Bus stop count	Bus stop count=>Minor	-0.004***	<0.001
17		Bus stop count=>Moderate	0.002***	0.004

***, **, and * represent significance at the 99 %, 95 %, and 90 % confidence level.

Table 6.5 Estimation results of mediation pathways for mediator variables.

No.	Mediator variable	Mediation pathway	β	p-value
1	Zebra crossing	Entertainment nearest distance=>Zebra crossing	0.001**	0.013
2		Medical facility nearest distance=>Zebra crossing	0.001***	0.006
3		Industrial land nearest distance=>Zebra crossing	0.160**	0.019
4		Living facility nearest distance=>Zebra crossing	0.317***	<0.001
5		Office area nearest distance=>Zebra crossing	-0.001**	0.027
6		Entertainment count=>Zebra crossing	-0.077**	0.011
7		Industrial land count=>Zebra crossing	-0.880***	0.005
8		Living facility count=>Zebra crossing	-0.001**	0.017
9		Traffic signal count=>Zebra crossing	0.069***	<0.001
10		Lane numbers=>Zebra crossing	0.139***	<0.001
11	VRU	Office area nearest distance=>VRU	0.001*	0.057

***, **, and * represent significance at the 99 %, 95 %, and 90 % confidence level.

6.4.3 Analysis of direct pathways

6.4.3.1 Crash characteristics

The estimation results reveal a dual AV severity pattern in head-on collisions, characterized by a decreased likelihood of minor damage severities ($\beta = -0.126$, $p = 0.055$) and an increased likelihood of moderate damages ($\beta = 0.135$, $p = 0.011$). This dichotomy arises from the following intertwined mechanisms. Firstly, head-on collisions inherently involve high kinetic energy due to the combined velocities of

colliding entities (Ren and Xu, 2023b), often exceeding mechanical damage thresholds for minor damage even when autonomous emergency braking (AEB) systems partially mitigate crash impacts (Zheng et al., 2025). For instance, in high-speed scenarios (e.g., closing speeds >60 km/h), preemptive AV interventions may either fully avert low-severity crashes or fail to sufficiently dissipate energy, leading to unavoidable collisions that bypass minor outcomes. Additionally, when crashes occur, AVs' evasive strategies—such as steering into partial-overlap configurations—prioritize fatality prevention by redirecting forces away from critical occupant zones. However, this redirection unevenly distributes residual energy across the vehicle frame, amplifying secondary damage mechanisms. Furthermore, structural limitations exacerbate these risks: modern crumple zones, optimized for controlled energy absorption in full-overlap crashes, may underperform in partial-overlap scenarios common with AV steering interventions (Kurpisz et al., 2023). This mismatch concentrates forces on narrower vehicle sections, overwhelming localized energy-absorption capacities and transferring higher deceleration forces to vehicle structures.

Broadside collisions exhibit a pronounced negative relationship with minor damages ($\beta = -0.141$, $p = 0.032$). Meanwhile, the progressive escalations to moderate ($\beta = 0.120$, $p = 0.027$) and major damages ($\beta = 0.067$, $p = 0.005$) underscore the limitations of lateral safety systems (Zhu et al., 2023), in which side airbags and reinforced frames may fail to mitigate trauma when crashes occur at acute angles or speeds exceeding sensor-response thresholds (Ren et al., 2024a), particularly in intersection scenarios where AVs' lateral detection fields are constrained. This pattern may also arise from the structural inadequacy of vehicle side panels, which lack crumple zones to dissipate low-impact forces, resulting in concentrated energy transfer to occupants and exacerbating AV damage severity even in nominally minor T-bone collisions. Therefore, in addition to improving the perception and control algorithms, AV enterprises should also strengthen the side protection structure of the body for the risk of broadside collision.

The significant positive association between AV hit-object collisions and major damages ($\beta = 0.042$, $p = 0.096$) mainly stems from high-speed impacts with rigid infrastructure (e.g., utility poles or concrete barriers), where localized force penetration overwhelms AV crumple zones, or from perception system failures in classifying irregular static objects (e.g., construction debris) (Kabir et al., 2025), leading to

unmitigated collisions that bypass energy-absorption thresholds of AVs.

The negative path from VRU involvement to moderate damage severities ($\beta = -0.164$, $p = 0.009$) indicates that AV-pedestrian/cyclist/scooter collisions disproportionately result in low-severity outcomes, potentially due to AVs' superior detection capabilities—LiDAR and cameras enable earlier VRU recognition (Silva et al., 2024), triggering aggressive braking to reduce impact speeds below moderate-injury thresholds. Additionally, AVs typically adopt conservative behaviours and VRUs may exhibit risk-compensatory behaviours (e.g., hesitating near AVs) (Ren and Xu, 2025), further lowering the collision energy.

Stopped conditions ($\beta = -0.065$, $p = 0.040$) and slowing/stopping maneuvers ($\beta = -0.117$, $p = 0.032$) both negatively correlate with moderate damages, highlighting AVs' proficiency in low-speed urban environments, where their precise torque control and collision-avoidance algorithms minimize kinetic energy transfer during stop-and-go traffic (Feng et al., 2021), confining harm to moderate outcomes such as bumper contacts.

6.4.3.2 Environment characteristics

The positive association between dark with streetlights and AV major damage ($\beta = 0.036$, $p = 0.013$) suggests that streetlight conditions may paradoxically elevate risks of severe structural harm. This phenomenon probably stems from sensor performance degradation under artificial lighting. Specifically, LiDAR and camera systems—critical for obstacle detection—are susceptible to glare and specular reflections from wet roads or metallic surfaces (Wang and Li, 2023), thus reducing detection range and delaying collision avoidance responses. For example, glare-induced blind spots could obscure static obstacles like curbs or debris. Concurrently, human drivers in lit environments may over trust AV capabilities (Lu et al., 2022), adopting riskier behaviours such as higher speeds or reduced following distances, which amplify collision energy when unexpected obstacles emerge. These dual mechanisms—sensor limitations and behavioural overcompensation—collectively explain the elevated major damage risks in seemingly safe nighttime conditions.

The positive link ($\beta = 0.083$, $p = 0.069$) between zebra crossings and minor AV damage reflects the prevalence of low-speed collisions in pedestrian-dense zones. AVs prioritize abrupt braking to avoid pedestrians, often resulting in rear-end collisions or

curb strikes at velocities below 15 km/h. It can be explained that as a clear sign of traffic rules, AVs' algorithm at zebra crossings is often accompanied by rules (such as slowing down and widening the margin of safety) for giving way to VRUs (e.g. pedestrians). Previous studies show that AVs detect the zebra crossings, even if there is no pedestrian on the zebra crossings, AV will also reduce the speed by default to reduce the collision possibility (Rezwana and Lownes, 2024; Tian et al., 2023). This pattern aligns with ethical algorithms that sacrifice minor cosmetic harm to prevent catastrophic pedestrian impacts, underscoring the trade-offs inherent in urban AV operation protocols.

6.4.3.3 Facility nearest distance and count characteristics

The negative relationship between the nearest distance to recreational facilities and major damage ($\beta = -0.001$, $p = 0.002$), as well as the strong positive relationship between recreational facility count and major damage ($\beta = 0.249$, $p < 0.001$), underscore the crash risks of high-activity leisure hubs. Crowded parks and event venues generate erratic pedestrian and cyclist movements (e.g., children darting, scooters diverging), forcing AVs into frequent evasive maneuvers. These maneuvers increase the probability of collisions with fixed infrastructure — such as lampposts or bike racks — that concentrate forces on sensor arrays or suspension components, exceeding their structural tolerance thresholds. The compounding effect of high pedestrian volume and constrained navigation space exacerbates these risks (Hou et al., 2023), often overwhelming AV path-planning algorithms.

Remote industrial areas exhibit heightened major damage risks ($\beta = 0.015$, $p = 0.084$) due to interactions with heavy vehicles operating in unstructured environments (Ren et al., 2024c). AVs navigating peripheral industrial corridors encounter unpredictable maneuvers from trucks and forklifts—such as sudden lane encroachments or unmarked loading zone stops—which could challenge predictive algorithms and increase the likelihood of high-speed lateral impacts.

The positive correlation between the medical facility counts and major damage ($\beta = 0.007$, $p = 0.052$) highlights the risks of navigating congested hospital zones. Frequent emergency vehicle movements, double-parked cars, and erratic pedestrian flows create chaotic traffic patterns that strain AV decision-making algorithms (Azimian et al., 2021). Sudden stops or swerves to avoid ambulances may redirect collision forces to vulnerable subsystems.

Frequent bus stops decrease the possibility of minor damage ($\beta = -0.004$, $p < 0.001$) and increase the possibility of moderate damage ($\beta = 0.002$, $p = 0.004$) through unstable speeds and repetitive lateral interactions with buses (Phillips et al., 2021). AVs navigating bus-dense zones face abrupt lane incursions during merges or passenger boarding, triggering sudden lateral conflicts. These collisions stress vehicle structures such as door panels or side-mounted LiDAR sensors, inducing misalignments or calibration drifts classified as moderate damage (Becker et al., 2021). The dual effect—speed reduction versus lateral complexity—illustrates the complexities in AV navigation near transit hubs.

6.4.4 Analysis of mediating pathways

The mediation analysis within the SEM framework reveals how supplementary POI features indirectly influence AV damage severities through zebra crossings and VRU interactions. Below, we integrate these path coefficients with mechanistic explanations to provide a comprehensive understanding of these mediation effects.

6.4.4.1 Zebra crossing as a mediator variable

The SEM identifies the zebra crossing as a critical mediator through which multiple POI characteristics indirectly affect AV crash damage outcomes.

(1) Entertainment nearest distance $\Rightarrow$ Zebra crossing ($\beta = 0.001$, $p = 0.013$)

The nearest distance to entertainment venues (e.g., theaters, stadiums) correlates with a marginally increased likelihood of zebra crossing presence, probably due to urban planning efforts to enhance pedestrian access in leisure hubs (Yadav and Kumari, 2024). However, these crossings often exist in environments with erratic traffic patterns—such as nighttime crowds or ride-hailing drop-offs—where AVs face conflicting sensor inputs, thus increasing the possibility of AV crashes. For example, glare from neon signage or headlights in entertainment districts may degrade camera-based pedestrian detection, forcing abrupt braking maneuvers.

(2) Medical facility nearest distance $\Rightarrow$ Zebra crossing ($\beta = 0.001$, $p = 0.006$)

The positive mediation between medical facility proximity and zebra crossing presence reflects prioritized pedestrian infrastructure near hospitals (Azimian et al., 2021). However, frequent emergency vehicle movements (e.g., ambulances bypassing signals) create unpredictable crossing behaviours. AVs navigating these zones may

misinterpret priority rules, execute sudden stops or swerve to yield to emergency traffic.

(3) Industrial land nearest distance => Zebra crossing ($\beta = 0.160$, $p = 0.019$)

Proximity to industrial zones correlates with increased zebra crossing presence. Industrial areas often feature irregular crossing designs (e.g., widened crossings for truck access) that confuse AV perception systems (Ren et al., 2024c). For instance, non-standard striping patterns or faded markings in these zones may delay LiDAR-based recognition, forcing abrupt stops that induce rear-end collisions with minor bumper damage. At the same time, it is crucial to consider that unconventional movement patterns of industrial vehicles, such as forklifts, exceed AV training data distribution (California Department of Motor Vehicles, 2024), which makes AV more difficult to deal with the industrial area.

(4) Living facility nearest distance => Zebra crossing ($\beta = 0.317$, $p < 0.001$)

Residential areas exhibit dense zebra crossing networks to accommodate pedestrian flows. While this enhances safety, clustered crossings in narrow streets create “stop-and-go” traffic patterns. AVs navigating these zones frequently engage in low-speed braking maneuvers, thus increasing the possibility of AV crashes.

(5) Office area nearest distance => Zebra crossing ($\beta = -0.001$, $p = 0.027$)

The nearest distance to office districts slightly reduces zebra crossing presence, as urban designs in commercial hubs often prioritize underground walkways or skybridges to segregate pedestrian and vehicular traffic. This infrastructure preference creates a mismatch for AVs reliant on ground-level sensor data: algorithms may misinterpret sparse above-ground pedestrian activity.

(6) Entertainment count => Zebra crossing ($\beta = -0.077$, $p = 0.011$)

Regions with high entertainment venue density exhibit reduced zebra crossing prevalence, reflecting urban planning compromises that favor vehicular throughput in nightlife and commercial clusters (Soltani and Roohani Qadikolaei, 2024). AVs navigating these zones may encounter unmarked or informally designated crossings, where delayed detection of jaywalkers—amidst visual clutter from digital billboards or crowded sidewalks—could force abrupt braking and increase the crash risk.

(7) Industrial land count => Zebra crossing ($\beta = -0.880$, $p = 0.005$)

Regions with numerous industrial facilities show reduced zebra crossing presence,

reflecting zoning policies that deprioritize pedestrian infrastructure in freight-dominated areas. AVs operating in these zones encounter unmarked crossings, leading to erratic braking behaviours when detecting jaywalkers.

(8) Living facility count $\Rightarrow$ Zebra crossing ($\beta = 0.001$, $p = 0.017$)

The count of living facilities exhibits a positive association with zebra crossing prevalence, creating a cascading risk scenario for AVs. This relationship manifests through three sequential mechanisms. First, residential POI concentration increases pedestrian flow and crossing frequency, necessitating additional zebra crossings as traffic calming measures. Second, the resulting road environment complexity forces AV perception systems to allocate disproportionate computational resources to non-critical object classification (Ghosh et al., 2023). Finally, the consequent “stop-and-go” driving patterns elevate AV collision risks due to reduced safety margins for reaction time and sensor occlusion from frequent pedestrian-vehicle interactions.

(9) Traffic signal count $\Rightarrow$ Zebra crossing ($\beta = 0.069$, $p < 0.001$)

High traffic signal density often coincides with marked crosswalks at intersections. This configuration creates an algorithmic conflict for AVs, where pedestrian right-of-way compliance often supersedes optimal deceleration process, resulting in abrupt stops that compromise safety margins.

(10) Lane numbers $\Rightarrow$ Zebra crossing ($\beta = 0.139$, $p < 0.001$)

The positive association between lane numbers and zebra crossing prevalence reflects urban road design principles where wider multi-lane roads require more frequent pedestrian crossings for safe traversal, thus impact the likelihood of AV crash risks.

6.4.4.2 VRU as a mediator variable

The nearest distance to office areas mediates VRU-related AV damage ($\beta = 0.001$, $p = 0.057$) through altered pedestrian traffic patterns. Office hubs generate concentrated commuter flows during peak hours, increasing pedestrian density at crosswalks. Therefore, the urban planners should implement targeted interventions, such as developing segregated pedestrian-vehicle pathways in office zones using physical barriers or elevated walkways (Arellana et al., 2022), and installing smart crosswalk systems in office districts that integrate with existing traffic signals and vehicle-to-

infrastructure communication networks (Sanguino et al., 2024).

6.5 Conclusion remarks

In this study, we expand the AV crash analysis by incorporating supplementary POI characteristics, thus providing a novel perspective on environmental and contextual factors influencing AV incidents. Beyond extracting information from the original AV collision records, this study further supplemented the dataset with precise geographic coordinates for each AV collision site. Subsequently, the POI characteristics were collected using python scripts interacting with the Overpass API, capturing details on road environment characteristics and multiple public facility distributions. This enriched dataset provides a comprehensive view of the building environment context for each AV-involved crash, supporting a more insightful analysis. Details on traffic signals, zebra crossings, the number of lanes, presence of bike paths, road types, and the nearest distance/counts of various public facilities (such as entertainment facilities, medical facilities, educational facilities, and bus stops) within a 500-meter radius of each AV crash site were collected. The categorical independent variables were then divided into crash characteristics and environment characteristics. Meanwhile, continuous variables (such as facility nearest distance) and count variables (such as traffic signal count) were respectively transformed using $\log x$ and $\log (x+1)$ to mitigate long-tail distributions. The AV crash damage severities (including major damage, moderate damage, minor damage, and none damage) were designated as the independent variables.

A SEM framework was subsequently used to disentangle the direct and mediation effects of multiple factors that influence AV crash damage severity outcomes. The direct effects of significant variables on AV crash damage severities were explored first. The results indicate that AV crash patterns are intricately shaped by collision dynamics, environmental conditions, and supplementary POI information. Head-on collisions prioritize the moderate damage over minor outcomes due to high-energy impacts and partial-overlap steering strategies that redistribute forces to vulnerable subsystems. Broadside collisions escalate more severe severity owing to inadequate side-panel energy absorption, while hit-object crashes correlate with major damage from rigid infrastructure impacts overwhelming crumple zones. Environmental factors further modulate AV crash risks. Specifically, dark with streetlights paradoxically elevate major damage via sensor glare and human risk compensation, while recreational POIs amplify

collision severity in crowded zones due to erratic pedestrian movements. Moreover, proximity to recreational facilities and frequent bus stops also increase the possibility of more severe damages. These results indicate that high-activity zones (such as medical and recreational hubs) could generate unpredictable interactions and traffic complexities that exceed AV predictive capacities, thus inducing more severe crash damage outcomes. Besides, AVs' algorithmic trade-offs—prioritizing pedestrian safety at zebra crossings or avoiding catastrophic outcomes in industrial corridors—highlight systemic tensions between safety protocols and AV structural resilience. These findings underscore the necessity of integrating POI-aware navigation algorithms, context-sensitive infrastructure designs, and enhanced lateral protection to align AV operational safety with real-world environmental complexities.

The mediation pathways of factors influencing AV crash outcomes were also explored in this study. The findings reveal the significant roles of two mediator variables, including zebra crossings and VRU. Zebra crossings act as critical mediators through which POI distributions indirectly shape AV crash damages. Proximity to industrial zones and residential areas increases the possibility of zebra crossing presence. Conversely, dense entertainment or industrial clusters reduce crossing prevalence, forcing AVs into erratic stops at crossings. Infrastructure rigidities—such as signalized intersections and multi-lane roads—exacerbate algorithmic conflicts, prioritizing abrupt pedestrian stops over smooth deceleration. Meanwhile, VRU interactions near office hubs mediate damage through peak-hour pedestrian surges. To mitigate these risks, adaptive infrastructure (e.g., context-aware crossings) and vehicle-to-infrastructure communication protocols must harmonize POI-driven pedestrian flows with AV operational constraints. As such, mediation pathways aid in discerning key contributing factors that do not directly affect AV crash damage severity outcomes.

Chapter 7 Association rule mining of damage severities in autonomous vehicle rear-end crashes with supplementary built environment data

7.1 Introduction

Rear-end crashes have been identified as one of the most pressing safety concerns associated with AVs, accounting for nearly half of AV-related traffic crashes and often leading to severe damage outcomes (Xu et al., 2019). Despite the growing interest in AV safety, empirical research on rear-end crash mechanisms remains limited due to the novelty of AV technologies and data scarcity (Liu and Feng, 2024). Existing research has primarily relied on simulation data (Feng et al., 2023), small-scale real-world crash records (Liu et al., 2024a; Ren and Xu, 2025; Zhu et al., 2023), reconstructed scenarios (Zhou et al., 2023), field testing (Lee and Hess, 2020), and traffic flow analysis (Pan et al., 2024) to understand the safety performance of AVs. For example, an intelligent simulated testing environment using dense deep reinforcement learning was developed by Feng et al. to significantly accelerate the AV safety validation process, thus enabling efficient evaluation and training of autonomous systems through AI-based agents that simulate real-world safety-critical scenarios (Feng et al., 2023). Using 245 AV collision records, Zhu and Meng employed a cost-sensitive classification and regression tree model to explore the factors influencing crash damage severities and solve the associated class imbalance (Zhu et al., 2023). In the study conducted by Zhou et al. (Zhou et al., 2023), a clustering framework based on deep embedding was used to identify six high-risk crash scenarios involving AVs and powered two-wheelers. Few studies have specifically investigated the mechanisms and risk factors underlying AV rear-end crashes, highlighting the urgent necessity for targeted empirical research to mitigate potential risks and prevent crashes.

Apart from the aforementioned limited number of AV crashes, one other key challenge in AV safety research is the limited number of variables available in AV crash reports. Built environment factors have long been recognized as an important dimension in traditional HDV crash research (Qu et al., 2023; Yu et al., 2024). Studies have demonstrated that factors such as road design (Das, 2023), traffic control measures (Ren and Xu, 2024a), and surrounding infrastructure (Shin, 2024) significantly impact the likelihood and severity of crashes. However, the integration of built environment

data into AV crash analysis remains underexplored. In this regard, Kutela et al. identified an increased probability of sideswipe collisions or the likelihood of an AV being at fault when one of the vehicles is parked (Kutela et al., 2022a). Additionally, roadside parking has been identified as a key factor contributing to more severe crash severities in AV-related crashes (Liu et al., 2024b). Another investigation revealed that out of 35 AV incidents involving vulnerable road users, 22.86% of them occurred at signalized intersections where the AV was attempting to yield the right-of-way to vulnerable road users (Kutela et al., 2022b). Therefore, it is necessary to incorporate built environment factors to provide a more comprehensive understanding of AV rear-end crash scenarios, as they account for critical external environmental influences that interact with AV systems. Additionally, given the fundamental differences in perception, decision-making, and control between AVs and HDVs, it is imperative to investigate whether environment, road, and crash-related conditions contribute to distinct crash mechanisms across these two vehicle types.

Given the complexity of AV operating characteristics and underexplored crash patterns, it is essential to analyse both contributing factors and interacting factor combinations to gain a comprehensive understanding of AV rear-end crash mechanisms. In particular, examining multi-variable association rules enables the identification of co-occurring risk conditions that may collectively increase the AV rear-end crash likelihood or severity. Moreover, conducting the comparative analysis between AV and HDV crash patterns is critical for distinguishing AV-specific vulnerabilities from conventional traffic safety concerns. Identifying these differences can not only clarify the unique crash mechanisms of AV systems but also advance the safe integration of AVs into real-world traffic environments.

7.2 Data collection and description

This study collects AV crash reports from the official website of CA DMV. Since 2014, the DMV's Autonomous Vehicles Branch has implemented regulations governing the testing and deployment of AVs on California roadways to enhance road safety while fostering technological innovation (California Department of Motor Vehicles, 2024). Manufacturers engaged in AV testing are required to report any collisions that result in fatalities, bodily injury, or property damage within a 10-day timeframe following the crash. As of April 12, 2024, which marks the commencement date of this study, the DMV had authorized more than 30 manufacturers to test autonomous vehicles on

California’s public roads and had recorded a total of 702 AV collision reports (California Department of Motor Vehicles, 2024). After excluding records with incomplete variable information, 584 AV collision samples with detailed crash determinants and well-defined AV damage severity levels were obtained. Subsequently, 278 rear-end crash samples were specifically screened out for this study. Figure 7.1 shows the detailed distribution of AV rear-end crashes and total crashes by year in California. A prominent reduction in total crash numbers was observed in 2020. This decline was attributed to the COVID-19 pandemic, during which the majority of companies suspended AV testing to prioritize safety. The overall distribution of crash severities reveals a predominance of minor incidents, while moderate, none, and major categories appear less frequently. Focusing specifically on the rear-end collision data extracted for this study, similar trends in the distribution of crash severities can also be observed.

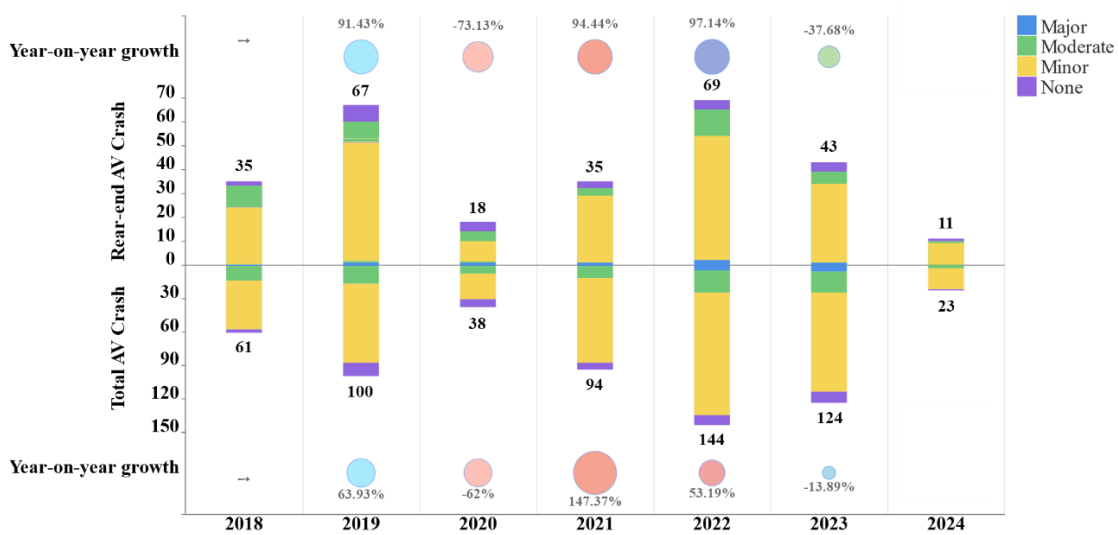


Figure 7.1 The number of AV rear-end crashes and total crashes by year in California.

Subsequently, this framework collected additional built environment characteristics, including road environment and infrastructure features, for each AV rear-end crash using Google Satellite Images based on the extracted geographical coordinates. Essential characteristics such as intersection type, road type, traffic signal presence, number of lanes, roadside parking details, and land use type were systematically collected. The final stage involved data pre-processing and categorization, where the enriched AV crash dataset was organized into distinct categories, facilitating a structured framework for further in-depth investigation. The categories of risk factors encompass crash characteristics, vehicle characteristics, road characteristics, environment characteristics, and temporal characteristics. Meanwhile,

the AV rear-end crash damage severities were originally classified into four levels, including major damage, moderate damage, minor damage, and none damage. However, given that the major damage category only contained six samples, it was then merged with the moderate damage category to form a new category called severe damage with 46 samples. As such, three crash damage severity levels, including severe damage, minor damage, and none damage, were used for the final analysis.

To compare the association rules of AV and HDV rear-end crashes and better demonstrate the uniqueness of AV rear-end crash patterns, we further adopted a spatially and temporally matched comparison design to collect a new dataset of HDV rear-end crashes that occurred within a 50-foot radius of each AV crash site during the same time window. Rear-end crash data for HDVs were first obtained from the Transportation Injury Mapping System (TIMS), a comprehensive crash database maintained by the Center for Safe Transportation Research and Education at the University of California, Berkeley (Center for Safe Transportation Research and Education at the University of California, Berkeley, 2025). Subsequently, a buffer with a radius of 50 feet was generated around each AV crash point to represent the potential impact area. A spatial join operation was then performed to identify all HDV crash points located within the AV buffer zones, thereby establishing a spatial matched pair between AV and HDV crashes. This spatial matching strategy helps to minimize the influence of unmeasured built environment and contextual factors (i.e., annual average daily traffic), ensuring a more meaningful comparison between the two vehicle types. A total of 2,013 HDV rear-end crash observations were identified that occurred within the same temporal window as the AV crash dataset. To ensure comparability between the AV and HDV datasets, all variables in the HDV records were carefully aligned with those in the AV dataset. This included aligning variable definitions, categories, and levels to enable consistent and meaningful comparisons.

The detailed explanatory variables are shown in Table 7.1. It is noteworthy that determinants with low observations and similar attributes were merged following the criteria detailed in the note section of Table 8.1, so as to mitigate possible bias (Xu et al., 2019). As a result, 54 candidate independent variables were utilized for subsequent association rule mining analysis.

Table 7.1 Explanatory variables in AV and HDV rear-end crashes.

Characteristics	Variables	Categories
	Vehicle Damage	None/Minor/Severe
Crash characteristics	Vulnerable Road User involved	With VRU/No VRU ^a
	AV movement preceding the crash	Backing/Stopped/Making turns/Slowing or Stopping/Proceeding straight/Parked or Parking/Other movements
Vehicle characteristics	Vehicle status	Moving/Stopped in traffic
	Driving mode	Autonomous mode/Conventional mode
	Number of vehicles involved	Single/Multiple
Road characteristics	Intersection	Non-intersection/Intersection
	Type of intersection	X-shaped/Y-shaped/T-shaped/Cross-shaped/Other-shaped
	Road type	Two-way with median/Two-way without median
	Traffic signal	With signal/No signal
	Number of lanes	1/2/3/4/5/6/7/8/9
	Roadside parking	With roadside parking/Without roadside parking
	Land use type	Residential/Commercial/Mixed
	Roadway surface	Dry/Adverse ^b
	Roadway condition	Unusual conditions/No unusual conditions ^c
Environment characteristics	Weather	Clear/Cloudy/ Raining/Foggy
	Lighting	Daylight/Dark with street lights/Dark without street lights
Temporal characteristics	Week	Weekday/Weekend
	Time of day	Early morning (0:00 -5:59)/Morning (6:00 - 11:59)/Afternoon (12:00 - 18:59)/Evening (19:00 - 23:59)

^aVulnerable Road User (VRU) refers to bicyclist, pedestrian, or scooter.

^bAdverse roadway surface refers to wet, snowy, or icy surface.

^cUnusual conditions refer to deep ruts, holes, loose material, obstructions, construction zones, reduced width of roadway, or other atypical conditions.

7.3 Methods

This study also used the association rule mining technique to discern the significant factors related to AV rear-end crashes and investigate their interrelationships. Unlike traditional regression models or causal inference methods, association rule mining was adopted due to its unsupervised, data-driven nature and ability to uncover hidden, multi-variable patterns without imposing restrictive model assumptions (Agrawal et al., 1996). It is well-suited for uncovering previously unknown and non-obvious co-occurrence patterns among multiple crash-related factors without prior specification (Ünvan, 2021). This makes it especially suitable for analysis in the context of AV crash research, where sample sizes are limited and causal structures are not yet well-established. Besides, this method can simultaneously identify multi-variable associations, which may be difficult to capture using conventional bivariate correlation or statistical models. This is particularly useful in complex contexts such as AV rear-end crashes, where multiple environmental and operational factors interact in complex ways. Therefore, it is one of the popular non-parametric data mining techniques in the domain of traffic safety research and is adopted in this study (Ashraf et al., 2021; Liu

et al., 2024a).

Suppose the set $I = \{i_1, i_2, i_3, \dots, i_n\}$ represents items related to the AV rear-end crash explanatory variables, such as land use types, intersection types, and road conditions in this study. The set $C = \{c_1, c_2, c_3, \dots, c_n\}$ represents a dataset containing transactions or records of crash data. Each c_i is a transaction or record that includes a set of items related to a specific crash. In other words, c_i describes the specific set of items present in a particular incident. Each transaction or record c_i in C occurs due to a unique combination of attributes from I , typically corresponding to a unique identifier used to distinguish different crash records (Hahsler, 2024). Therefore, each causal relationship in C includes a subset of items from I . Association rules are usually expressed as $X \rightarrow Y$ where X and Y are item sets, $X, Y \subseteq I$ and $X \cap Y = \emptyset$. Here, X is the antecedent, and Y is the consequent. The core components of association rule mining include support, confidence, and lift. These measures help in identifying the strength and relevance of the discovered rules.

Support measures how often an item set appears in the dataset, which is the ratio of the number of records containing the item set to the total number of records, representing the percentage of the dataset covered by the rule. $P(X)$ denotes the proportion of X , and $P(Y)$ denotes the proportion of Y . When X and Y occur together, the support is calculated as follows

$$Support(X) = P(X) = \frac{Count(X)}{N} \quad (7.1)$$

$$Support(Y) = P(Y) = \frac{Count(Y)}{N} \quad (7.2)$$

$$Support(X \rightarrow Y) = P(X \cap Y) = \frac{Count(X \cap Y)}{N} \quad (7.3)$$

where N represents the total number of AV rear-end crashes; $Count(X)$ denotes the total number of incidents that involve the antecedent X , while $Count(Y)$ signifies the number of incidents associated with the consequent Y ; $Count(X \cap Y)$ indicates the number of incidents that contain both the antecedent X and the consequent Y . Additionally, $Support(X)$ and $Support(Y)$ denote the support values for the antecedent X and consequent Y , respectively, whereas $Support(X \rightarrow Y)$ pertains to the support associated with the rule $X \rightarrow Y$.

Confidence measures the reliability of the inferred rules and indicates how often items in Y appear in crashes that contain X . In other words, it is the probability that Y appears when X appears, represented as $P(Y|X)$. The formula for calculating confidence is as follows

$$Confidence(X \rightarrow Y) = P(Y|X) = \frac{P(X \cap Y)}{P(X)} = \frac{Support(X \rightarrow Y)}{Support(X)} \quad (7.4)$$

Lift is used to evaluate the strength of a rule over random chance or the degree of influence that the antecedent has on the consequent in a rule. A lift greater than 1 indicates that the occurrence of X increases the probability of Y , suggesting a positive correlation between X and Y . A lift less than 1 implies that the occurrence of X decreases the probability of Y , while a lift equal to 1 indicates no correlation. The formula for calculating lift is as follows:

$$Lift(X \rightarrow Y) = \frac{P(Y|X)}{P(Y)} = \frac{P(X \cap Y)}{P(X) * P(Y)} = \frac{Confidence(X \rightarrow Y)}{Support(Y)} \quad (7.5)$$

This study uses the Apriori algorithm to identify association rules and analyse the AV rear-end crash data (Hahsler et al., 2005). This method first searches for frequent item sets in the crash dataset by repeatedly calculating the support and then iteratively combines these items to form larger candidate item sets. Once candidate item sets are generated, the algorithm applies a pruning step to eliminate those that do not satisfy a predefined minimum support threshold. The core idea is to use the property of frequent itemset: if an item set is infrequent, then all its super-sets are also infrequent. This step is crucial for enhancing computational efficiency by focusing only on item sets that are frequent enough to be of interest. Finally, by setting thresholds for the core components of association rule mining including support, confidence, and lift, the strength of these associations can be evaluated and meaningful association rules can be filtered out, thereby revealing valuable information hidden in the AV rear-end crash data.

7.4 Results and discussions

This section provides an analysis and interpretation of the study's findings, focusing on the application of association rule mining to identify crash patterns in rear-end crashes involving AVs and HDVs. Notably, to enhance the interpretability and statistical robustness of our association mining results, we intentionally limited the

analysis to 2-item and 3-item rules. This selection was guided by the following considerations. First, statistical validity under limited data conditions was a key concern. As the number of items increases in the association rule mining, the support for each item rule naturally decreases due to the combinatorial explosion of possible item combinations. This can lead to a large number of rules with very low support, which are statistically unstable and potentially spurious. This issue is especially pronounced in the context of AV crash research, where sample sizes are limited and causal structures are not yet well-established. Therefore, limiting the rule length to 2 or 3 items helps maintain statistical robustness and ensures that the generated rules remain generalizable. Second, interpretability and practical applicability were also prioritized. In the context of early-stage studies of AV-specific crash mechanisms, 2-item and 3-item rules offer a balance between complexity and interpretability. These rules are sufficient to uncover meaningful co-occurrence patterns while remaining understandable and actionable for practitioners, as has been demonstrated in safety and reliability domains (Hou et al., 2020).

The analysis in this study was performed in two distinct aspects: (1) Short-term association rules, including 2-item and 3-item rules, were identified to uncover the co-occurrence of contributing factors across all AV and HDV rear-end crashes, thus providing a comprehensive view of the interdependencies. (2) Association rules for three crash damage severity categories, including severe damage, minor damage, and none damage, were separately identified. This stratified analysis allowed for an understanding of how contributing factors differ based on diverse vehicle types and damage severities.

To address potential multicollinearity among categorical predictors, we also performed a Pearson correlation analysis after applying one-hot encoding (Pearson, 1895). A threshold of $|r| > 0.7$ was used to identify highly correlated variable pairs (Pearson, 1895). Two strong negative correlations were captured in AV rear-end crashes, including (1) dark with street lights and daylight ($r = -0.903$), and (2) clear weather and cloudy weather ($r = -0.835$). This analysis was also conducted for the HDV rear-end crashes. To avoid redundancy, we ensured that both variables from any highly correlated pair were not simultaneously included in any single association rule or analytical model.

The threshold selection process in association rule mining is conceptually similar

to hyperparameter tuning in machine learning. Since association rule mining is an unsupervised learning technique, there is no predefined loss function to guide parameter optimization. Based on the previous studies, an effective rule commonly should have high support and confidence (Cao et al., 2025; Montella, 2011). Meanwhile, the lift was set to be larger than 1 to mine non-random and strong rules (Liu et al., 2024a). Therefore, it is necessary to further set a minimum threshold for support (S_{min}) and confidence (C_{min}). Only those association rules that surpass the minimum thresholds of three measures are regarded as “valid” (Agrawal et al., 1996). This study refers to thresholds used in previous traffic safety research to preset the values for support (commonly ranging from 0 to 0.6, excluding 0) and confidence (commonly ranging from 0.1 to 0.8) (Cao et al., 2025; Lan et al., 2022; Montella, 2011), which provided a domain-informed starting point for parameter selection. We adopted an iterative grid search approach, using a step size of 0.05 to systematically explore combinations of support and confidence thresholds. The final thresholds were chosen based on the interpretability, coverage, and stability of the resulting rule sets. Similar to previous studies (Cao et al., 2025; Lan et al., 2022; Montella, 2011), extensive trial-and-error experiments were conducted to identify the most appropriate parameter thresholds for the Apriori algorithm, based on the “arules” package in the R programming environment (Hahsler et al., 2005). A detailed summary of the final metric thresholds used for analysis is provided in Table 7.2.

Based on the optimal threshold values for the AV rear-end crash dataset, we further applied the same set of thresholds to the HDV crash data in order to ensure consistency and comparability across AV and HDV rule mining analyses. This alignment enhances the validity of the comparative analysis between the two vehicle types and can effectively demonstrate the uniqueness of AV rear-end crashes.

Table 7.2 Thresholds of support, confidence, and lift for AV and HDV rear-end crash models.

Rear-end crash	Model	S_{min}	C_{min}	L_{min}
Number of items	2 items	0.20	0.70	1
	3 items	0.50	0.70	1
Damage severity	Severe damage	0.05	0.20	1
	Minor damage	0.15	0.50	1
	None damage	0.05	0.30	1

7.4.1 Association rule analysis for AV and HDV rear-end crashes

7.4.1.1 Analysis of 2-item association rules

A total of 239 rules were identified in the analysis of 2-item association rules for AV rear-end crashes, providing a comprehensive overview of the relationships between factors and rear-end crash outcomes. The scatter plot, network graph, and matrix plot are provided to visually represent the association rules within the AV dataset. The scatter plot in Figure 7.2 presents the distribution of all identified AV association rules by mapping their support, confidence, and lift values. Rules with higher lift values are shown in deeper shades of purple, signifying stronger associations. The variation among the rules suggests that some factor combinations exhibit stronger associations with crash occurrences. The network graph in Figure 7.3 provides a visual representation of the relationships among pairwise variables contributing to AV rear-end crashes. Nodes represent individual factors, while edges signify the connections between these factors in the rules. The size of the nodes corresponds to the confidence level, and node color represents the lift value. This graph emphasizes the central role of factors, such as multiple vehicles and the intersection. Certain variables act as bridges within the network, such as residential land type to connect distinct clusters of rules. The matrix plot in Figure 7.4 offers a condensed view of the most significant association rules in AV rear-end crashes, facilitating the recognition of critical combinations of factors. Note that lhs refers to the left-hand-side variable (i.e., the antecedent), and rhs refers to the right-hand-side variable (i.e., the consequent). Each point represents a rule, with the color intensity indicating confidence levels. For instance, specific factors such as multiple vehicles demonstrate strong associations with other variables with high lifts and confidence levels, implying their explanatory power in real-world contexts.

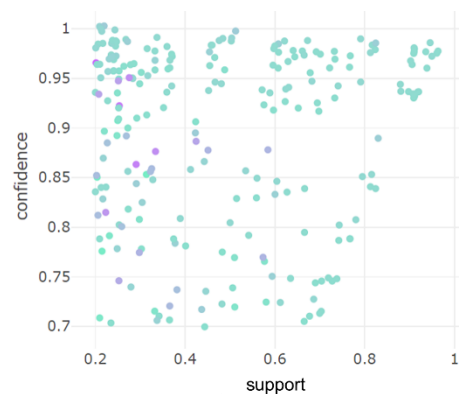


Figure 7.2 Scatter plot of the 2-item association rules for AV rear-end crashes.

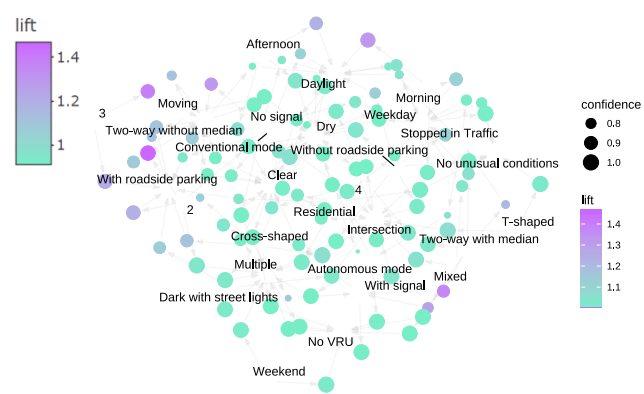


Figure 7.3 Network graph of the 2-item association rules for AV rear-end crashes.

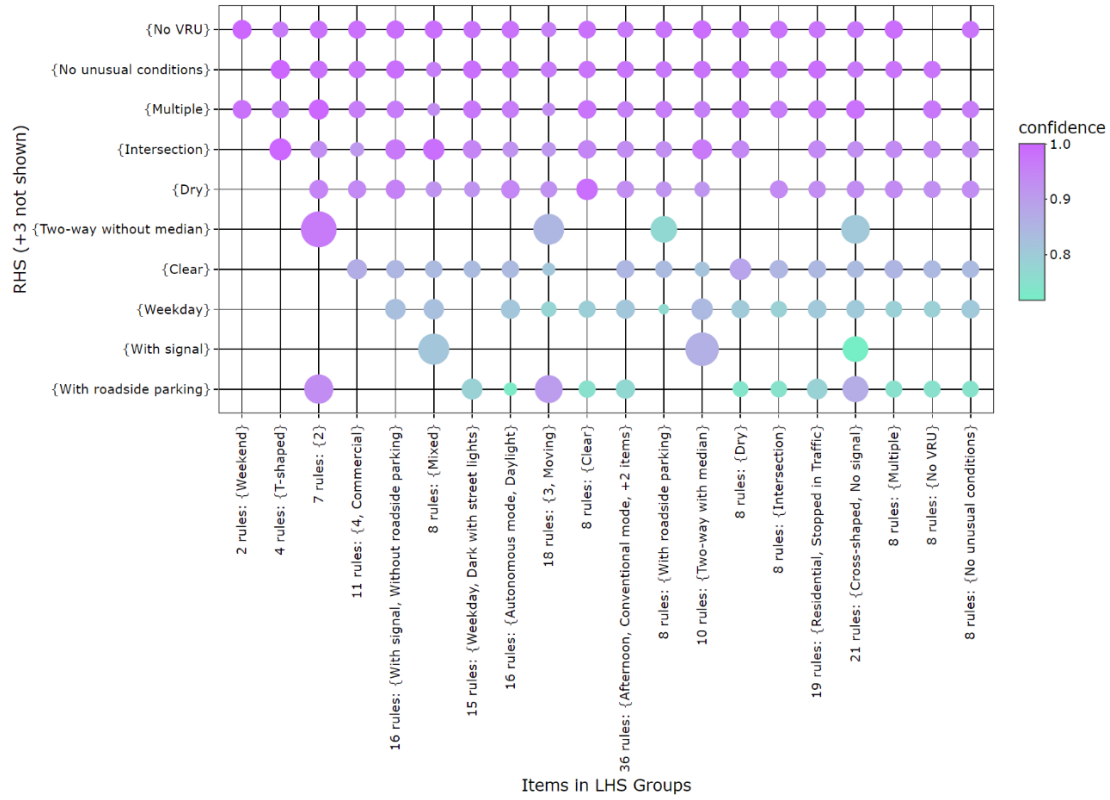


Figure 7.4 Matrix plot of the 2-item association rules for AV rear-end crashes.

While these visualizations demonstrate the diversity and complexity of the relationships, the sheer volume of association rules necessitates a filtering process to focus on the most impactful associations. Moreover, to better understand the distinct risk mechanisms underlying AV and HDV rear-end crashes, the top 15 2-item rules for each vehicle type, ranked based on their lift values, are distilled and presented in Table 7.3. Figure 7.5 further visualizes the distribution of the association rules for AV crashes (Note that the darker the red color, the larger the lift value). Several overlapping factors emerged, yet notable differences in rule lift and contextual relevance were also observed, revealing divergent challenges between the two vehicle types.

Both AV and HDV rear-end crashes were strongly associated with two-way roads without median. In the AV dataset, this is reflected in Rule 1 and Rule 2, where two lanes and three lanes are frequently paired with two-way without median (Ren and Xu, 2024a), showing high lift values. HDVs exhibit a similar association in Rule 1, but with a lower lift value, suggesting that AVs are more vulnerable to crashes without physical separation. Additionally, AV Rule 4 and Rule 11 further emphasize this configuration as a dominant risk factor. Meanwhile, HDV rear-end crashes more frequently involved commercial environments, as seen in Rule 3, Rule 9, and Rule 13, which link

commercial land use to two-way without median, non-intersection, and with roadside parking, respectively. These findings underscore the importance of incorporating physical medians in the design of roads to mitigate crash risks (Xu et al., 2019).

Signal-related variables demonstrated stronger associations with AV crashes. For example, Rule 3, Rule 5, and Rule 13 reflect how AVs are frequently involved in crashes within signalized environments. The elevated lift values in these rules indicate that traffic control devices may interact with AV decision-making in complex ways, possibly due to sensor interpretation challenges or overly conservative behaviour at intersections (Yue, 2024). In contrast, signal-related patterns in HDVs are limited to Rule 1 and Rule 4, suggesting a more adaptive driver response in the absence of traffic signals (Liu et al., 2024a).

Roadside parking appeared as a prominent contributing factor for AVs and HDVs, but the patterns differ in contextual complexity. In AV crashes, Rules 6, 7, 10, 11, 12, and 14 show repeated combinations of with roadside parking with three lanes, two-way without median, cross-shaped intersections, and dark with street lights. These configurations suggest that AVs may face challenges in managing reduced lane widths and visual occlusions introduced by roadside parking, especially in low-light or geometrically complex settings (Xu et al., 2019). HDV crashes also show associations with roadside parking, as seen in Rule 2, Rule 5, Rule 8, Rule 13, and Rule 14, though the diversity of combinations is less pronounced, indicating a more general exposure rather than interaction-specific sensitivity (Ren and Xu, 2025).

Vehicle status showed a stronger contextual pattern in AV crashes. Rule 8 and Rule 9 imply that both static and dynamic driving states may lead to elevated crash risk depending on roadway configuration (Liu et al., 2024b). In HDV rules, vehicle movement appears in broader associations, such as Rule 4 and Rule 10, without strong geometric pairings, which may reflect more flexible driver adaptation in varied environments. Lighting conditions were also a common risk factor. Both AV Rule 14 and HDV Rule 8 demonstrate that dark with street lights in combination with roadside parking increases rear-end crash risk. While this combination likely compromises visibility in both cases, it may pose greater challenges for AV sensor systems and human drivers relying on consistent illumination for object detection (Ren and Xu, 2023b).

In summary, although certain environmental risk factors such as two-way roads

without median and roadside parking affect both AVs and HDVs, the dominant association patterns for AVs concentrate more around geometric constraints, signalization, and environmental sensing limitations, while HDV crashes are more frequently influenced by behavioural context and land use. These findings emphasize the importance of tailored infrastructure design and control strategies that account for the distinct vulnerabilities of AV systems.

Table 7.3 Top 15 2-item association rules ranked by lift values for AV/HDV rear-end crashes.

No.	Antecedent	Consequent	Support	Confidence	Lift
AV					
[1]	{2 lanes}	{Two-way without median}	0.209	0.967	1.468
[2]	{3 lanes}	{Two-way without median}	0.248	0.920	1.398
[3]	{Two-way with median}	{With signal}	0.295	0.863	1.379
[4]	{No signal}	{Two-way without median}	0.327	0.875	1.329
[5]	{Mixed}	{With signal}	0.219	0.813	1.299
[6]	{3 lanes}	{With roadside parking}	0.255	0.947	1.259
[7]	{2 lanes}	{With roadside parking}	0.201	0.933	1.241
[8]	{Two-way with median}	{Stopped in Traffic}	0.255	0.747	1.215
[9]	{Moving}	{Two-way without median}	0.299	0.776	1.178
[10]	{Cross-shaped}	{With roadside parking}	0.450	0.880	1.171
[11]	{Two-way without median}	{With roadside parking}	0.579	0.880	1.170
[12]	{With roadside parking}	{Two-way without median}	0.579	0.770	1.170
[13]	{Cross-shaped}	{With signal}	0.367	0.718	1.148
[14]	{Dark with street lights}	{With roadside parking}	0.209	0.853	1.135
[15]	{Cross-shaped}	{Two-way without median}	0.378	0.739	1.123
HDV					
[1]	{No signal}	{Two-way without median}	0.403	0.813	1.245
[2]	{Two-way without median}	{With roadside parking}	0.567	0.868	1.185
[3]	{Commercial}	{Two-way without median}	0.302	0.767	1.175
[4]	{No signal}	{Moving}	0.376	0.758	1.119
[5]	{No signal}	{With roadside parking}	0.400	0.807	1.101
[6]	{Mixed}	{Daylight}	0.244	0.705	1.084
[7]	{Afternoon}	{Non-intersection}	0.251	0.759	1.082
[8]	{Dark with street lights}	{With roadside parking}	0.232	0.790	1.078
[9]	{Commercial}	{Non-intersection}	0.297	0.754	1.076
[10]	{4 lanes}	{Moving}	0.250	0.725	1.071
[11]	{Two-way without median}	{Non-intersection}	0.488	0.748	1.067
[12]	{4 lanes}	{Non-intersection}	0.256	0.741	1.057
[13]	{Commercial}	{With roadside parking}	0.303	0.768	1.048
[14]	{Proceeding straight}	{With roadside parking}	0.376	0.768	1.048
[15]	{Two-way without median}	{Moving}	0.462	0.709	1.046

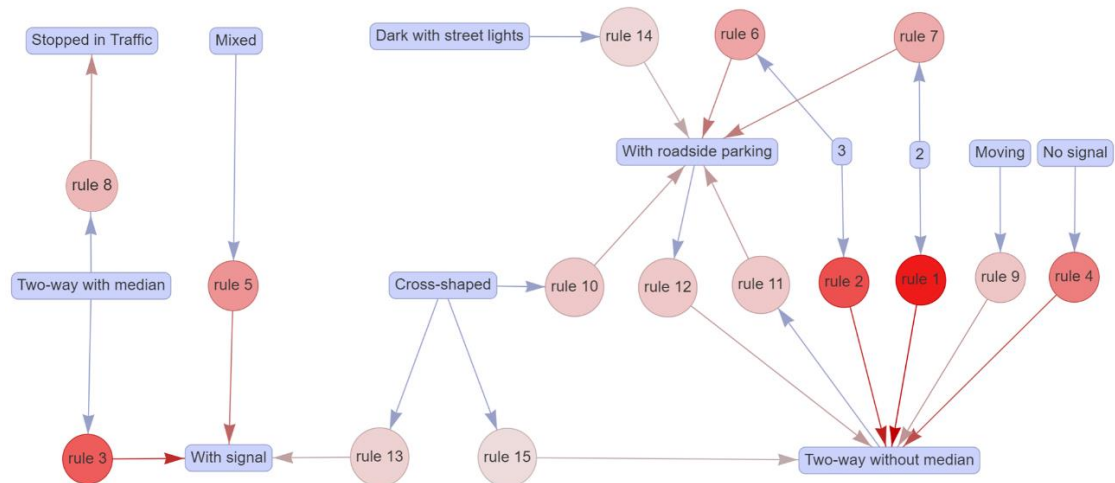


Figure 7.5 Network graph of top 15 2-item association rules for AV rear-end crashes.

7.4.1.2 Analysis of 3-item association rules

A total of 378 AV association rules involving three items were identified, providing deeper insights into the interplay between multiple factors contributing to AV rear-end crashes. The scatter plot, network graph, and matrix plot (see Figure 7.6–Figure 7.8), were used to comprehensively illustrate these associations in AV rear-end crashes. Figure 7.6 shows that most rules exhibit low support but high confidence, suggesting less frequent yet significant factor combinations. Figure 7.7 illustrates that central nodes, such as intersections and with roadside parking, are prominent, highlighting their recurring importance in identified rules. Figure 7.8 organizes AV rules by groups, with two-way without median and clear weather frequently appearing in multi-factor combinations.

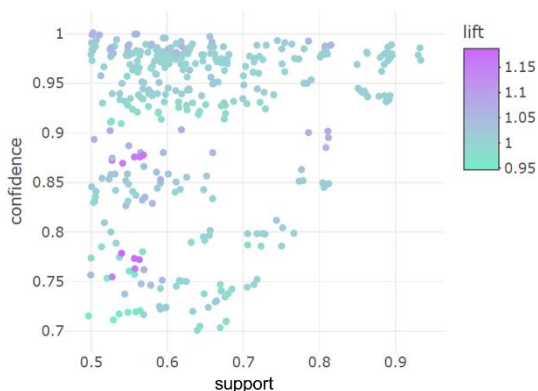


Figure 7.6 Scatter plot of the 3-item association rules for AV rear-end crashes.

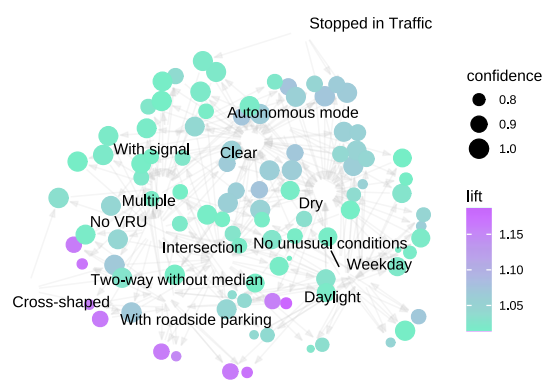


Figure 7.7 Network graph of the 3-item association rules for AV rear-end crashes.

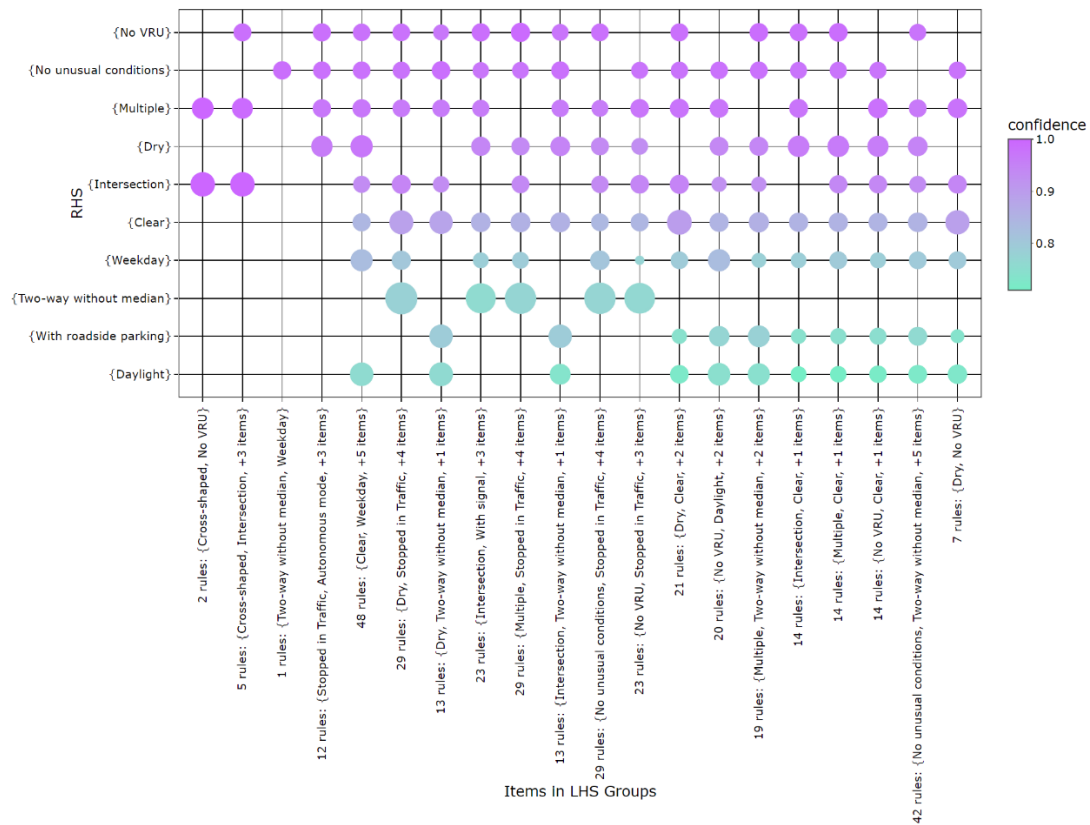


Figure 7.8 Matrix plot of the 3-item association rules for AV rear-end crashes.

Similarly, the top 15 3-item rules ranked by their lift values were extracted for AVs and HDVs to enhance the interpretability of the findings, as shown in Table 7.4. Figure 7.9 further presents the network graph of these association rules for AV rear-end crashes. Compared to 2-item rules, the 3-item association rules provide more nuanced insights into how combinations of environmental, road, and vehicle-related factors interact to influence AV and HDV rear-end crashes.

For both AVs and HDVs, high-risk combination rules involve with roadside parking, dry conditions, and two-way roads without median (AV Rules 1, 2, and 3, HDV Rules 1, 2, and 5). These patterns reinforce that roadside parking continues to be a critical factor, especially when coupled with geometric constraints and increased bidirectional exposure. However, AV rules demonstrate slightly higher contextual specificity, such as the presence of multiple vehicles in Rule 3, implying that AVs are more sensitive to constrained, dynamic environments that require complex spatial reasoning (Xu et al., 2019).

Intersections and road user presence also show differential effects. In AV Rule 5, the combination of intersection and two-way roads without median leading to with roadside parking suggests that AV crashes are concentrated at high-conflict zones where

Table 7.4 Top 15 3-item association rules ranked by lift values for AV/HDV rear-end crashes.

No.	Antecedent	Consequent	Support	Confidence	Lift
AV					
[1]	{Dry, With roadside parking}	{Two-way without median}	0.540	0.781	1.187
[2]	{No unusual conditions, With roadside parking}	{Two-way without median}	0.565	0.773	1.175
[3]	{Multiple, With roadside parking}	{Two-way without median}	0.558	0.771	1.171
[4]	{No VRU, Two-way without median}	{With roadside parking}	0.561	0.876	1.166
[5]	{Intersection, Two-way without median}	{With roadside parking}	0.529	0.875	1.164
[6]	{Dry, With signal}	{Clear}	0.529	0.902	1.076
[7]	{Dry, With roadside parking}	{Clear}	0.622	0.901	1.075
[8]	{Dry, Multiple}	{Clear}	0.813	0.900	1.074
[9]	{Autonomous mode, Clear}	{Dry}	0.561	1.000	1.073
[10]	{Dry, Intersection}	{Clear}	0.788	0.898	1.071
[11]	{Daylight, No unusual conditions}	{Weekday}	0.594	0.851	1.070
[12]	{Cross-shaped, Multiple}	{Intersection}	0.507	1.000	1.069
[13]	{Cross-shaped, No VRU}	{Intersection}	0.504	1.000	1.069
[14]	{Clear, Stopped in Traffic}	{Dry}	0.507	0.993	1.066
[15]	{Dry, Two-way without median}	{Clear}	0.550	0.890	1.061
HDV					
[1]	{Dry, With roadside parking}	{Two-way without median}	0.516	0.779	1.194
[2]	{No VRU, With roadside parking}	{Two-way without median}	0.549	0.779	1.193
[3]	{Multiple, Two-way without median}	{With roadside parking}	0.567	0.868	1.185
[4]	{No unusual conditions, Two-way without median}	{With roadside parking}	0.549	0.865	1.180
[5]	{Dry, Two-way without median}	{With roadside parking}	0.516	0.861	1.175
[6]	{Clear, Two-way without median}	{Dry}	0.566	0.975	1.063
[7]	{Dry, Non-intersection}	{Clear}	0.613	0.954	1.061
[8]	{Clear, Multiple}	{Dry}	0.874	0.973	1.061
[9]	{Clear, Weekday}	{Dry}	0.654	0.968	1.056
[10]	{Clear, With roadside parking}	{Dry}	0.625	0.965	1.053
[11]	{Dry, Two-way without median}	{Clear}	0.566	0.945	1.052
[12]	{Moving, Multiple}	{With roadside parking}	0.519	0.766	1.045
[13]	{Multiple, With roadside parking}	{Moving}	0.519	0.708	1.045
[14]	{Moving, No unusual conditions}	{With roadside parking}	0.504	0.761	1.038
[15]	{Daylight, Multiple}	{Weekday}	0.508	0.781	1.027

visibility and maneuverability are limited (Ren and Xu, 2024b). A similar structure appears in HDV Rule 3 and Rule 4, yet the emphasis shifts more toward typical driver behaviour and situational condition, lacking the same intersectional specificity observed in AVs. Environmental factors (e.g., clear, dry, no unusual conditions) appears frequently in both groups, with AV Rules 6–10 and HDV Rules 6–11 showing strong associations between clear weather and crash occurrence. This highlights that AV

crashes are not limited to adverse conditions. Instead, errors in interpretation or coordination can occur even under ideal settings (Ashraf et al., 2021).

Vehicle motion status further distinguishes AVs from HDVs. AV Rule 14 suggests that AVs face risk when managing deceleration or stationary states in clear conditions, whereas HDV Rules 12–14 emphasize moving status in combination with roadside parking or no unusual conditions, reflecting risks tied to human behaviour such as distraction or misjudgment (Ren and Xu, 2025). Temporal factors also differ between AVs and HDVs. AV Rule 11 shows that weekday travel under daylight and normal conditions is a common crash context, while HDV Rule 15 reflects a more general weekday and daylight pattern with less contextual constraint, again suggesting that AVs are more vulnerable in regular but interaction-heavy scenarios (Liu et al., 2024b).

In sum, the 3-item rules deepen prior findings: while both AVs and HDVs are affected by the same foundational risk factors (e.g., roadside parking, Two-way without median), AV-specific patterns are more concentrated in constrained geometries, structured intersections, and autonomous operation under otherwise favorable conditions. These findings call for infrastructure and algorithmic adaptations that explicitly address these multidimensional risk settings in AV deployment strategies.

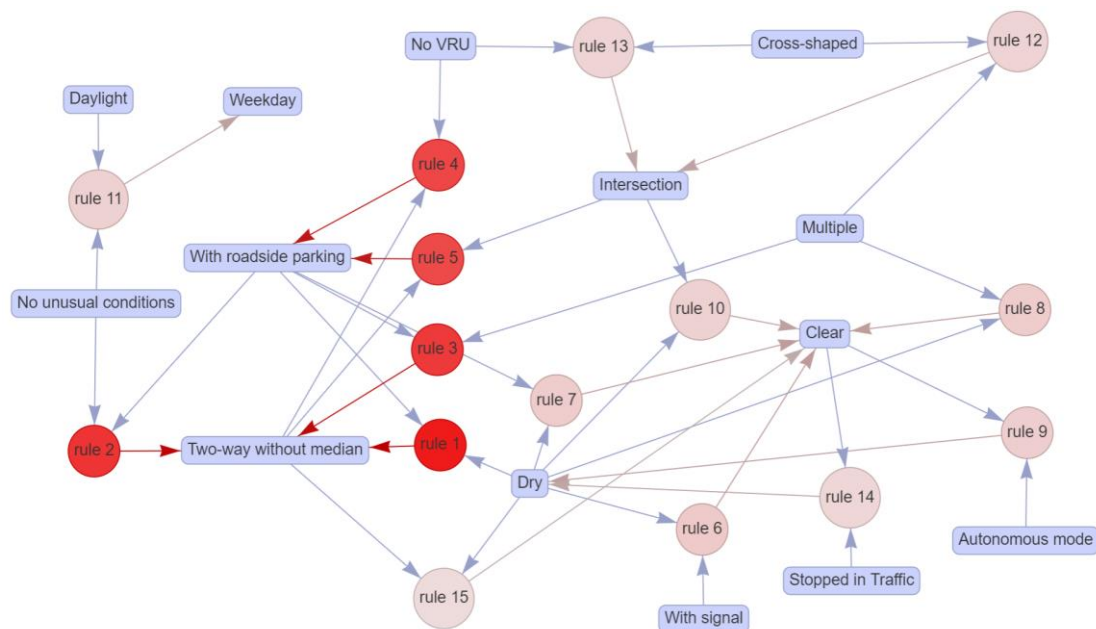


Figure 7.9 Network graph of top 15 3-item association rules for AV rear-end crashes.

7.4.2 Association rule analysis for different AV and HDV rear-end damage severity levels

7.4.2.1 Association rules for severe damage crashes

A total of 204 association rules were identified for severe damage AV rear-end crashes, offering insights into the interplay of various factors contributing to such incidents. To effectively present these rules, the scatter plot in Figure 7.10, the network graph in Figure 7.11, and the matrix plot in Figure 7.12 were provided. Figure 7.10 highlights the distribution of rules, with most rules clustering around support values lower than 0.08, indicating that severe AV rear-end crashes are often associated with specific, less frequent combinations of factors. The network graph in Figure 7.11 emphasizes the central role of factors like cross-shaped and residential land type, which frequently co-occur in severe AV rear-end crashes. The matrix plot in Figure 7.12 organizes the association rules into groups based on the number of items in the antecedent and the consequent, with severe damage consistently appearing as the consequent. The matrix plot illustrates how combinations of diverse factors, such as environmental conditions, road configurations, and traffic patterns, contribute to severe AV rear-end crashes.

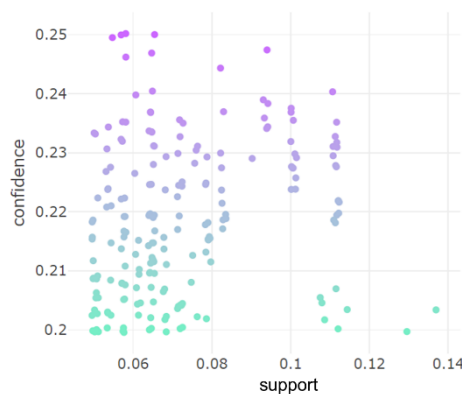


Figure 7.10 Scatter plot of the association rules for severe damage AV rear-end crashes.

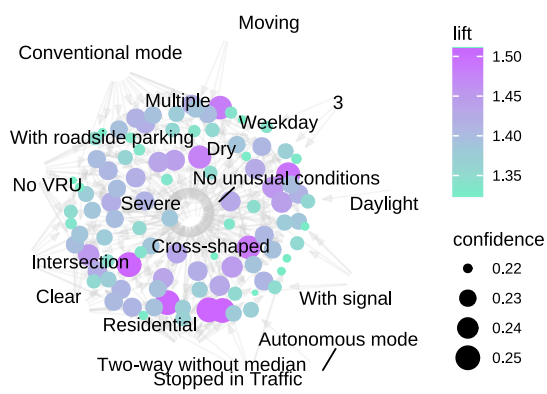


Figure 7.11 Network graph of the association rules for severe damage AV rear-end crashes.

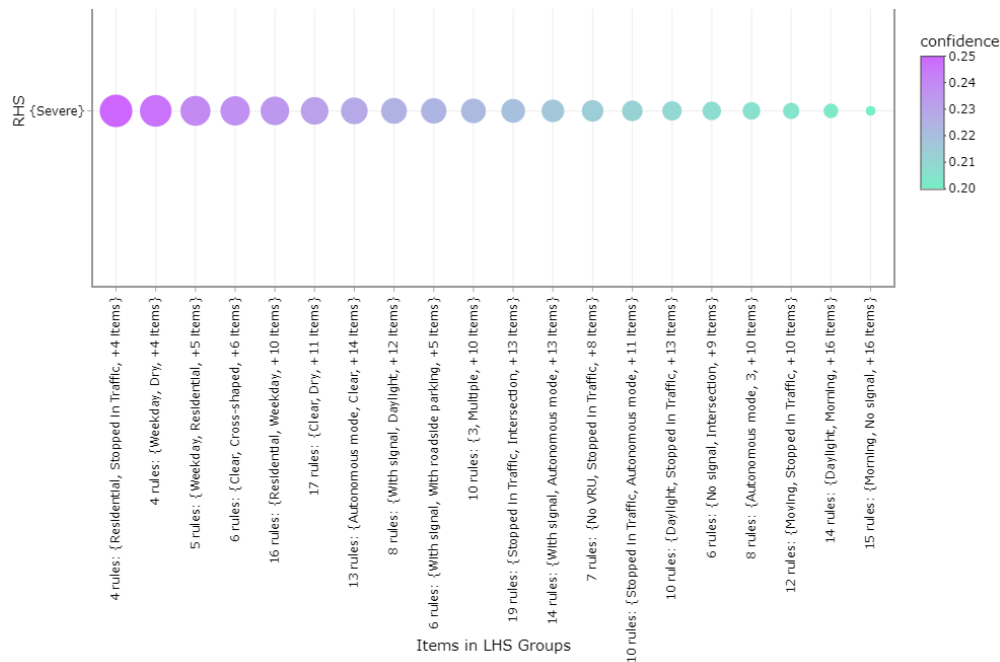


Figure 7.12 Matrix plot of the association rules for severe damage AV rear-end crashes.

The top 5 representative association rules in AV and HDV rear-end crashes were selected for detailed analysis. These rules, presented in Table 7.5 and Fig. 7.13, reveal critical combinations of factors that contribute to severe damage in rear-end crashes. Both AV and HDV rear-end crashes leading to severe damage share several high-risk environmental and operational contexts, though the nature of their associations reveals key differences in crash mechanisms.

Residential land use type consistently appears as a core spatial risk factor in both groups. In the AV rear-end crashes, residential areas are present in Rule 1, Rule 2, and Rule 5, typically in conjunction with cross-shaped intersections and multiple vehicles. Similarly, in the HDV rear-end crashes, residential settings dominate all top five severe damage rules, often paired with roadside parking (Rule 2), two-way roads without medians (Rule 1), and weekday conditions (Rule 3). This consistency suggests that densely populated or mixed-use environments inherently increase risks for rear-end crashes, regardless of automation.

However, the surrounding roadway configuration and interaction context differ between these two types of vehicles. AV rules highlight cross-shaped intersections (Rule 1, Rule 2, Rule 3, Rule 5) and two-way roads without medians (Rules 1 and 3) as frequent antecedents, suggesting that AVs are particularly sensitive to high-complexity, multi-directional layouts where decision-making demands increase. The presence of

stopped-in-traffic conditions in Rule 3 further illustrates how AVs may be challenged by real-time judgment in congested or variable-speed settings (Moradloo et al., 2024). In contrast, HDV severe crash rules focus more on simpler traffic environments under routine conditions, such as dry and clear weather (Rule 4), weekday (Rule 3), and non-complex road configurations. These patterns suggest that while AV severe crashes are more often triggered by operational complexity, HDV crashes may stem from human behavioural factors (e.g., inattention, misjudgment) in less demanding conditions (Adnan et al., 2024).

Roadside parking also plays a substantial role in both AV and HDV severe crashes. In AV Rule 2 and Rule 5, roadside parking co-occurs with residential zones and intersection complexity, reinforcing the concern that parking infrastructure impairs AV sensor performance and reduces available maneuvering space. For HDVs, Rule 2 and Rule 5 also show strong associations between roadside parking, residential areas, and severe outcomes, but without the same intersectional or dynamic vehicle contexts. This may reflect differing crash mechanisms, i.e., sensor occlusion and cautious AV braking in AVs versus spatial misjudgment or limited reaction time in human drivers (Tengilimoglu et al., 2023). Notably, multi-vehicle involvement appears in AV Rule 5 but only in HDV Rule 5 with no additional variables. This reinforces that AV crashes may more often involve cascading or interaction-driven complexity. To address these issues, AVs can benefit from real-time communication with other vehicles via vehicle-to-vehicle (V2V) technology to share information about braking intentions and surrounding traffic conditions (Adnan et al., 2024), allowing trailing vehicles to respond proactively. Additionally, the use of cooperative adaptive cruise control systems in AVs can help maintain safe following distances and reduce multi-vehicle collisions (Mosharafian and Velni, 2022).

In summary, both vehicle types exhibit increased severe crash risk in residential areas with two-way roads lacking medians and roadside parking, yet the crash context diverges: AV crashes are more embedded in intersectional complexity, stopping behaviour, and multi-vehicle interactions, while HDV crashes are impacted by conditions where human error or behavioral risk dominates. These insights emphasize the need for infrastructure modifications and context-sensitive AV design improvements, as well as behavioral safety interventions for HDV drivers in residential areas.

Table 7.5 Top 5 representative association rules for AV/HDV severe damage rear-end crashes.

No.	Antecedent	Consequent	Support	Confidence	Lift
AV					
[1]	{Cross-shaped, Residential, Two-way without median}	{Severe}	0.054	0.250	1.511
[2]	{Cross-shaped, Residential, With roadside parking}	{Severe}	0.065	0.250	1.511
[3]	{Cross-shaped, Stopped in Traffic, Two-way without median}	{Severe}	0.058	0.250	1.511
[4]	{Conventional mode, Dry, Weekday}	{Severe}	0.058	0.246	1.488
[5]	{Cross-shaped, Multiple, Residential}	{Severe}	0.065	0.237	1.431
HDV					
[1]	{Residential, Two-way without median}	{Severe}	0.013	0.255	10.262
[2]	{Residential, With roadside parking}	{Severe}	0.013	0.250	10.065
[3]	{Residential, Weekday}	{Severe}	0.011	0.240	9.646
[4]	{Clear, Residential}	{Severe}	0.013	0.234	9.430
[5]	{Multiple, Residential}	{Severe}	0.013	0.217	8.723

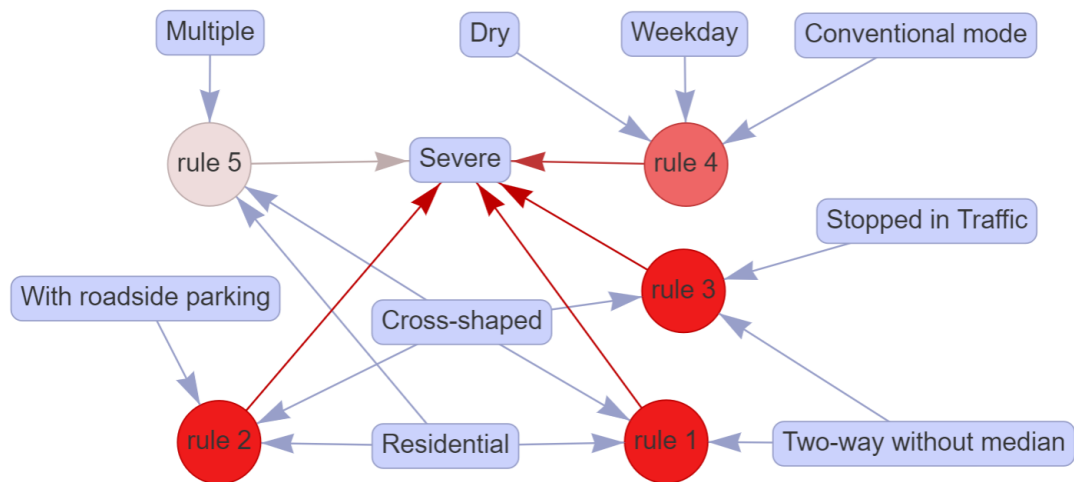


Figure 7.13 Network graph of top 5 association rules for severe damage AV rear-end crashes.

7.4.2.2 Association rules for minor damage crashes

A total of 1,115 association rules were derived to analyse minor damage AV rear-end crashes, offering detailed insights into the factors influencing such incidents. These rules are presented through a scatter plot in Figure 7.14, a network graph in Figure 7.15, and a matrix plot in Figure 7.16. Figure 7.14 shows the rule distribution, where the majority of the rules are concentrated at lower support values but exhibit high confidence levels. The network graph in Figure 7.15 highlights key contributing factors, such as without roadside parking, two-way with median, and stopped in traffic, which frequently appear together in minor damage AV crashes. The matrix plot in Figure 7.16 offers a systematic view of the association rules, grouping them by the number of items

in the antecedent and the consequent (i.e., minor damage) in AV rear-end crashes. The matrix plot highlights specific combinations, such as without roadside parking and autonomous mode, which are strongly associated with minor damage crashes, supported by high confidence and lift values.

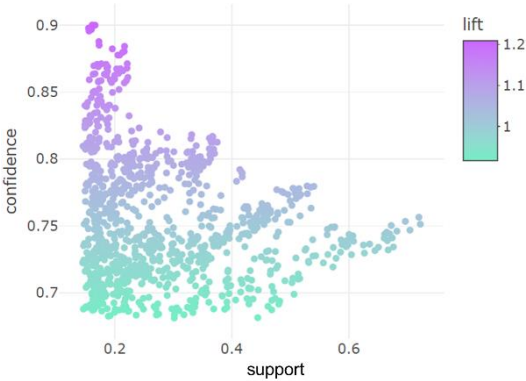


Figure 7.14 Scatter plot of the association rules for minor damage AV rear-end crashes.

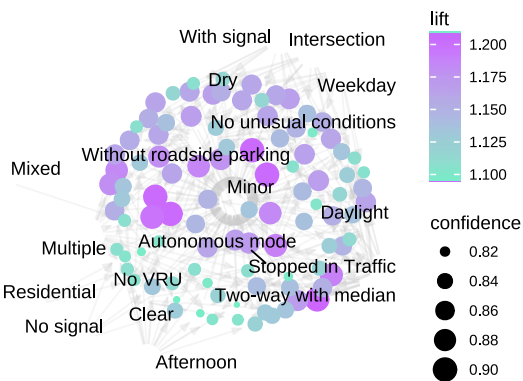


Figure 7.15 Network graph of the association rules for minor damage AV rear-end crashes.

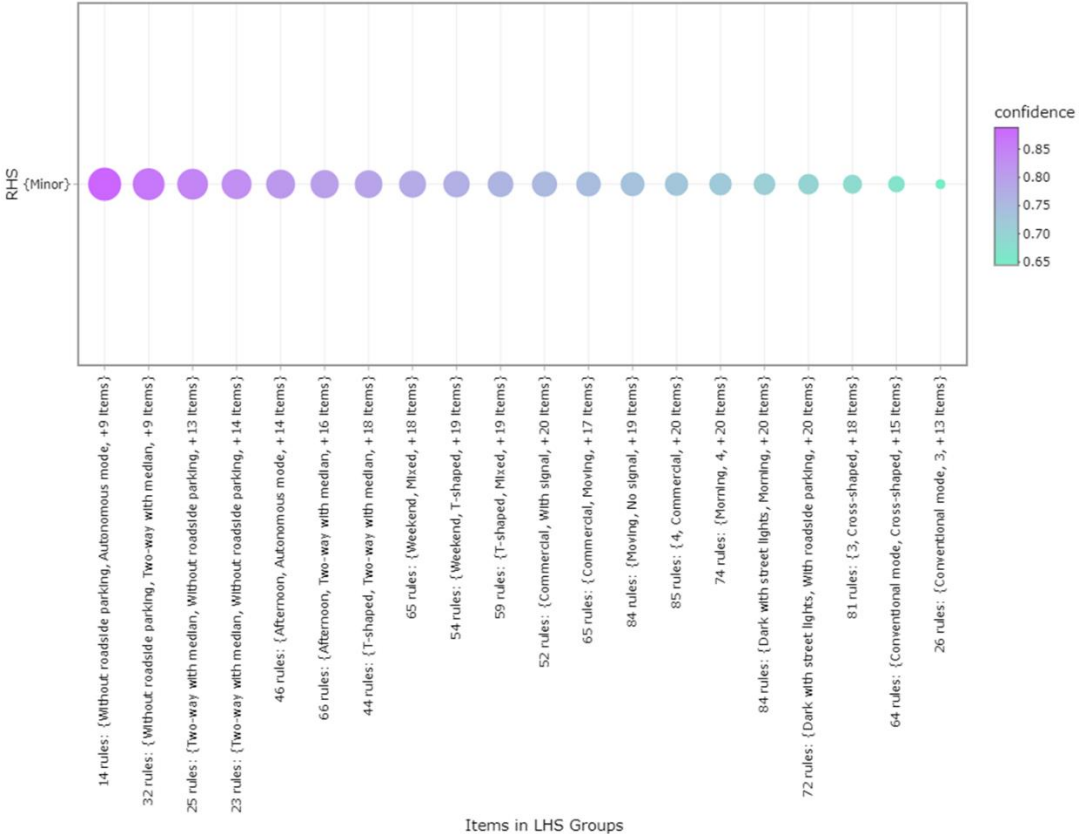


Figure 7.16 Matrix plot of the association rules for minor damage AV rear-end crashes.

The top 5 representative association rules were selected for in-depth analysis to better understand the factors contributing to minor damage rear-end crashes involving AVs and HDVs. These rules, as displayed in Table 7.6 and Figure 7.17, highlight key combinations of variables that frequently occur in such crashes.

For AV rear-end crashes, the presence of autonomous driving mode consistently appears across Rules 1–3, frequently in combination with stopped-in-traffic conditions, multiple vehicles, or the absence of roadside parking. These patterns suggest that AVs, when operating autonomously in structured but constrained environments, such as two-way roads with medians (Rule 1) and intersections without VRUs (Rule 5), would also experience minor damages. This may reflect the conservative driving behaviour of AV systems, which tend to avoid extreme maneuvers and prioritize gradual responses (Li et al., 2021). The repeated presence of without roadside parking (Rules 2–5) also indicates that fewer lateral obstructions may reduce the likelihood of more severe outcomes by offering clearer visibility and maneuvering space for AVs (Zhou et al., 2024).

Table 7.6 Top 5 representative association rules for AV/HDV minor damage rear-end crashes.

No.	Antecedent	Consequent	Support	Confidence	Lift
AV					
[1]	{Autonomous mode, Stopped in Traffic, Two-way with median}	{Minor}	0.162	0.900	1.209
[2]	{Autonomous mode, Without roadside parking}	{Minor}	0.158	0.898	1.206
[3]	{Autonomous mode, Multiple, Without roadside parking}	{Minor}	0.151	0.894	1.200
[4]	{No VRU, Stopped in Traffic, Without roadside parking}	{Minor}	0.169	0.887	1.191
[5]	{Intersection, No VRU, Without roadside parking}	{Minor}	0.205	0.877	1.178
HDV					
[1]	{Commercial, Dark without street lights}	{Minor}	0.012	1.000	4.827
[2]	{Dark without street lights, With roadside parking}	{Minor}	0.012	1.000	4.827
[3]	{Dark without street lights, No VRU}	{Minor}	0.014	0.875	4.224
[4]	{Dark without street lights, Multiple}	{Minor}	0.014	0.875	4.224
[5]	{Commercial, Dark without street lights, No signal}	{Minor}	0.013	0.788	3.803

In contrast, HDV minor damage crashes are highly concentrated around low-visibility and low-infrastructure environments, especially dark conditions without street lighting, which appear in all five rules. For example, Rules 1, 2, and 3 show combinations of commercial land use, roadside parking, and no VRUs, all co-occurring with dark without street lights, which dramatically increases lift values. These associations suggest that HDVs are particularly vulnerable in poorly lit environments, where limited visibility may impair driver perception and reaction time, leading to minor collisions. Additionally, the presence of multiple vehicles (Rule 4) and lack of signals (Rule 5) further emphasizes the risk posed by nighttime driving.

Taken together, the AV minor damage patterns reflect outcomes shaped by system-

level caution in relatively constrained conditions, whereas HDV minor damage crashes are more likely to result from environmental insufficiencies, such as inadequate lighting or missing control devices, that impair human decision-making. This contrast underscores the importance of infrastructure reliability (e.g., street lighting and signalization) for HDV crash mitigation and behavioral calibration of AV systems to further reduce crashes (Zhou et al., 2024).

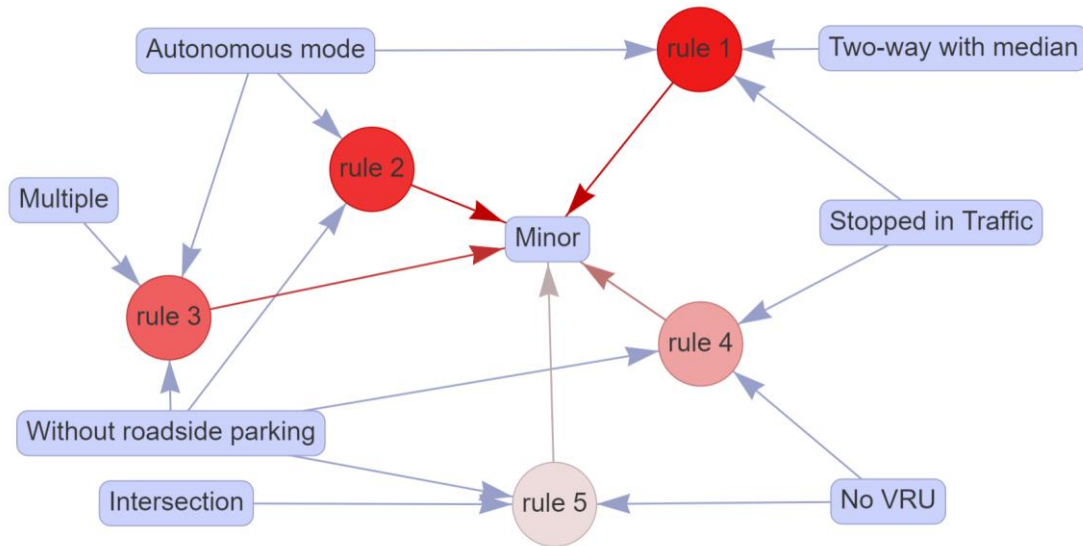


Figure 7.17 Network graph of top 5 association rules for minor damage AV rear-end crashes.

7.4.2.3 Association rules for none damage crashes

A total of 172 association rules were identified for none damage AV rear-end crashes. The scatter plot in Figure 7.18 illustrates the distribution of the rules, where most are concentrated at lower support values while maintaining relatively high confidence. The network graph in Figure 7.19 highlights key factors such as X-shaped intersection and VRU, which frequently appear in none damage rear-end crashes. The matrix plot in Figure 7.20 provides a structured representation of the rules. None damage consistently appears as the consequent, while the antecedents include various combinations of factors. The matrix plot highlights specific variables, such as moving and with VRU, that are strongly associated with none damage rear-end crashes involving AVs.

The top 5 representative association rules were selected for detailed analysis to uncover the factors contributing to none damage in AV and HDV rear-end crashes. These rules were summarized in Table 7.7 and visualized in Figure 7.21.

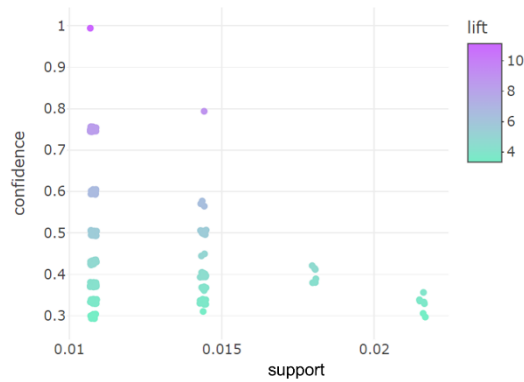


Figure 7.18 Scatter plot of the association rules for none damage rear-end crashes.

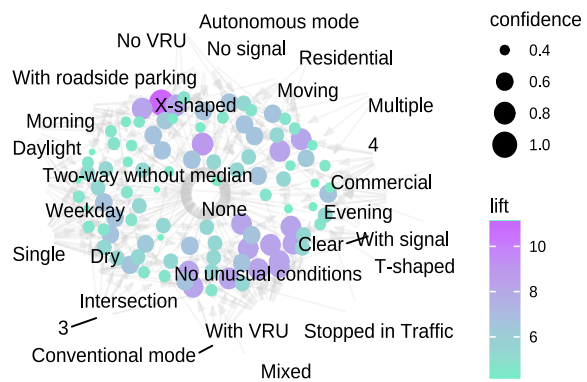


Figure 7.19 Network graph of the association rules for none damage rear-end crashes.

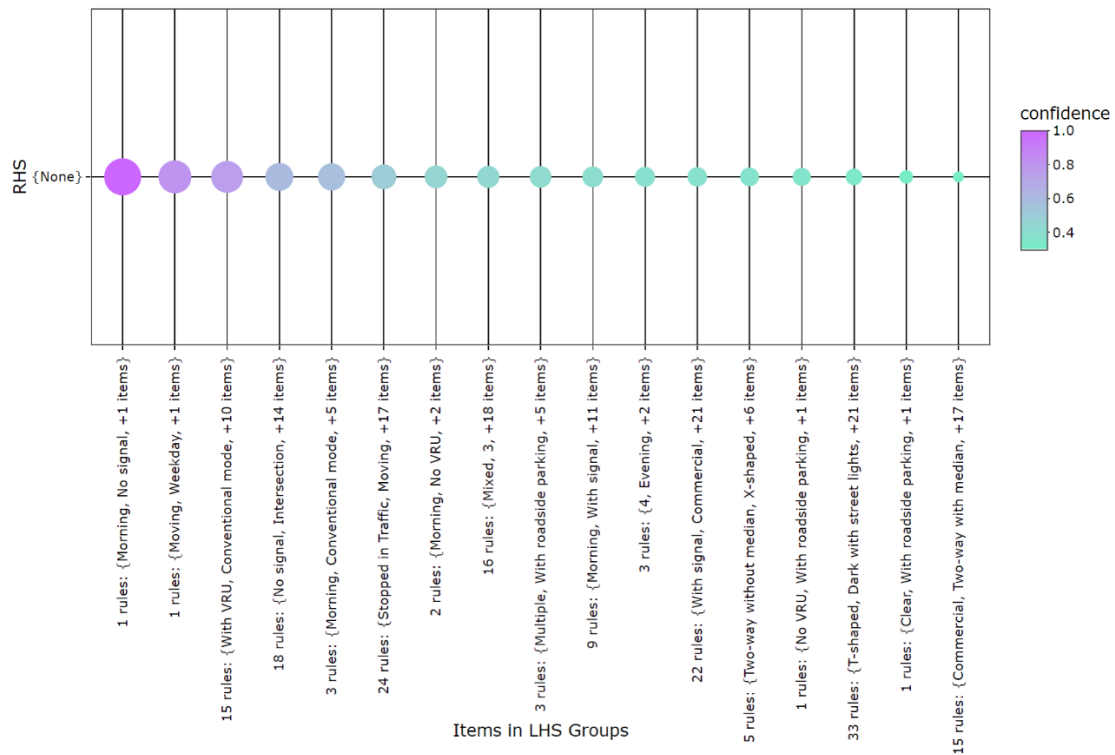


Figure 7.20 Matrix plot of the association rules for none damage AV rear-end crashes.

Intersection emerges as a common factor for both vehicle types. In AV rules, intersection-related contexts appear in Rule 1, Rule 2, and Rule 5, where intersections combine with factors like morning, weekday, or VRUs. Similarly, four HDV rules feature intersections as a key spatial element, often paired with afternoon or evening (Rules 1–4), and roadway settings such as two-way roads without medians (Rule 4) or mixed land use (Rule 3). However, the nature of vehicle control and surrounding conditions plays a more differentiated role. In AV rules, the presence of VRUs is prominent (Rules 3–5), along with conventional driving mode (Rule 3) and clear weather conditions (Rule 4). These settings suggest that AVs may experience minor disturbances or conservative maneuvers, such as abrupt braking or avoidance behaviour in the presence of pedestrians and cyclists, especially when human drivers are in control

(Adnan et al., 2024). In contrast, HDV rules reflect more standard operational patterns, such as high-volume traffic periods (afternoon/evening), presence of multiple vehicles (Rule 1), and roadside parking (Rule 2).

Lighting conditions further differentiate AV and HDV none-damage events. In HDV Rule 1 through Rule 5, afternoon and evening hours dominate, reflecting times when visibility may be declining but driver alertness remains high. AV rules, on the other hand, are more concentrated in morning and clear weather settings (Rules 1 and 4), where environmental clarity may enhance sensor performance or allow for smoother decision-making (Kuo et al., 2024). This suggests that AV none damage outcomes are more likely under optimal visibility and predictable behaviour (Xu et al., 2019), while HDVs tolerate a broader range of conditions through human adaptability.

In summary, none-damage rear-end crashes for AVs and HDVs often occur in intersection-dense environments, yet their triggers differ: AVs tend to engage in low-impact events due to cautious responses to VRUs or ambiguous priority situations, while HDVs exhibit broader environmental tolerance, relying more on human perception and behavioral adjustments. These findings underscore the need to optimize AV-human interaction protocols, particularly around intersections and VRUs, while continuing to enhance situational awareness and real-time decision-making algorithms.

Table 7.7 Top 5 representative association rules for AV/HDV none damage rear-end crashes.

No.	Antecedent	Consequent	Support	Confidence	Lift
AV					
[1]	{Morning, No signal, X-shaped}	{None}	0.011	1.000	11.120
[2]	{Moving, Weekday, X-shaped}	{None}	0.014	0.800	8.896
[3]	{Conventional mode, With VRU}	{None}	0.011	0.750	8.340
[4]	{Clear, With VRU}	{None}	0.011	0.750	8.340
[5]	{Intersection, With VRU}	{None}	0.011	0.600	6.672
HDV					
[1]	{Afternoon, Intersection, Multiple}	{None}	0.076	0.944	1.229
[2]	{Afternoon, Intersection, With roadside parking}	{None}	0.055	0.940	1.224
[3]	{Intersection, Mixed, Weekday}	{None}	0.076	0.927	1.207
[4]	{Evening, Intersection, Two-way without median}	{None}	0.057	0.920	1.198
[5]	{Evening, Two-way without median, Weekend}	{None}	0.055	0.917	1.194

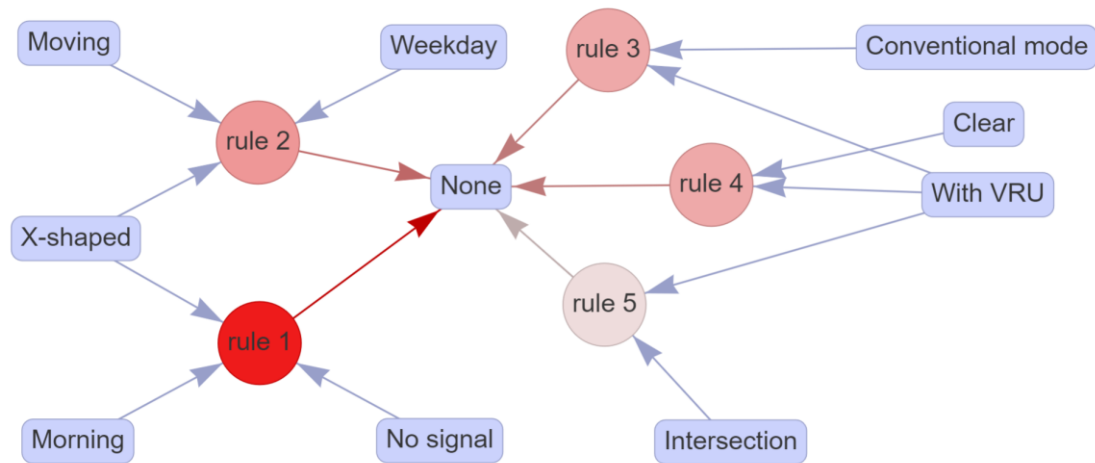


Figure 7.21 Network graph of top 5 association rules for none damage AV rear-end crashes.

7.5 Conclusion remarks

This study contributes to the existing body of research on AV safety by offering a dedicated and comprehensive investigation of rear-end crashes. In addition, a comparative analysis between AV and HDV rear-end crashes was conducted to highlight the unique crash patterns associated with autonomous driving systems. A total of 2013 HDV rear-end crashes that occurred within a 50-foot radius of each AV crash site and within the same time window were also collected to conduct the comparative analysis between AV and HDV rear-end crashes. The association rule mining was employed to uncover the combinations of contributing factors that frequently co-occur in AV and HDV rear-end crashes. Short-term association rules, including 2-item and 3-item rules, were identified across all rear-end crashes. Furthermore, association rules for different damage severities were also investigated.

Apart from the extracted variables from CA DMV AV crash reports, this study has demonstrated that augmented built environment factors could significantly influence the occurrence of rear-end crashes involving AVs. In this regard, critical factors such as roadside parking, two-way without medians, multiple vehicles, traffic signal, intersection type, land type, and stopped in traffic dominate majority rules, highlighting their pivotal role in contributing to AV crashes. Roads without medians consistently emerged as high-risk areas, as the absence of physical separation between traffic directions increases exposure to conflicts, particularly on narrow two-way roads or at intersections. Roadside parking further aggravates the situation by reducing roadway width and creating unpredictable obstacles, such as pedestrians or vehicles suddenly entering the traffic flow. Similarly, traffic control measures and intersection complexity

are critical contributors. Non-signalized intersections and cross-shaped configurations were identified as hazardous, while signalized intersections with medians, though potentially safer, still present challenges due to dynamic traffic flows. Additionally, clear weather and weekday peak traffic conditions were also frequently associated with crashes, suggesting that AV systems face difficulties even under favorable conditions, primarily due to interactions with other road users.

The results confirm the existence of distinct patterns and co-occurrence mechanisms that are unique to AV systems under real-world conditions. In terms of insights from different crash severity analyses, severe damage AV rear-end crashes were strongly associated with complex road configurations, such as cross-shaped intersections and two-way roads without medians. These scenarios often overwhelm current AV algorithms due to their dynamic and unpredictable nature. Roadside parking in residential areas was another critical factor, as it obstructs AV sensors and reduces maneuvering space, increasing the likelihood of severe collisions. Minor damage crashes, on the other hand, were often linked to conservative AV behaviours, such as abrupt braking in response to sudden stops or traffic congestion. Additionally, minor crashes tend to occur more frequently in autonomous mode. For none damage crashes, interactions with VRUs, such as pedestrians and cyclists, were a recurring theme. These incidents often occurred at intersections or during morning and weekday traffic, highlighting the need for AV systems to better manage VRU interactions in complex traffic scenarios.

Chapter 8 Conclusions and recommendations

8.1 Overview and research contributions

This thesis specifically analyses post-crash severities in the context of both HDVs and AVs across diverse contexts, thus providing insights for evidence-based policies to foster a safer transportation environment.

Using a three-year single-vehicle crash dataset under adverse road surface conditions in Ohio from 2015 to 2017, Chapter 3 investigates the heterogeneous impacts, temporal instability, and non-transferability of various determinants on driver injury severities across different vehicle impact locations for HDVs. Three groups of random parameters logit models with the heterogeneity in the means (and variances) corresponding to center, left-side, and right-side crashes were employed. The results of likelihood ratio tests indicate an overall temporal instability and locational non-transferability, while some indicators, such as hitting animals, old drivers, safety restraint usage, female drivers, physically impaired drivers, and vehicles with insurance, were observed to be of temporal stability and impact location transferability. This study also examines the impact of year-to-year and location-to-location shifts by comparing the probability differences between out-of-sample predictions and within-sample observations. The results show varying magnitudes and inconsistent directions of distribution characteristics, including mean, skewness, kurtosis, and prediction accuracy, across different locations and periods. Furthermore, this study suggests that the net effects of aggregate location-to-location shifts were greater than the net effects of year-to-year shifts.

Chapter 4 conducts the predictive analysis of undivided two-way traffic HRGC crashes by utilizing the XGBoost algorithm along with the SHAP to investigate the dominant factors affecting injury severity outcomes for HDVs. The results suggest that the XGBoost model has varying performances in predicting different injury severities, with the killed model having the highest accuracy of 93.36%. Some significant predictors overlap between the killed and injured models, such as old driver and truck, while the other different significant factors reveal that the XGBoost model can distinguish between different severity levels. The application of SHAP values further enhances the interpretability of XGBoost models, offering a granular perspective on the influence of individual features. The detailed distributions of the respective top three

significant variables that emerged from the analysis are presented, such as train speed > 45 MPH, driver was in vehicle, truck, old driver, and female driver. Chapter 4 further compares factors affecting HRGC crash injury severities before (2018-2019) and during (2020-2021) the COVID-19 pandemic. This study indicates that the existence of old drivers and illuminated crossings generated random parameters with heterogeneity in means during the pandemic, which were affected by the driver in vehicle, estimated train speed, and crossing AADT indicators. As for the pre-pandemic period, no significant random parameters and unobserved heterogeneity were captured. Significant variables also differ markedly between these two periods, with no significant driver-related or vehicle-related indicators identified from 2018 to 2019. The results reveal that factors, including estimated vehicle speed, estimated train speed, commercial land type, female driver, driver in vehicle, van, and other vehicles increased the possibility of severe injury outcomes during the pandemic. The findings underscore the significance of considering unobserved heterogeneity of factors that impact HRGC crashes during the COVID-19 pandemic and could be used to develop targeted interventions to enhance road and railway safety.

Subsequently, the post-crash injury severity analysis is conducted in the context of AVs. To understand the real-world AV crash patterns and identify key factors influencing the associated damage severity, 584 AV collision reports from the California Department of Motor Vehicles are first extracted and augmented by a highly automatic and fast variable extraction framework. Chapter 5 applies a methodology integrating the latent class analysis and multinomial logit model to explore the heterogeneity in AV crash patterns. The findings reveal a significant correlation between moderate/major damage crashes and various risk factors, such as head-on, intersection, multiple vehicles, dark with street lights, dark without street lights, and early morning. Two heterogeneous clusters are determined based on the skewed distributions of vehicle status and driving mode. The model estimation results indicate significant differences among the variables influencing the damage severity across two distinct subclasses. Furthermore, partitioning the AV crash dataset into heterogeneous subsets facilitates the identification of critical factors that remain obscured when the dataset is analysed as a whole, such as the evening indicator.

Chapter 6 employs the structural equation modelling framework to disentangle the direct and mediation effects of key factors on AV crash damage severities,

considering additional point-of-interest characteristics. The results indicate direct pathways between AV crash outcomes and multiple risk factors, such as dark with streetlights and bus stop count. Results also reveal the impacts and influencing factors of two mediator variables, including zebra crossing and vulnerable road user. Additionally, the findings indicate that high-activity zones (such as medical and recreational facilities) could generate unpredictable interactions and traffic complexities that exceed AV predictive capacities, thus inducing more severe crash damage outcomes.

Chapter 7 utilizes the association rule mining to uncover the combinations of contributing factors that frequently co-occur in AV rear-end crashes. Short-term association rules, including 2-item and 3-item rules, are identified across all AV rear-end crashes. Furthermore, association rules for different damage severities are also investigated. Results demonstrate that in addition to the variables extracted from AV crash reports, supplementary building environment factors can also significantly influence the occurrence of AV rear-end crashes. Critical factors such as two-way without medians and stopped in traffic play pivotal roles in AV rear-end crashes, dominating most rules. Besides, HDVs rear-end crashes that occurred within a 50-foot radius of each AV crash and within the same time window are collected to conduct the comparative analysis between AV and HDV rear-end crashes. The results confirm the existence of distinct patterns, risk factors, and co-occurrence mechanisms that are unique to AV systems under real-world conditions. Although certain environmental risk factors such as two-way roads without median and roadside parking affect both AVs and HDVs, the dominant association patterns for AVs concentrate more around geometric constraints, signalization, and environmental sensing limitations, while HDV crashes are more frequently influenced by behavioural context and land use. These findings emphasize the importance of tailored infrastructure design and control strategies that account for the distinct vulnerabilities of AV systems.

This thesis makes several key contributions. Methodologically, it demonstrates the critical value of employing heterogeneity models (random parameters, latent class) and data driven techniques to move beyond associative insights toward causal understanding in safety science. The results highlight the importance of accounting for unobserved heterogeneity, temporal instability, mediation effects, and built environment factors when analysing post-crash injury/damage severity outcomes.

Empirically, it provides comprehensive, methodologically rigorous comparisons of AV and HDV crash patterns, identifying AV-specific risk patterns tied to the operational design domain and interaction with the built environment. Practically, the findings offer actionable intelligence for policymakers and engineers, advocating for context-specific countermeasures for HDVs and highlighting the need for AV-focused infrastructure adaptation and sensor fusion strategies to mitigate identified environmental and interaction-based risks. Collectively, this thesis advances the theoretical and practical framework for analysing crash severity in a transitioning mobility landscape. These obtained insights can inform the development of evidence-based safety strategies and targeted interventions that can contribute to a safer transportation system.

8.2 Limitations and recommendations for future research

For the driver injury severity analysis of HDV crashes, the self-selectivity problem associated with non-random samples may exist, i.e., less safe drivers may be over-represented in the accident data since safer drivers may avoid driving under adverse road surface conditions considering the substantial increase in risks. It should also be noted that severe injury crashes are a minority in the crash dataset and the imbalanced dataset could potentially introduce bias in parameter estimation and result in inaccurate inferences. In the future, sampling techniques such as under-sampling or over-sampling methods can be employed to balance the number of samples across different categories. Additionally, combining the finite element analysis software and crash test to load impact forces in different directions can also provide a supplementary way to comprehensively uncover the driver injury mechanism, which is beneficial to optimize the vehicle structure, promote the development of vehicle shock absorbers, and improve overall driver safety.

As accident dynamics and transportation practices evolve, continuous data collection is paramount, and the machine learning model would benefit from using an expanded dataset to devise more targeted and effective safety strategies. Besides, a database with more detailed information on crashes should be constructed to further provide insights into the trends and patterns of HRGC crashes. In the future, a comparative analysis between during-COVID and post-COVID periods can also be conducted to identify consistent patterns, emerging trends, and potential reasons for any evolution in the impact of factors over time. Additionally, by employing additional sensors, Internet of Things devices, and data analytics platforms, future studies could

integrate advanced analytics with real-time road infrastructure monitoring to predict and prevent possible real-time conflict points between vehicular traffic and trains. Given that injury severity outcomes may vary over different regions, it is also important to conduct future studies that take into consideration the spatial instability to gain a more comprehensive understanding of the injury severity analysis of HDV crashes.

For the analysis of heterogeneous patterns and factor identification in AV crashes, although this thesis attempts to extract and argument more AV crash records from the expanding dataset, the potential statistical challenge may still exist, and it necessitates cautious approaches to minimize bias and maximize the utility of available data. Techniques such as Bayesian inference, which can incorporate prior knowledge and adjust uncertainty in estimates, or machine learning models designed to deal with sparse data, can be considered in the future to offer pathways to more robust findings. Such methods would not only enhance theoretical interpretability of results but also support the development of more targeted intervention strategies for improving AV safety. Moreover, the dynamic improvement cycle of AV technology means that the causation patterns identified currently might evolve as new iterations of software and hardware are deployed. This constant evolution adds another layer of complexity to this research. However, due to insufficient sample size, temporal stability was not examined in this study, a critical aspect that should be addressed in future research with more mature longitudinal data. Last but not least, since real-time crash data can provide more valuable insights into the dynamic process of crash occurrences compared to the post-hoc analysis conducted in this study, future research could aim to aggregate such real-time data to improve the safety of automated vehicles more effectively.

By incorporating the additional layer of built environment information, this thesis also provides a more comprehensive understanding of the factors contributing to AV rear-end crashes and their interrelationships. Nevertheless, the current research is limited by the long-tail effect in crash distribution. Rare but high-risk scenarios may not have been fully captured due to the scarcity of comprehensive AV crash data. These rare events, though infrequent, pose significant safety challenges. Besides, the categorical representation of key variables limits the ability to capture potential nonlinear effects in this study. Future work will prioritize collecting high-resolution continuous data, such as traffic signal density and traffic volume, to support nonlinear threshold analysis using advanced machine learning techniques. Also, the inherent

complexities introduced by AVs operating in diverse environments and interacting with human drivers, pedestrians, and other road users are not yet fully understood. The absence of control variables such as regional traffic volume, time-of-day traffic patterns, and local enforcement intensity (e.g., speed limit enforcement or presence of traffic control devices) could also influence the generalizability of the current analysis. Future studies should address these limitations by incorporating more enriched or diversified datasets (such as naturalistic driving data or simulations) and exploring advanced methodologies to better account for these rare and complex crash scenarios. Last but not least, the implementation of a case-control or matched-cohort study design using a consistent California dataset is a key direction for future research to ensure the apple-to-apple HDV and AV crash comparison.

References

- Adanu, E.K., Hainen, A., Jones, S., 2018. Latent class analysis of factors that influence weekday and weekend single-vehicle crash severities. *Accident Analysis & Prevention* 113, 187–192.
- Adanu, E.K., Okafor, S., Penmetsa, P., Jones, S., 2022. Understanding the factors associated with the temporal variability in crash severity before, during, and after the COVID-19 shelter-in-place order. *Safety* 8(2), 42.
- Adnan Yusuf, S., Khan, A., Souissi, R., 2024. Vehicle-to-everything (V2X) in the autonomous vehicles domain – A technical review of communication, sensor, and AI technologies for road user safety. *Transportation Research Interdisciplinary Perspectives* 23, 100980.
- Agrawal, R., Mannila, H., Srikant, R., Toivonen, H., Verkamo, A.I., 1996. Fast discovery of association rules. *Advances in Knowledge Discovery and Data Mining* 12(1), 307–328.
- Ahmed, S.S., Corman, F., Anastasopoulos, P.Ch., 2023. Accounting for unobserved heterogeneity and spatial instability in the analysis of crash injury-severity at highway-rail grade crossings: A random parameters with heterogeneity in the means and variances approach. *Analytic Methods in Accident Research* 37, 100250.
- Akaike, H., 1974. A new look at the statistical model identification. *IEEE Transactions on Automatic Control* 19(6), 716–723.
- Alnawmasi, N., Mannering, F., 2023. An analysis of day and night bicyclist injury severities in vehicle/bicycle crashes: A comparison of unconstrained and partially constrained temporal modeling approaches. *Analytic Methods in Accident Research* 40, 100301.
- Alnawmasi, N., Mannering, F., 2022a. The impact of higher speed limits on the frequency and severity of freeway crashes: Accounting for temporal shifts and unobserved heterogeneity. *Analytic Methods in Accident Research* 34, 100205.
- Alnawmasi, N., Mannering, F., 2022b. A temporal assessment of distracted driving injury severities using alternate unobserved-heterogeneity modeling approaches. *Analytic Methods in Accident Research* 34, 100216.
- Alnawmasi, N., Mannering, F., 2019. A statistical assessment of temporal instability in the factors determining motorcyclist injury severities. *Analytic Methods in Accident Research* 22, 100090.
- Alogaili, A., Mannering, F., 2022. Differences between day and night pedestrian-injury severities: Accounting for temporal and unobserved effects in prediction.

- Analytic Methods in Accident Research 33, 100201.
- Alozi, A.R., Hussein, M., 2022. Evaluating the safety of autonomous vehicle–pedestrian interactions: An extreme value theory approach. *Analytic Methods in Accident Research* 35, 100230.
- Amini, M., Bagheri, A., Delen, D., 2022. Discovering injury severity risk factors in automobile crashes: A hybrid explainable AI framework for decision support. *Reliability Engineering & System Safety* 226, 108720.
- Apronti, D., Ksaibati, K., Gerow, K., Hepner, J.J., 2016. Estimating traffic volume on Wyoming low volume roads using linear and logistic regression methods. *Journal of Traffic and Transportation Engineering* 3(6), 493–506.
- Arellana, J., Fernández, S., Figueroa, M., Cantillo, V., 2022. Analyzing pedestrian behaviour when crossing urban roads by combining RP and SP data. *Transportation Research Part F: Traffic Psychology and Behaviour* 85, 259–275.
- Arvin, R., Khattak, A.J., Qi, H., 2021. Safety critical event prediction through unified analysis of driver and vehicle volatilities: Application of deep learning methods. *Accident Analysis & Prevention* 151, 105949.
- Ashraf, M.T., Dey, K., Mishra, S., Rahman, M.T., 2021. Extracting rules from autonomous-vehicle-involved crashes by applying decision tree and association rule methods. *Transportation Research Record* 2675(11), 522–533.
- Awad-Núñez, S., Julio, R., Gomez, J., Moya-Gómez, B., González, J.S., 2021. Post-COVID-19 travel behaviour patterns: impact on the willingness to pay of users of public transport and shared mobility services in Spain. *European Transport Research Review*. 13(1), 20.
- Azimi, G., Rahimi, A., Asgari, H., Jin, X., 2020. Severity analysis for large truck rollover crashes using a random parameter ordered logit model. *Accident Analysis & Prevention* 135, 105355.
- Azimian, A., Dimitra Pyrialakou, V., Lavrenz, S., Wen, S., 2021. Exploring the effects of area-level factors on traffic crash frequency by severity using multivariate space-time models. *Analytic Methods in Accident Research* 31, 100163.
- Behnood, A., Mannering, F., 2019. Time-of-day variations and temporal instability of factors affecting injury severities in large-truck crashes. *Analytic Methods in Accident Research* 23, 100102.
- Behnood, A., Mannering, F., 2017. Determinants of bicyclist injury severities in bicycle-vehicle crashes: A random parameters approach with heterogeneity in means and variances. *Analytic Methods in Accident Research* 16, 35–47.
- Behnood, A., Mannering, F.L., 2015. The temporal stability of factors affecting driver-injury severities in single-vehicle crashes: Some empirical evidence. *Analytic*

- Methods in Accident Research 8, 7–32.
- Ben-Akiva, M.E., Lerman, S.R., 1985. Discrete choice analysis: theory and application to travel demand. MIT press.
- Bhagavathula, R., Gibbons, R.B., 2023. Lighting strategies to increase nighttime pedestrian visibility at midblock crosswalks. *Sustainability* 15(2), 1455.
- Billah, K., Sharif, H.O., Dessouky, S., 2022. How gender affects motor vehicle crashes: A case study from San Antonio, Texas. *Sustainability* 14(12), 7023.
- Boggs, A.M., Wali, B., Khattak, A.J., 2020. Exploratory analysis of automated vehicle crashes in California: A text analytics & hierarchical Bayesian heterogeneity-based approach. *Accident Analysis & Prevention* 135, 105354.
- Bowen, N.K., Guo, S., 2011. Structural equation modeling. Oxford University Press.
- Cabral, M.F.F., Albuquerque, F.S., de Freitas Neto, O., Albuquerque, T.M.A., 2015. Study of mechanisms that generate traffic noise in the tire–pavement interface for low-volume roads in Brazil. *Transportation Research Record* 2474(1), 98–107.
- Çakır, E., Fışkın, R., Sevgili, C., 2021. Investigation of tugboat accidents severity: An application of association rule mining algorithms. *Reliability Engineering & System Safety* 209, 107470.
- California Department of Motor Vehicles, 2024. Autonomous Vehicle Collision Reports. California DMV. URL <https://www.dmv.ca.gov/portal/vehicle-industry-services/autonomous-vehicles/autonomous-vehicle-collision-reports/> (accessed 5.30.24).
- Calvi, A., Cafiso, S.D., D’Agostino, C., Kieć, M., Petrucci, G., 2023. A driving simulator study to evaluate the effects of different types of median separation on driving behaviour on 2 + 1 roads. *Accident Analysis & Prevention* 180, 106922.
- Canadian Council of Motor Transport Administrators, 2021. 2020 Road Safety Annual Report. CCMTA. URL <https://ccmta.ca/en/road-safety> (accessed 3.1.23).
- Cao, Y., Iulia, M., Majumdar, A., Feng, Y., Xin, X., Wang, X., Wang, H., Yang, Z., 2025. Investigation of the risk influential factors of maritime accidents: A novel topology and robustness analytical framework. *Reliability Engineering & System Safety* 254, 110636.
- Center for Safe Transportation Research and Education at the University of California, Berkeley, 2025. TIMS - Transportation Injury Mapping System. URL <https://tims.berkeley.edu/> (accessed 7.12.25).
- Cerwick, D.M., Gkritza, K., Shaheed, M.S., Hans, Z., 2014. A comparison of the mixed

- logit and latent class methods for crash severity analysis. *Analytic Methods in Accident Research* 3–4, 11–27.
- Champahom, T., Jomnonkwao, S., Watthanaklang, D., Karoonsoontawong, A., Chatpattananan, V., Ratanavaraha, V., 2020. Applying hierarchical logistic models to compare urban and rural roadway modeling of severity of rear-end vehicular crashes. *Accident Analysis & Prevention* 141, 105537.
- Chand, S., Yee, E., Alsultan, A., Dixit, V.V., 2021. A descriptive analysis on the impact of COVID-19 lockdowns on road traffic incidents in Sydney, Australia. *International Journal of Environmental Research and Public Health* 18(21), 11701.
- Chen, H., Chen, Q., Chen, L., Zhang, G., 2016. Analysis of risk factors affecting driver injury and crash injury with drivers under the influence of alcohol (DUI) and non-DUI. *Traffic Injury Prevention* 17(8), 796–802.
- Chen, P., Ni, H., Wang, L., Yu, G., Sun, J., 2024. Safety performance evaluation of freeway merging areas under autonomous vehicles environment using a co-simulation platform. *Accident Analysis & Prevention* 199, 107530.
- Chen, S., Kuhn, M., Prettnner, K., Bloom, D.E., 2019. The global macroeconomic burden of road injuries: estimates and projections for 166 countries. *The Lancet Planetary Health* 3(9), 390–398.
- Chen, T., Guestrin, C., 2016. XGBoost: A scalable tree boosting system, in: *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD'16*. Association for Computing Machinery, New York, NY, USA, 785–794.
- Chen, T., Wong, Y.D., Shi, X., Wang, X., 2022. Optimized structure learning of Bayesian Network for investigating causation of vehicles' on-road crashes. *Reliability Engineering & System Safety* 224, 108527.
- Chen, X., Ma, X., Jia, L., Chen, F., 2025. Risk assessment of main accident causes at highway-rail grade crossings. *Reliability Engineering & System Safety* 256, 110764.
- Dabbour, E., Easa, S., Haider, M., 2017. Using fixed-parameter and random-parameter ordered regression models to identify significant factors that affect the severity of drivers' injuries in vehicle-train collisions. *Accident Analysis & Prevention* 107, 20–30.
- Das, D.K., 2023. Exploring the significance of road and traffic factors on traffic crashes in a South African city. *International Journal of Transportation Science and Technology* 12(2), 414–427.
- De Lapparent, M., 2008. Willingness to use safety belt and levels of injury in car

- accidents. *Accident Analysis & Prevention* 40(3), 1023–1032.
- Deng, M., Gluck, A., Zhao, Y., Li, D., Menassa, C.C., Kamat, V.R., Brinkley, J., 2024. An analysis of physiological responses as indicators of driver takeover readiness in conditionally automated driving. *Accident Analysis & Prevention* 195, 107372.
- Ding, H., Lu, Y., Sze, N.N., Chen, T., Guo, Y., Lin, Q., 2022. A deep generative approach for crash frequency model with heterogeneous imbalanced data. *Analytic Methods in Accident Research* 34, 100212.
- Dong, X., Xie, K., Yang, H., 2022. How did COVID-19 impact driving behaviours and crash Severity? A multigroup structural equation modeling. *Accident Analysis & Prevention* 172, 106687.
- Dziak, J.J., Coffman, D.L., Lanza, S.T., Li, R., Jermin, L.S., 2012. Sensitivity and Specificity of Information Criteria. *Briefings in bioinformatics* 21(2), 553–565
- Elamrani Abou Ellassad, Z., Mousannif, H., Al Moatassime, H., 2020a. A proactive decision support system for predicting traffic crash events: A critical analysis of imbalanced class distribution. *Knowledge-Based Systems* 205, 106314.
- Elamrani Abou Ellassad, Z., Mousannif, H., Al Moatassime, H., 2020b. Class-imbalanced crash prediction based on real-time traffic and weather data: A driving simulator study. *Traffic Injury Prevention* 21(3), 201–208.
- El-Basyouny, K., Sayed, T., 2009. Accident prediction models with random corridor parameters. *Accident Analysis & Prevention* 41(5), 1118–1123.
- Ester, M., Kriegel, H.-P., Sander, J., Xu, X., 1996. A density-based algorithm for discovering clusters in large spatial databases with noise, in: *KDD*, 226–231.
- Fan, P., Guo, J., Wang, Y., Wijnands, J.S., 2022. A hybrid deep learning approach for driver anomalous lane changing identification. *Accident Analysis & Prevention* 171, 106661.
- Federal Railroad Administration, 2022. Highway-Rail Grade Crossing and Trespassing Research. URL <https://railroads.dot.gov/research-development/program-areas/highway-rail-grade-crossing/highway-rail-grade-crossing-and> (accessed 5.1.23).
- Federal Railroad Administration, 2021. Highway-Rail Grade Crossing Incidents. URL <https://railroads.dot.gov/accident-and-incident-reporting/highwayrail-grade-crossing-incidents/highwayrail-grade-crossing> (accessed 3.1.23).
- Feng, S., Qian, Y., Wang, Y., 2021. Collision avoidance method of autonomous vehicle based on improved artificial potential field algorithm. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering* 235(14), 3416–3430.

- Feng, S., Sun, H., Yan, X., Zhu, H., Zou, Z., Shen, S., Liu, H.X., 2023. Dense reinforcement learning for safety validation of autonomous vehicles. *Nature* 615, 620–627.
- Finch, W.H., Bronk, K.C., 2011. Conducting confirmatory latent class analysis using Mplus. *Structural Equation Modeling: A Multidisciplinary Journal* 18(1), 132–151.
- Fountas, G., Anastasopoulos, P.Ch., 2018. Analysis of accident injury-severity outcomes: The zero-inflated hierarchical ordered probit model with correlated disturbances. *Analytic Methods in Accident Research* 20, 30–45.
- Fountas, G., Fonzone, A., Gharavi, N., Rye, T., 2020. The joint effect of weather and lighting conditions on injury severities of single-vehicle accidents. *Analytic Methods in Accident Research* 27, 100124.
- Gao, L., Lu, P., Ren, Y., 2021. A deep learning approach for imbalanced crash data in predicting highway-rail grade crossings accidents. *Reliability Engineering & System Safety* 216, 108019.
- Ghadi, M., Török, Á., 2019. A comparative analysis of black spot identification methods and road accident segmentation methods. *Accident Analysis & Prevention* 128, 1–7.
- Ghomi, H., Bagheri, M., Fu, L., Miranda-Moreno, L.F., 2016. Analyzing injury severity factors at highway railway grade crossing accidents involving vulnerable road users: A comparative study. *Traffic Injury Prevention* 17(8), 833–841.
- Ghosh, S., Zaboli, A., Hong, J., Kwon, J., 2023. An integrated approach of threat analysis for autonomous vehicles perception system. *IEEE Access* 11, 14752–14777.
- Goodman, L.A., 1970. The multivariate analysis of qualitative data: Interactions among multiple classifications. *Journal of the American Statistical Association* 65(329), 226–256.
- Goswamy, A., Abdel-Aty, M., Islam, Z., 2023. Factors affecting injury severity at pedestrian crossing locations with Rectangular RAPID Flashing Beacons (RRFB) using XGBoost and random parameters discrete outcome models. *Accident Analysis & Prevention* 181, 106937.
- Guo, Z., Pang, H., Zhang, Jingyu, Zhang, Jun, Wang, J., He, C., Li, C., 2023. Using HFACS to understand human error in railway dispatcher performance: a study of proactive safety inspection records. *Ergonomics*, 1–14.
- Gupta, N., Bamney, A., Rostami, A., Kamjoo, E., Savolainen, P.T., 2023. How did the COVID-19 pandemic affect driver speed selection and crash risk on rural freeways? *Transportation Research Part F: Traffic Psychology and Behaviour*

97, 181–206.

- Hahsler, M., 2024. An R companion for introduction to data mining. *Journal of Open Source Education* 7(82), 223.
- Hahsler, M., Grün, B., Hornik, K., 2005. arules - A computational environment for mining association rules and frequent item sets. *Journal of Statistical Software* 14, 1–25.
- Haleem, K., Gan, A., 2015. Contributing factors of crash injury severity at public highway-railroad grade crossings in the U.S. *Journal of Safety Research* 53, 23–29.
- Halton, J.H., 1960. On the efficiency of certain quasi-random sequences of points in evaluating multi-dimensional integrals. *Numerische Mathematik* 2, 84–90.
- Hamim, O.F., Ukkusuri, S.V., 2022. Determining prominent factors across system hierarchies to improve road safety in LMICs: A case study of Bangladesh. *Safety Science* 150, 105709.
- Hao, W., Kamga, C., Daniel, J., 2015. The effect of age and gender on motor vehicle driver injury severity at highway-rail grade crossings in the United States. *Journal of Safety Research* 55, 105–113.
- Hausman, J., McFadden, D., 1984. Specification tests for the multinomial logit model. *Econometrica* 52(5), 1219–1240.
- He, L., Yu, B., Chen, Y., Bao, S., Gao, K., Kong, Y., 2023. An interpretable prediction model of illegal running into the opposite lane on curve sections of two-lane rural roads from drivers' visual perceptions. *Accident Analysis & Prevention* 186, 107066.
- Hou, J., Zhang, E., Long, Y., 2023. Measuring pedestrian flows in public spaces: Inferring walking for transport and recreation using Wi-Fi probes. *Building and Environment* 230, 109999.
- Hou, L., Wu, X., Wu, Z., Wu, S., 2020. Pattern identification and risk prediction of domino effect based on data mining methods for accidents occurred in the tank farm. *Reliability Engineering & System Safety* 193, 106646.
- Hou, Q., Huo, X., Leng, J., Mannering, F., 2022. A note on out-of-sample prediction, marginal effects computations, and temporal testing with random parameters crash-injury severity models. *Analytic Methods in Accident Research* 33, 100191.
- Huang, H., Peng, Y., Wang, J., Luo, Q., Li, X., 2018. Interactive risk analysis on crash injury severity at a mountainous freeway with tunnel groups in China. *Accident Analysis & Prevention* 111, 56–62.

- Igolkina, A.A., and Meshcheryakov, G., 2020. semopy: A python package for structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal* 27(6), 952–963.
- Ihssian, A., Ismail, K., 2023. Modelling pedestrian safety at urban intersections using user perception. *Accident Analysis & Prevention* 180, 106912.
- Islam, M., Alnawmasi, N., Mannering, F., 2020. Unobserved heterogeneity and temporal instability in the analysis of work-zone crash-injury severities. *Analytic methods in accident research* 28, 100130.
- Islam, M., Alogaili, A., Mannering, F., Maness, M., 2023. Evidence of sample selectivity in highway injury-severity models: The case of risky driving during COVID-19. *Analytic Methods in Accident Research* 38, 100263.
- Islam, M., Mannering, F., 2021. The role of gender and temporal instability in driver-injury severities in crashes caused by speeds too fast for conditions. *Accident Analysis & Prevention* 153, 106039.
- Islam, M., Mannering, F., 2020. A temporal analysis of driver-injury severities in crashes involving aggressive and non-aggressive driving. *Analytic Methods in Accident Research* 27, 100128.
- Islam, Z., Abdel-Aty, M., Mahmoud, N., 2022. Using CNN-LSTM to predict signal phasing and timing aided by High-Resolution detector data. *Transportation Research Part C: Emerging Technologies* 141, 103742.
- Jahan, M.I., Bhowmik, T., Eluru, N., 2023. Evaluation of freeway demand in Florida during the COVID-19 pandemic from a spatiotemporal perspective. *Journal of Transportation Engineering, Part A: Systems* 149(8), 04023071.
- Jamal, A., Zahid Khattak, M., Rahman, M.T., Hasan, A., Almoshaogeh, M., Farooq, D., Ahmad, M., 2021. Injury severity prediction of traffic crashes with ensemble machine learning techniques: a comparative study. *International Journal of Injury Control and Safety Promotion* 28(4), 408–427.
- Jia, R., Khadka, A., Kim, I., 2018. Traffic crash analysis with point-of-interest spatial clustering. *Accident Analysis & Prevention* 121, 223–230.
- Jiang, H., Fang, S., Chen, Y., Ma, Z., 2013. A spatial autocorrelation-based approach for identifying hot spots on urban road. *Journal of Tongji University (Natural Science)* 41(5), 664–669.
- Jiang, W., Xing, X., Huang, A., Chen, J., 2022. Research on performance limitations of visual-based perception system for autonomous vehicle under severe weather conditions. Presented at the 2022 IEEE Intelligent Vehicles Symposium (IV), pp. 586–593.
- Jooa, J., Bangb, S., Parka, G., 2016. Implementation of a recommendation system using

- association rules and collaborative filtering. *Procedia Computer Science* 91, 944–952.
- Kabir, M.M., Jim, J.R., Istenes, Z., 2025. Terrain detection and segmentation for autonomous vehicle navigation: A state-of-the-art systematic review. *Information Fusion* 113, 102644.
- Keramati, A., Lu, P., Iranitalab, A., Pan, D., Huang, Y., 2020. A crash severity analysis at highway-rail grade crossings: The random survival forest method. *Accident Analysis & Prevention* 144, 105683.
- Khan, M.N., Ahmed, M.M., 2020. Trajectory-level fog detection based on in-vehicle video camera with TensorFlow deep learning utilizing SHRP2 naturalistic driving data. *Accident Analysis & Prevention* 142, 105521.
- Khan, W.A., Khattak, A.J., 2018. Injury severity of truck drivers in crashes at highway-rail grade crossings in the United States. *Transportation Research Record* 2672(10), 38–47.
- Khattak, A.J., Rocha, M., 2003. Are SUVs “supremely unsafe vehicles”? Analysis of rollovers and injuries with sport utility vehicles. *Transportation Research Record* 1840(1), 167–177.
- Khogali, H.O., Mekid, S., 2023. The blended future of automation and AI: Examining some long-term societal and ethical impact features. *Technology in Society* 73, 102232.
- Kim, J.-K., Ulfarsson, G.F., Kim, S., Shankar, V.N., 2013. Driver-injury severity in single-vehicle crashes in California: A mixed logit analysis of heterogeneity due to age and gender. *Accident Analysis & Prevention* 50, 1073–1081.
- Kim, S.H., 2023. How heterogeneity has been examined in transportation safety analysis: A review of latent class modeling applications. *Analytic Methods in Accident Research* 40, 100292.
- Kim, S.H., Mokhtarian, P.L., 2023. Finite mixture (or latent class) modeling in transportation: Trends, usage, potential, and future directions. *Transportation Research Part B: Methodological* 172, 134–173.
- Kuo, P.-F., Hsu, W.-T., Lord, D., Putra, I.G.B., 2024. Classification of autonomous vehicle crash severity: Solving the problems of imbalanced datasets and small sample size. *Accident Analysis & Prevention* 205, 107666.
- Kurpisz, D., Obst, M., Szymczak, T., Wilde, R., 2023. Analytical approach for vehicle body structures behaviour under crash at aspects of overloading and crumple zone length. *Acta Mechanica et Automatica* 17(1), 68–75.
- Kutela, B., Avelar, R.E., Bansal, P., 2022a. Modeling automated vehicle crashes with a focus on vehicle at-fault, collision type, and injury outcome. *Journal of*

- Transportation Engineering, Part A: Systems 148(6), 04022024.
- Kutela, B., Das, S., Dadashova, B., 2022b. Mining patterns of autonomous vehicle crashes involving vulnerable road users to understand the associated factors. *Accident Analysis & Prevention* 165, 106473.
- Kutela, B., Kidando, E., Kitali, A.E., Mwende, S., Langa, N., Novat, N., 2022c. Exploring pre-crash gate violations behaviours of drivers at highway-rail grade crossings using a mixed multinomial logit model. *International Journal of Injury Control and Safety Promotion* 29(2), 226–238.
- Labbo, M.S., Qu, L., Xu, C., Bai, W., Ayele Atumo, E., Jiang, X., 2024. Understanding risky driving behaviours among young novice drivers in Nigeria: A latent class analysis coupled with association rule mining approach. *Accident Analysis & Prevention* 200, 107557.
- Lan, H., Ma, X., Qiao, W., Deng, W., 2023. Determining the critical risk factors for predicting the severity of ship collision accidents using a data-driven approach. *Reliability Engineering & System Safety* 230, 108934.
- Lan, H., Ma, X., Qiao, W., Ma, L., 2022. On the causation of seafarers' unsafe acts using grounded theory and association rule. *Reliability Engineering & System Safety* 223, 108498.
- Lanza, S.T., Tan, X., Bray, B.C., 2013. Latent class analysis with distal outcomes: A flexible model-based approach. *Structural Equation Modeling: A Multidisciplinary Journal* 20(1), 1–26.
- Lee, D., Hess, D.J., 2020. Regulations for on-road testing of connected and automated vehicles: Assessing the potential for global safety harmonization. *Transportation Research Part A: Policy and Practice* 136, 85–98.
- Lee, J., Huang, H., Wang, J., Quddus, M., 2022. Road safety under the environment of intelligent connected vehicles. *Accident Analysis & Prevention* 170, 106645.
- Li, G., Yang, Y., Zhang, T., Qu, X., Cao, D., Cheng, B., Li, K., 2021. Risk assessment based collision avoidance decision-making for autonomous vehicles in multi-scenarios. *Transportation research part C: emerging technologies* 122, 102820.
- Li, J., Zhao, Z., 2022. Impact of COVID-19 travel-restriction policies on road traffic accident patterns with emphasis on cyclists: A case study of New York City. *Accident Analysis & Prevention* 167, 106586.
- Li, X., Zhu, R., Ye, H., Jiang, C., Benslimane, A., 2021. MetaInjury: Meta-learning framework for reusing the risk knowledge of different construction accidents. *Safety Science* 140, 105315.
- Li, Z., Wu, Q., Ci, Y., Chen, C., Chen, X., Zhang, G., 2019. Using latent class analysis and mixed logit model to explore risk factors on driver injury severity in single-

- vehicle crashes. *Accident Analysis & Prevention* 129, 230–240.
- Lin, Z., Fan, W. (David), 2021. Exploring bicyclist injury severity in bicycle-vehicle crashes using latent class clustering analysis and partial proportional odds models. *Journal of Safety Research* 76, 101–117.
- Linzer, D.A., Lewis, J.B., 2011. poLCA: An R package for polytomous variable latent class analysis. *Journal of statistical software* 42, 1–29.
- Liu, H.X., Feng, S., 2024. Curse of rarity for autonomous vehicles. *nature communications* 15(1), 4808.
- Liu, P., Fan, W., 2020. Exploring injury severity in head-on crashes using latent class clustering analysis and mixed logit model: A case study of North Carolina. *Accident Analysis & Prevention* 135, 105388.
- Liu, P., Fan, W. (David), 2021. Analysis of head-on crash injury severity using a partial proportional odds model. *Journal of Transportation Safety & Security* 13(7), 714–734.
- Liu, P., Zhang, Y., He, Z., 2019. The effect of population age on the acceptable safety of self-driving vehicles. *Reliability Engineering & System Safety* 185, 341–347.
- Liu, P., Guo, Y., Liu, Pan, Ding, H., Cao, J., Zhou, J., Feng, Z., 2024. What can we learn from the AV crashes? – An association rule analysis for identifying the contributing risky factors. *Accident Analysis & Prevention* 199, 107492.
- Liu, Q., Wang, X., Liu, S., Yu, C., Glaser, Y., 2024. Analysis of pre-crash scenarios and contributing factors for autonomous vehicle crashes at intersections. *Accident Analysis & Prevention* 195, 107383.
- Liu, Q., Wang, X., Wu, X., Glaser, Y., He, L., 2021. Crash comparison of autonomous and conventional vehicles using pre-crash scenario typology. *Accident Analysis & Prevention* 159, 106281.
- Liu, R., Yan, X., Ma, S., Xue, Q., 2022. Eye movement as a function to explore the effects of improved signs design and audio warning on drivers' behaviour at STOP-sign-controlled grade crossings. *Accident Analysis & Prevention* 172, 106693.
- Lombardi, D.A., Horrey, W.J., Courtney, T.K., 2017. Age-related differences in fatal intersection crashes in the United States. *Accident Analysis & Prevention* 99, 20–29.
- Lu, J., Gan, A., Haleem, K., Wu, W., 2013. Clustering-based roadway segment division for the identification of high-crash locations. *Journal of Transportation Safety & Security* 5(3), 224–239.
- Lu, Y., Yi, B., Song, X., Zhao, S., Wang, J., Cao, H., 2022. Can we adapt to highly

- automated vehicles as passengers? The mediating effect of trust and situational awareness on role adaption moderated by automated driving style. *Transportation Research Part F: Traffic Psychology and Behaviour* 90, 269–286.
- Lundberg, S.M., Lee, S.-I., 2017. A unified approach to interpreting model predictions, in: *Advances in neural information processing systems*. *Advances in neural information processing systems*, 30.
- Ma, Y., Zhang, J., Lu, J., Chen, S., Xing, G., Feng, R., 2023. Prediction and analysis of likelihood of freeway crash occurrence considering risky driving behaviour. *Accident Analysis & Prevention* 192, 107244.
- Mahmud, S.M.S., Ferreira, L., Hoque, Md.S., Tavassoli, A., 2022. Overtaking risk modeling in two-lane two-way highway with heterogeneous traffic environment of a low-income country using naturalistic driving dataset. *Journal of Safety Research* 80, 380–390.
- Mannering, F., 2018. Temporal instability and the analysis of highway accident data. *Analytic Methods in Accident Research* 17, 1–13.
- Mannering, F., Bhat, C.R., Shankar, V., Abdel-Aty, M., 2020. Big data, traditional data and the tradeoffs between prediction and causality in highway-safety analysis. *Analytic Methods in Accident Research* 25, 100113.
- Mannering, F.L., Bhat, C.R., 2014. Analytic methods in accident research: Methodological frontier and future directions. *Analytic Methods in Accident Research* 1, 1–22.
- Mannering, Fred L, Shankar, V., Bhat, C.R., 2016. Unobserved heterogeneity and the statistical analysis of highway accident data. *Analytic Methods in Accident Research* 11, 1–16.
- Mateo Sanguino, T. de J., Manuel Lozano Domínguez, J., Joaquín Redondo González, M., Miguel Davila Martin, J., 2024. New approach to intelligent pedestrian detection and signaling on crosswalks. *IEEE Transactions on Intelligent Transportation Systems* 25(12), 21416–21428.
- Mathew, J., Benekohal, R.F., 2021. Highway-rail grade crossings accident prediction using Zero Inflated Negative Binomial and Empirical Bayes method. *Journal of Safety Research* 79, 211–236.
- Matin, A., Dia, H., 2023. Impacts of connected and automated vehicles on road safety and efficiency: A systematic literature review. *IEEE Transactions on Intelligent Transportation Systems* 24(3), 2705–2736.
- McFadden, D., 1981. Econometric models of probabilistic choice. *Structural analysis of discrete data with econometric applications* 198272.
- Merlin, L.A., Guerra, E., Dumbaugh, E., 2020. Crash risk, crash exposure, and the built

- environment: A conceptual review. *Accident Analysis & Prevention* 134, 105244.
- Mimi, M.S., Chakraborty, R., Liu, J., Barua, S., Das, S., 2025. Exploring patterns in older pedestrian involved crashes during nighttime. *Accident Analysis & Prevention* 209, 107815.
- Mokhtarimousavi, S., Kitali, A.E., Anderson, J.C., Alluri, P., Mehrabi, A., 2022. COVID-19 and injury severity of drivers involved in run-off-road crashes: Analyzing the impact of contributing factors. *Transportation Research Record* 03611981221097093.
- Monfort, S.S., Cicchino, J.B., Patton, D., 2021. Weekday bicycle traffic and crash rates during the COVID-19 pandemic. *Journal of Transport & Health* 23, 101289.
- Montella, A., 2011. Identifying crash contributory factors at urban roundabouts and using association rules to explore their relationships to different crash types. *Accident Analysis & Prevention* 43(4), 1451–1463.
- Moradloo, N., Mahdinia, I., Khattak, A.J., 2024. Safety in higher level automated vehicles: Investigating edge cases in crashes of vehicles equipped with automated driving systems. *Accident Analysis & Prevention* 203, 107607.
- Morgan, A., Mannering, F.L., 2011. The effects of road-surface conditions, age, and gender on driver-injury severities. *Accident Analysis & Prevention* 43(5), 1852–1863.
- Mosharafian, S., Velni, J.M., 2022. Cooperative adaptive cruise control in a mixed-autonomy traffic system: A hybrid stochastic predictive approach incorporating lane change. *IEEE Transactions on Vehicular Technology* 72(1), 136–148.
- Muley, D., Ghanim, M.S., Mohammad, A., Kharbeche, M., 2021. Quantifying the impact of COVID–19 preventive measures on traffic in the State of Qatar. *Transport Policy* 103, 45–59.
- Najaf, P., Thill, J.-C., Zhang, W., Fields, M.G., 2017. Direct and indirect effects of city-level urban form on traffic safety: A structural equation modeling analysis. Presented at the Transportation Research Board 96th Annual Meeting Transportation Research Board.
- National Highway Traffic Safety, Administration, 2022. Traffic Crash Data. URL <https://www.nhtsa.gov/> (accessed 3.1.23).
- NHTSA, 2024. Standing General Order on Crash Reporting. URL <https://www.nhtsa.gov/laws-regulations/standing-general-order-crash-reporting> (accessed 6.1.24).
- Novat, N., Kidando, E., Kutela, B., Kitali, A.E., 2023. A comparative study of collision types between automated and conventional vehicles using Bayesian

- probabilistic inferences. *Journal of Safety Research* 84, 251–260.
- Nylund, K.L., Asparouhov, T., Muthén, B.O., 2007. Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo Simulation study. *Structural Equation Modeling: A Multidisciplinary Journal* 14(4), 535–569.
- Nylund-Gibson, K., Choi, A.Y., 2018. Ten frequently asked questions about latent class analysis. *Translational Issues in Psychological Science* 4(4), 440–461.
- Olbricht, R., 2011. Overpass api. Anwenderkonferenz für Freie und open source Software für Geoinformationssysteme.
- Pan, Y., Wu, Y., Xu, L., Xia, C., Olson, D.L., 2024. The impacts of connected autonomous vehicles on mixed traffic flow: A comprehensive review. *Physica A: Statistical Mechanics and its Applications* 635, 129454.
- Pandharipande, A., Cheng, C.-H., Dauwels, J., Gurbuz, S.Z., Ibanez-Guzman, J., Li, G., Piazzoni, A., Wang, P., Santra, A., 2023. Sensing and machine learning for automotive perception: A review. *IEEE Sensors Journal* 23(11), 11097–11115.
- Pawar, D.S., Yadav, A.K., Choudhary, P., Velaga, N.R., 2021. Modelling work- and non-work-based trip patterns during transition to lockdown period of COVID-19 pandemic in India. *Travel Behaviour and Society* 24, 46–56.
- Pearson, K., 1895. Note on regression and inheritance in the case of two parents. *Proceedings of the Royal Society of London* 58, 240–242.
- Peng, Y., Song, G., Guo, M., Wu, L., Yu, L., 2023. Investigating the impact of environmental and temporal features on mobile phone distracted driving behaviour using phone use data. *Accident Analysis & Prevention* 180, 106925.
- Pervez, A., Lee, J., Huang, H., 2022. Exploring factors affecting the injury severity of freeway tunnel crashes: A random parameters approach with heterogeneity in means and variances. *Accident Analysis & Prevention* 178, 106835.
- Phillips, R.O., Hagen, O.H., Berge, S.H., 2021. Bus stop design and traffic safety: An explorative analysis. *Accident Analysis & Prevention* 153, 105917.
- Qu, X., Xiao, X., Zhu, X., Wu, H., Gong, J., Li, D., 2023. 6Ds-HLM: Hierarchical models of road traffic crash influencing factor analysis considering the urban built environment of intersection visibility. *International Journal of Applied Earth Observation and Geoinformation* 123, 103472.
- Rafiq, R., McNally, M.G., 2021. Heterogeneity in activity-travel patterns of public transit users: An application of latent class analysis. *Transportation Research Part A: Policy and Practice* 152, 1–18.
- Rahman, M.T., Dey, K., Dimitra Pyrialakou, V., Das, S., 2023. Factors influencing

- safety perceptions of sharing roadways with autonomous vehicles among vulnerable roadway users. *Journal of Safety Research* 85, 266–277.
- Rashmi, B.S., Marisamynathan, S., 2023. Factors affecting truck driver behaviour on a road safety context: A critical systematic review of the evidence. *Journal of Traffic and Transportation Engineering (English Edition)* 10(5), 835-865.
- Ren, Q., He, J., Liu, Z., Xu, M., 2024a. Traffic flow characteristics and traffic conflict analysis in the downstream area of expressway toll station based on vehicle trajectory data. *Asian Transport Studies* 10, 100138.
- Ren, Q., Xu, M., 2025. Heterogeneity in crash patterns of autonomous vehicles: The latent class analysis coupled with multinomial logit model. *Accident Analysis & Prevention* 209, 107827.
- Ren, Q., Xu, M., 2024a. Exploring factors affecting the injury severity of highway-rail grade crossing crashes during the COVID-19 pandemic. *Transportation Letters* 17(5), 816–826.
- Ren, Q., Xu, M., 2024b. Injury severity analysis of highway-rail grade crossing crashes in non-divided two-way traffic scenarios: A random parameters logit model. *Multimodal Transportation* 3(1), 100109.
- Ren, Q., Xu, M., 2023. Exploring variations and temporal instability of factors affecting driver injury severities between different vehicle impact locations under adverse road surface conditions. *Analytic Methods in Accident Research* 40, 100305.
- Ren, Q., Xu, M., Yan, X., 2024a. An investigation of heterogeneous impact, temporal stability, and aggregate shift in factors affecting the driver injury severity in single-vehicle rollover crashes. *Accident Analysis & Prevention* 200, 107562.
- Ren, Q., Xu, M., Zhou, B., Chung, S.-H., 2024b. Traffic safety assessment and injury severity analysis for undivided two-way highway-rail grade crossings. *Mathematics* 12(4), 519.
- Rezwana, S., Lownes, N., 2024. Interactions and behaviours of pedestrians with autonomous vehicles: A synthesis. *Future Transportation* 4(3), 722–745.
- Rigdon, E.E., 1996. CFI versus RMSEA: A comparison of two fit indexes for structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 369-379.
- Roque, C., Moura, F., Lourenço Cardoso, J., 2015. Detecting unforgiving roadside contributors through the severity analysis of ran-off-road crashes. *Accident Analysis & Prevention* 80, 262–273.
- Rostami, A., Kamjoo, E., Bamney, A., Gupta, N., Savolainen, P.T., Zockaie, A., 2023. Investigating changes in travel behaviour over time in response to the COVID-19 pandemic. *Transportation Research Part F: Traffic Psychology and*

Behaviour 96, 133–154.

- Said, M., Tahlyan, D., Stathopoulos, A., Mahmassani, H., Walker, J., Shaheen, S., 2023. In-person, pick up or delivery? Evolving patterns of household spending behaviour through the early reopening phase of the COVID-19 pandemic. *Travel Behaviour and Society* 31, 295–311.
- Sameen, M.I., Pradhan, B., 2017. Severity prediction of traffic accidents with recurrent neural networks. *Applied Sciences* 7(6), 476.
- Samerei, S.A., Aghabayk, K., 2024. Analyzing the transition from two-vehicle collisions to chain reaction crashes: A hybrid approach using random parameters logit model, interpretable machine learning, and clustering. *Accident Analysis & Prevention* 202, 107603.
- Sarker, A., Shen, H., Rahman, M., Chowdhury, M., Dey, K., Li, F., Wang, Y., Narman, H.S., 2020. A review of sensing and communication, human factors, and controller aspects for information-aware connected and automated vehicles. *IEEE Transactions on Intelligent Transportation Systems* 21(1), 7–29.
- Schultz, G.G., Lunt, C.C., Pew, T., Warr, R.L., 2023. Using complementary intersection and segment analyses to identify crash hot spots. *Safety Science* 163, 106121.
- Schwarz, G., 1978. Estimating the dimension of a model. *The Annals of Statistics* 6(2), 461–464.
- Selvaraj, D.C., Vitale, C., Panayiotou, T., Kolios, P., Chiasserini, C.F., Ellinas, G., 2023. Edge-assisted ML-aided uncertainty-aware vehicle collision avoidance at urban intersections. *IEEE Transactions on Intelligent Vehicles* 1–17.
- Shafique, R., Rustam, F., Murtala, S., Jurcut, A.D., Choi, G.S., 2024. Advancing autonomous vehicle safety: Machine learning to predict sensor-related accident severity. *IEEE Access* 12, 25933–25948.
- Shang, X., Eskandarian, A., 2023. Emergency collision avoidance and mitigation using model predictive control and artificial potential function. *IEEE Transactions on Intelligent Vehicles* 8(5), 3458–3472.
- Sharara, L., Politis, A., Syed, H., Kronell, E., Dunsmore, D., Thierfelder, T., Wolf, J., Süß, J., Mansour, L., Thelen, K., Alazzawi, L., Ismail, M., 2023. A real-time automotive safety system based on advanced AI facial detection algorithms. *IEEE Transactions on Intelligent Vehicles* 1–22.
- Shelat, S., Cats, O., van Cranenburgh, S., 2022. Traveller behaviour in public transport in the early stages of the COVID-19 pandemic in the Netherlands. *Transportation Research Part A: Policy and Practice* 159, 357–371.
- Shi, D., Lee, T., Maydeu-Olivares, A., 2019. Understanding the model size effect on

- SEM fit indices. *Educational and Psychological Measurement* 79(2), 310–334.
- Shin, E.J., 2024. Factors associated with different types of freight crashes: A macro-level analysis. *Journal of Safety Research* 88, 244–260.
- Shirley, R.B., Smidts, C., 2018. Bridging the simulator gap: Measuring motivational bias in digital nuclear power plant environments. *Reliability Engineering & System Safety* 177, 191–209.
- Silva, R.M., Azevedo, G.F., Berto, M.V.V., Rocha, J.R., Fidelis, E.C., Nogueira, M.V., Lisboa, P.H., Almeida, T.A., 2024. Vulnerable road user detection and safety enhancement: A comprehensive survey. *Expert Systems with Applications*, 128529.
- Silverman, B.W., 2018. *Density estimation for statistics and data analysis*. Routledge.
- Sinha, A., Chand, S., Vu, V., Chen, H., Dixit, V., 2021. Crash and disengagement data of autonomous vehicles on public roads in California. *Sci Data* 8(1), 298.
- Sivasankaran, S.K., Balasubramanian, V., 2020. Exploring the severity of bicycle–vehicle crashes using latent class clustering approach in India. *Journal of Safety Research* 72, 127–138.
- Soleimani, S., Mousa, S.R., Codjoe, J., Leitner, M., 2019. A comprehensive railroad-highway grade crossing consolidation model: A machine learning approach. *Accident Analysis & Prevention* 128, 65–77.
- Soltani, A., Roohani Qadikolaei, M., 2024. Space-time analysis of accident frequency and the role of built environment in mitigation. *Transport Policy* 150, 189–205.
- Soto, F., Kitali, A.E., Asif Raihan, M., Alluri, P., 2022. Influence of built environment on pedestrian crashes: A case study of miami-dade county. *Transportation Research Record: Journal of the Transportation Research Board* 2676(9), 677–692.
- Sun, M., Sun, X., Shan, D., 2019. Pedestrian crash analysis with latent class clustering method. *Accident Analysis & Prevention* 124, 50–57.
- Sun, P., Algeri, N., Boukerche, A., 2020. Machine learning-based models for real-time traffic flow prediction in vehicular networks. *IEEE Network* 34(3), 178–185.
- Taheri, A., Azarasa, N., Iranmanesh, M., Seyedabrishami, S., O’Hern, S., Lord, D., 2023. The influences of strict and post-strict lockdowns due to the Covid-19 pandemic on crash severity on rural roads: A case study of Khorasan Razavi, Iran. *Transportation Research Part F: Traffic Psychology and Behaviour* 97, 231–245.
- Tang, J., Zheng, L., Han, C., Yin, W., Zhang, Y., Zou, Y., Huang, H., 2020. Statistical and machine-learning methods for clearance time prediction of road incidents:

- A methodology review. *Analytic Methods in Accident Research* 27, 100123.
- Tang, X., Yang, K., Wang, H., Wu, J., Qin, Y., Yu, W., Cao, D., 2022. Prediction-uncertainty-aware decision-making for autonomous vehicles. *IEEE Transactions on Intelligent Vehicles* 7(4), 849–862.
- Tengilimoglu, O., Carsten, O., Wadud, Z., 2023. Implications of automated vehicles for physical road environment: A comprehensive review. *Transportation Research Part E: Logistics and Transportation Review* 169, 102989.
- Tesla, 2024. Tesla Vehicle Safety Report. Tesla. URL <https://www.tesla.com/VehicleSafetyReport> (accessed 6.19.24).
- Tian, K., Tzigieras, A., Wei, C., Lee, Y.M., Holmes, C., Leonetti, M., Merat, N., Romano, R., Markkula, G., 2023. Deceleration parameters as implicit communication signals for pedestrians' crossing decisions and estimations of automated vehicle behaviour. *Accident Analysis & Prevention* 190, 107173.
- Train, K.E., 2009. Discrete choice methods with simulation. Cambridge press.
- Umair, M., Rana, I.A., Lodhi, R.H., 2022. The impact of urban design and the built environment on road traffic crashes: A case study of Rawalpindi, Pakistan. *Case Studies on Transport Policy* 10(1), 417–426.
- Ünvan, Y.A., 2021. Market basket analysis with association rules. *Communications in Statistics - Theory and Methods* 50(7), 1615–1628.
- Wang, C., Chen, F., Zhang, Y., Wang, S., Yu, B., Cheng, J., 2022. Temporal stability of factors affecting injury severity in rear-end and non-rear-end crashes: A random parameter approach with heterogeneity in means and variances. *Analytic Methods in Accident Research* 35, 100219.
- Wang, H., Li, Y.-F., 2023. Bioinspired membrane learnable spiking neural network for autonomous vehicle sensors fault diagnosis under open environments. *Reliability Engineering & System Safety* 233, 109102.
- Wang, L., Wang, Y., Chen, Y., Pan, X., Zhang, W., 2020. Performance shaping factors dependence assessment through moderating and mediating effect analysis. *Reliability Engineering & System Safety* 202, 107034.
- Wang, X., Abdel-Aty, M., 2008. Analysis of left-turn crash injury severity by conflicting pattern using partial proportional odds models. *Accident Analysis & Prevention* 40(5), 1674–1682.
- Waseem, M., Ahmed, A., Saeed, T.U., 2019. Factors affecting motorcyclists' injury severities: An empirical assessment using random parameters logit model with heterogeneity in means. *Accident Analysis & Prevention* 123, 12–19.
- Washington, S., Karlaftis, M., Mannering, F., Anastasopoulos, P., 2020. Statistical and

- econometric methods for transportation data analysis. Chapman and Hall/CRC.
- Waymo, 2024. Safety. Waymo. URL <https://waymo.com/safety/> (accessed 6.19.24).
- World Health Organization, 2022. Preventing injuries and violence: an overview. URL <https://www.who.int/publications-detail-redirect/9789240047136> (accessed 12.27.23).
- World Health Organization, 2020. Second decade of action for road safety. URL <https://www.who.int/teams/social-determinants-of-health/safety-and-mobility/decade-of-action-for-road-safety-2021-2030> (accessed 12.27.23).
- Wu, C., Guo, Y., Guo, H., Yuan, J., Ru, L., Chen, H., Du, B., Zhang, L., 2021. An investigation of traffic density changes inside Wuhan during the COVID-19 epidemic with GF-2 time-series images. *International Journal of Applied Earth Observation and Geoinformation* 103, 102503.
- Wu, J., Flannagan, C., Sander, U., Bärgrman, J., 2024. Model-based generation of representative rear-end crash scenarios across the full severity range using pre-crash data. *IEEE Transactions on Intelligent Transportation Systems*, 2025.
- Wu, Q., Chen, F., Zhang, G., Liu, X.C., Wang, H., 2014. Mixed logit model-based driver injury severity investigations in single- and multi-vehicle crashes on rural two-lane highways. *Accident Analysis & Prevention* 72, 105–115.
- Xu, C., Ding, Z., Wang, C., Li, Z., 2019. Statistical analysis of the patterns and characteristics of connected and autonomous vehicle involved crashes. *Journal of Safety Research* 71, 41–47.
- Xu, C., Li, D., Li, Z., Wang, W., Liu, P., 2018a. Utilizing structural equation modeling and segmentation analysis in real-time crash risk assessment on freeways. *KSCE Journal of Civil Engineering* 22(7), 2569–2577.
- Xu, C., Wang, Y., Liu, P., Wang, W., Bao, J., 2018b. Quantitative risk assessment of freeway crash casualty using high-resolution traffic data. *Reliability Engineering & System Safety* 169, 299–311.
- Xu, P., Zhou, H., Wong, S.C., 2021. On random-parameter count models for out-of-sample crash prediction: Accounting for the variances of random-parameter distributions. *Accident Analysis & Prevention* 159, 106237.
- Yadav, A., Kumari, R., 2024. Gender safety perspective in urban planning: The case of pedestrian mobility in Kanpur city. *Cities* 147, 104845.
- Yadav, A.K., Velaga, N.R., 2022. Alcohol-impaired driving and road safety: Examining the impact of alcohol on driving errors of Indian drivers. *Safety science* 145, 105516.
- Yan, D., Li, K., Zhu, Q., Liu, Y., 2023. A railway accident prevention method based on

- reinforcement learning – Active preventive strategy by multi-modal data. *Reliability Engineering & System Safety* 234, 109136.
- Yan, X., He, J., Wu, G., Zhang, C., Liu, Z., Wang, C., 2021a. Weekly variations and temporal instability of determinants influencing alcohol-impaired driving crashes: A random thresholds random parameters hierarchical ordered probit model. *Analytic Methods in Accident Research* 32, 100189.
- Yan, X., He, J., Zhang, C., Liu, Z., Qiao, B., Zhang, H., 2021b. Single-vehicle crash severity outcome prediction and determinant extraction using tree-based and other non-parametric models. *Accident Analysis & Prevention* 153, 106034.
- Yan, X., He, J., Zhang, C., Liu, Z., Wang, C., Qiao, B., 2021c. Spatiotemporal instability analysis considering unobserved heterogeneity of crash-injury severities in adverse weather. *Analytic Methods in Accident Research* 32, 100182.
- Yan, X., He, J., Zhang, C., Liu, Z., Wang, C., Qiao, B., 2021d. Temporal analysis of crash severities involving male and female drivers: A random parameters approach with heterogeneity in means and variances. *Analytic Methods in Accident Research* 30, 100161.
- Yan, X., He, J., Wu, G., Zhang, C., Wang, C., Ye, Y., 2022. Differences of overturned and hit-fixed-object crashes on rural roads accompanied by speeding driving: Accommodating potential temporal shifts. *Analytic Methods in Accident Research* 35, 100220.
- Yan, X., He, J., Zhang, C., Wang, C., Ye, Y., Qin, P., 2023. Temporal instability and age differences of determinants affecting injury severities in nighttime crashes. *Analytic Methods in Accident Research* 38, 100268.
- Yan, X., Richards, S., Su, X., 2010. Using hierarchical tree-based regression model to predict train–vehicle crashes at passive highway-rail grade crossings. *Accident Analysis & Prevention* 42(1), 64–74.
- Yang, K., Tang, X., Li, J., Wang, H., Zhong, G., Chen, J., Cao, D., 2023. Uncertainties in onboard algorithms for autonomous vehicles: Challenges, mitigation, and perspectives. *IEEE Transactions on Intelligent Transportation Systems* 24(9), 8963–8987.
- Yasin, Y.J., Grivna, M., Abu-Zidan. Global impact of COVID-19 pandemic on road traffic collisions. *World Journal of Emergency Surgery* 16(1), 51.
- Yu, C., Hua, W., Yang, C., Fang, S., Li, Y., Yuan, Q., 2024. From sky to road: Incorporating the satellite imagery into analysis of freight truck-related crash factors. *Accident Analysis & Prevention* 200, 107491.
- Yu, H., Li, Z., Zhang, G., Liu, P., 2019. A latent class approach for driver injury severity

- analysis in highway single vehicle crash considering unobserved heterogeneity and temporal influence. *Analytic Methods in Accident Research* 24, 100110.
- Yu, H., Li, Z., Zhang, G., Liu, P., Ma, T., 2021. Fusion convolutional neural network-based interpretation of unobserved heterogeneous factors in driver injury severity outcomes in single-vehicle crashes. *Analytic Methods in Accident Research* 30, 100157.
- Yu, M., Zheng, C., Ma, C., 2020. Analysis of injury severity of rear-end crashes in work zones: A random parameters approach with heterogeneity in means and variances. *Analytic Methods in Accident Research* 27, 100126.
- Yu, R., Wang, Y., Zou, Z., Wang, L., 2020. Convolutional neural networks with refined loss functions for the real-time crash risk analysis. *Transportation Research Part C: Emerging Technologies* 119, 102740.
- Yuan, C., Li, Ye, Huang, H., Wang, S., Sun, Z., Li, Yan, 2022. Using traffic flow characteristics to predict real-time conflict risk: A novel method for trajectory data analysis. *Analytic Methods in Accident Research* 35, 100217.
- Yuan, K.-H., 2005. Fit indices versus test statistics. *Multivariate Behavioral Research* 40(1), 115-148.
- Yue, H., 2024. Investigating the influence of streetscape environmental characteristics on pedestrian crashes at intersections using street view images and explainable machine learning. *Accident Analysis & Prevention* 205, 107693.
- Zhang, J., Feng, B., Wu, Y., Xu, P., Ke, R., Dong, N., 2021. The effect of human mobility and control measures on traffic safety during COVID-19 pandemic. *PLOS ONE* 16(3), e0243263.
- Zhang, T., Zhan, J., Shi, J., Xin, J., Zheng, N., 2023. Human-like decision-making of autonomous vehicles in dynamic traffic scenarios. *IEEE/CAA Journal of Automatica Sinica* 10(10), 1905–1917.
- Zhang, Z., Gong, Y., Yang, X., 2024. Secondary crashes identification and modeling along highways in Utah. *Transportation Research Record* 2678(3), 613–624.
- Zhang, Z., Lin, C.-Y., 2025. Risk analysis of weather-related railroad accidents in the United States. *Reliability Engineering & System Safety* 255, 110647.
- Zhao, X., Fang, Y., Min, H., Wu, X., Wang, W., Teixeira, R., 2024. Potential sources of sensor data anomalies for autonomous vehicles: An overview from road vehicle safety perspective. *Expert Systems with Applications* 236, 121358.
- Zheng, L., Sayed, T., 2020. A bivariate Bayesian hierarchical extreme value model for traffic conflict-based crash estimation. *Analytic Methods in Accident Research* 25, 100111.

- Zheng, M., Li, T., Zhu, R., Chen, J., Ma, Z., Tang, M., Cui, Z., Wang, Z., 2019. Traffic accident's severity prediction: A deep-learning approach-based CNN network. *IEEE Access* 7, 39897–39910.
- Zheng, X., Liu, Q., Li, Y., Wang, B., Qin, W., 2025. Safety risk assessment for connected and automated vehicles: Integrating FTA and CM-improved AHP. *Reliability Engineering & System Safety* 257, 110822.
- Zhou, B., Hu, S., Yang, Y., Na, X., Escibano, J., Ma, D., Jin, S., Zhang, B., Lee, D.-H., 2024. Transit signal priority strategy with heterogeneous graph-based deep reinforcement learning for autonomous public transit vehicles. *IEEE Transactions on Intelligent Vehicles* 1–19.
- Zhou, R., Huang, H., Lee, J., Huang, X., Chen, J., Zhou, H., 2023. Identifying typical pre-crash scenarios based on in-depth crash data with deep embedded clustering for autonomous vehicle safety testing. *Accident Analysis & Prevention* 191, 107218.
- Zhu, C., Brown, C.T., Dadashova, B., Ye, X., Sohrabi, S., Potts, I., 2023. Investigation on the driver-victim pairs in pedestrian and bicyclist crashes by latent class clustering and random forest algorithm. *Accident Analysis & Prevention* 182, 106964.
- Zhu, S., Meng, Q., 2022. What can we learn from autonomous vehicle collision data on crash severity? A cost-sensitive CART approach. *Accident Analysis & Prevention* 174, 106769.
- Zhu, Z., Tang, X., Qin, Y., Huang, Y., Hashemi, E., 2023. A survey of lateral stability criterion and control application for autonomous vehicles. *IEEE Transactions on Intelligent Transportation Systems* 24(10), 10382–10399.