INVESTIGATING THE CONTRIBUTING FACTORS TO AV-ROAD USER CONFLICTS: A DATA-DRIVEN APPROACH

INVESTIGATING THE CONTRIBUTING FACTORS TO AV-ROAD USER CONFLICTS: A DATA-DRIVEN APPROACH

By

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Lay Abstract

This thesis conducted two studies to analyze the factors contributing to AV safety. The first study analyzed the impact of various factors on AV conflict frequency. For road segments, results indicated that AV conflicts increased on major and divided roads but decreased on roads with bike lanes. The posted speed, presence of bus stops, and the density of access points were identified as key factors that impact conflict frequency. For intersections, posted speed and the presence of traffic signals, medians, and pedestrian crossing were the key factors that influence AV conflicts. The second study investigated the factors that impact AV conflict severity. For road segments, the speed of vehicles around AVs and road user volume were found to be the most important factors that determine conflict severity. At intersections, road user volume, speed of vehicles around AVs, and treatment of left-turn movements demonstrated the largest impact on conflict severity.

Abstract

This thesis aims to develop a solid understanding of the factors that impact the safety level of Autonomous vehicles (AVs). To that end, two studies were conducted. The two studies utilized the Woven prediction and validation dataset to extract AV-road user conflicts. The extracted conflicts were classified by type, location (road segment and intersection), and severity (severe and non-severe).

In the first study, a copula-based modelling approach was used to investigate the impact of a wide range of factors on the frequency of conflicts. For road segments, the results showed that the hourly rates of conflicts increased on large, major, and divided roads but decreased on roads with bike lanes. The posted speed, presence of bus stops, presence of on-street parking, and the density of access points were identified as the key factors that impact conflict occurrence. For intersections, the results show that posted speed, presence of median, and presence of pedestrian crossing are the key contributing factors to the hourly conflict rates, while the presence of traffic signals and bike lanes was shown to be associated with lower rates of severe AV conflicts.

The second study investigated the impact of various variables on the severity level of AV conflicts, using the Logistic regression and ML Multilayer Perceptron modelling approaches. Results showed that the average speed of vehicles around the AV, road user volume, land use, and road type are the key variables that determine conflict severity in road segments. At intersections, traffic control devices, road user volume, the presence of protected left turn phases, and the average speed of vehicles around the AV were the most impactful factors. For both road segments and intersections, pedestrian volume was directly associated with higher conflict severity, while the presence of bus stops, bike lanes, and parking lanes led to less severe conflicts.

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List of all Abbreviations and Symbols

AADT	Average Annual Daily Traffic
AIC	Akaike Information Criterion
AI	Artificial Intelligence
ANN	Artificial Neural Network
AV	Autonomous Vehicles
AVT	Autonomous Vehicle Tester
B-Spline	Basis Spline
DMV	Department of Motor Vehicles
EVT	Extreme Value Theory
LiDAR	Light Detection and Ranging
LSTM	Long Short-Term Memory
ML	Machine Learning
NHTSA	National Highway Traffic Safety Administration
PET	Post-Encroachment Time
RMSE	Root Mean Square Error
SHAP	SHapley Additive EXplanation
SSMs	Surrogate Safety Measurements
TTC	Time-To-Collision

Declaration of Academic Achievement

Mahdi Gabaire is the main contributor to this thesis. The contributions of the co-authors of the two academic papers presented in the thesis, Dr. Haniyeh Ghomi and Dr. Mohamed Hussein, are outlined in the preamble sections in Chapter 2 and Chapter 3.

Preface

This thesis is formed under the sandwich thesis structure as dictated by the School of Graduate Studies. The following submitted journal papers are included in the thesis:

1. Gabaire, M., Ghomi, H., and Hussein, M. "Investigating the Contributing Factors Affecting the Frequency of AV Conflicts: A Copula-based Approach", which is presented in Chapter 2. The manuscript was submitted for publication in September 2024.
2. Gabaire, M., Ghomi, H., and Hussein, M. "Investigating the Contributing Factors Affecting the Severity of AV-related Conflicts", which is presented in Chapter 3. The manuscript was submitted for publication in September 2024.

Mahdi Gabaire is the main contributor and the first author of these submissions. His contributions included study design, data collection and processing, model development, results interpretation, and manuscript writing. The study is co-authored by Dr. Haniyeh Ghomi and Dr. Mohamed Hussein. Dr. Ghomi contributed to the study design, results interpretation, and manuscript writing. Dr. Hussein's contributions included supervision, funding, study conceptualization and design, and manuscript reviewing and editing.

Chapter 1 Introduction

1.1 Background

Since the dawn of the field of transportation engineering, the efficient movement of individuals, goods, and services has long been sought as it has been widely regarded as a precursor to great economic expansion. With the rapid expansions of urban centres in the 21st century, congestion and road collisions have been recognized as the major issues that face urban transportation. In Canada, congestion is linked to severe losses in productivity, equity, and living standards, which imposes a huge economic burden on major Canadian cities (Mara Bullock et al., 2024). Similarly, the latent societal cost of collisions was witnessed to apply additional economic pressure on the Canadian economy, with reports estimating losses from fatalities in 2020 approximating to be $8.7 billion (Transport Canada, 2020).

In the last two decades, the Canadian Government has produced numerous national road safety strategies with the ultimate goal of reducing traffic collisions and obtaining the ‘safest roads in the world’ (Canadian Council of Motor Transportation Administrators, 2016). These national road safety strategies have had remarkable effects as the number of fatalities resulting from road collisions dropped by 21% from 2010 to 2019 (The International Transport Forum, 2022). Personal injury resulting from road collisions has also seen a reduction of approximately 24% during the same period (Canadian Motor Vehicle Traffic Collision Statistics, 2022). However, the past few years have seen stagnation in fatality rates with the lowest rate occurring during the COVID pandemic in 2020 (0.66%) which is widely seen as an anomaly. Human errors are still the leading cause of motorized vehicle collisions, with distracted driving, speeding, and driving under the influence contributing to 19.9%, 21.9%, and 23% of collisions, respectively (Canadian Motor Vehicle Traffic Collision Statistics, 2022). Further decreasing the fatality rates through

conventional means is proving to be more challenging than ever before. Ultimately, this has set up the stage for Autonomous Vehicles (AVs) to completely overhaul our current transportation system by removing the necessity of humans to operate vehicles; thus, eliminating these contributing factors completely. Domestically, in order to enhance the pace of adoption and responsible integration of AVs, numerous initiatives have been introduced across Canada. For instance, the Alberta Motor Transport Association (AMTA) in cooperation with Transport Canada led a trial program for semi-automated truck platooning (Shahbakhti & Ahmed, 2022). In Ontario, a ten-year pilot program introduced in 2016 has granted manufacturers permits for testing of driverless automated vehicles on public roads (Leci, Akins, et al., 2023; Ontario Ministry of Transportation, 2019).

1.2 Benefits of AVs

Aside from the substantial improvement in safety, the introduction of AVs into our traffic ecosystem is generally viewed to generate several remarkable benefits as well. As highlighted by Geary & Danks (2019), AVs are predicted to greatly improve mobility without the need to sacrifice road user safety. Particularly with advanced platooning and optimal route selection, AVs are predicted to inherently decrease congestion and reduce travel times sustainably. Locally, for the Greater Toronto and Hamilton Area, the impact would undoubtedly reduce the social and economic costs associated with congestion by approximately $3.3 billion (City of Toronto, 2014; Metrolinx, 2008). Moreover, the introduction of AVs would lead to a significant reduction in fuel consumption, which in return would dramatically reduce greenhouse gas emissions (Fagnant & Kockelman, 2015; Geary & Danks, 2019), thus allowing nations to achieve their climate change goals more comfortably. Equity in transportation is another area that is expected to benefit greatly from AVs. Currently in the Greater Toronto and Hamilton Area, low levels of transit accessibility

and car ownership rates are observed to disproportionally affect low-income households the most (Farber & Allen, 2019). In addition, active modes of travel such as walking or cycling in some low-income neighbourhoods are considered to be dangerous as they lack proper infrastructure and high crime rates are major concerns (World Health Organization, 2004). The introduction of AVs is expected to aid in dismantling these issues by providing competitive pricing to traditional riding-sharing services as well as being able to service and provide a reliable method of transport to all, including the elderly population and the physically impaired.

1.3 Limitations with current AV studies

Despite these tremendous potential benefits of AVs, comprehensive studies analyzing the impacts of AVs are still severely under-researched in the literature. Tafidis et al. (2022) conducted a comprehensive review of published AV safety studies between the years 2014 and 2020. Even though the study supported the assertion that AVs would increase road safety strongly, it highlighted that it is premature to claim that AV collisions will be extremely rare events. Elsewhere, Nascimento et al. (2020) conducted a similar study that assessed available AV safety literature between 1987 and 2018. Ultimately, the study found that the literature focuses primarily on the optimization and computational performance of the Artificial Intelligence aspect of AVs, with little interest given to studying the safety consequences of the technology.

Generally, current studies analyzing AV safety can be categorized based on their respective data sources into collision-based, simulation-based, and sensory-based studies, each has its benefits and drawbacks. AV collision reports are mostly provided by safety institutions, such as the National Safety Council and the Department of Motor Vehicles, as a part of the recent legislative reform that seeks to promote transparency and increase public trust in AVs. This lawfully mandates all AV manufacturers to report any collisions that occur during testing. With the testing and research of

AV technology conducted predominantly in California, studies that examine AV safety using collision reports (e.g., (Channamallu et al., 2023; F. M. Favarò et al., 2017; Pamidimukkala et al., 2023; Ren et al., 2021)) are mostly geographically concentrated in one location, which limits the generalization of the outcomes. Developments in major initiatives such as the Autonomous Vehicle Tester (AVT) Program and AVT Driverless Program have allowed for disengagement-based safety studies (F. Favarò et al., 2018; Khattak et al., 2021). Here, disengagement refers to incidents where the AVs conclude an event to be highly unsafe and relinquish control back to the human operator. These situations are more abundant and allow researchers to have more data to analyze safety. Although, it is known that collision avoidance systems use credible forms of surrogate measures of safety (mainly Time-To-Collision), research into how disengagements correlate with collisions remains unspecified.

The second and probably popular approach in the literature to analyze the effects of AVs on road safety is through computer simulations. Not only does it overcome the scarcity of collision data but also allows researchers to study AVs under different scenarios (Hammami & Borsos, 2024; Morando et al., 2017; Virdi et al., 2019) and locations Zhu & Tasic (2021). Largely, the framework utilized in these studies often consists of a microscopic simulating program such as PTV Vissim or Aimsun, where the goal is to represent road users using established models. On the other hand, the AV is simulated using a modified car-following model. Following the simulation, the trajectories from these scenarios are then extracted. Using Safety Surrogate Measures (SSMs), risky interactions between AVs and road users are analyzed and used to quantify safety. Historically, conflicts are established in multiple studies to have a strong correlation with collisions (El-Basyouny & Sayed, 2013; Sacchi et al., 2013; Sacchi & Sayed, 2016). Overall, the most commonly used conflict indicators in these types of studies are Time-To-Collision (TTC) and Post-

Encroachment Time (PET). TTC conveys the time in seconds remaining from a potential collision under the condition that road participants maintain their current velocity and bearing (Hyden, 1996) while PET expresses the difference in time between when a road user exits an area of conflict and another road user arrives (Allen et al., 1978). The main limitations of simulation-based studies are the multiple assumptions required to model the behavior of the AV and the difficulty of reflecting the real-world behavior of road users in the micro-simulation models.

Finally, AV manufacturers have published recently high-quality sensory data to encourage development and build trust among the population (e.g., Lyft Level 5 (Houston et al., 2020), nuScenes (Caesar et al., 2019), ITE Vision Zero (City of Bellevue, 2020), Argoverse (Wilson et al., 2023) and Waymo (Sun et al., 2019)). This has ultimately granted researchers access to trajectory and speed data of unsupervised AVs interacting with road users in challenging environments (Alozi & Hussein, 2022, 2023; Kamel et al., 2023); thus, allowing for a more accurate view of the safety performance of AVs. Since these datasets are relatively new and require intense pre-processing to access, studies utilizing this novel source of data are limited and still emerging.

1.4 Problem statement

While enhancing safety is being promoted as the main benefit of AVs, credible quantitative assessments of AV safety using high-quality data remain largely unexplored. Research that relied on computer simulations to study AV safety implications often has trouble conveying the actual uncertain nature of real-world traffic conditions. Moreover, with the recent introduction of several AV datasets that reflect realistic interaction behaviour between AV and road users, research that utilized these data (e.g., (Alozi & Hussein, 2022, 2023; Kamel et al., 2023)) focused on predicting AV collisions and understand how they differ from conventional vehicle collisions rather than

understanding the contributing factors that impact the frequency and severity of AV-road user conflicts. There is a lack of research evaluating the impact of factors such as road characteristics, traffic parameters, and built-environment factors on AV safety performance. There is a need to conduct an in-depth assessment of the impact of different traffic and network-related factors on AV safety performance to enhance our understanding of AV safety implications and accelerate the optimal integration of AVs into urban traffic.

1.5 Thesis Objectives

In order to address the gaps discussed in the previous section, this thesis strives to accomplish the following specific objectives:

1. Utilize high-quality real-world data to analyze AV safety, which enhances the reliability of the analysis.
2. Assess the impact of a wide range of factors on the frequency of AV-road user conflicts at different road network components, mainly intersections and road segments.
3. Assess the contributing factors that impact the severity of AV-road user conflicts at intersections and road segments.
4. Rank the identified contributing factors in terms of their importance in determining AV conflict frequency and severity.
5. Examine the benefits of utilizing advanced methods, such as Machine Learning and Coupla-based models, in identifying the contributing factors to the frequency and severity of AV conflicts compared to the traditional methods that are typically used in the road safety literature.

1.6 Thesis Structure

The thesis consists of four chapters, integrating two studies to achieve the study objectives. Chapter 1 presents a quick introduction to the thesis as well as the problem statement and specific research objectives. Chapter 2 presents the details of the first study, titled "Investigating the Contributing Factors Affecting the Frequency of AV Conflicts: A Copula-based Approach". In this study, hourly AV-road user conflicts extracted from real-world AV sensory data are modelled using the Copula-based modelling approach to assess the impact of a wide range of traffic, network, and external factors on the frequency of AV-road user conflicts. The study addresses primarily the second objective and contributes to achieving the first, fourth, and fifth objectives of the thesis. Next, Chapter 3 presents the details of the second study, titled "Investigating the Contributing Factors Affecting the Severity of AV-related Conflicts". This study utilizes two modelling approaches, namely the Logistic Regression and the Machine Learning Multilayer Perception model to identify and rank the factors that impact AV-road user conflict severity. The study addresses primarily the third objective and contributes to achieving the first, fourth, and fifth objectives of the thesis. Lastly, Chapter 4 concludes the thesis with a summary of the important findings from the two studies, a discussion of the limitations of the current work, and recommendations for future studies.

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Chapter 2 Investigating the Contributing Factors Affecting the Frequency of AV Conflicts: A Copula-based Approach

2.1 Preamble

As outlined in Chapter 1, this chapter presents the details of a study that aims to investigate the factors that impact the frequency of AV-road user conflicts using real-world AV sensory data. The study addresses primarily the second objective of the thesis and contributes to achieving the first, fourth, and fifth objectives. This study was submitted for publication in August 2024, as Gabaire, M., Ghomi, H., and Hussein, M. "Investigating the Contributing Factors Affecting the Frequency of AV Conflicts: A Copula-based Approach". Mahdi Gabaire is the main contributor and the first author of this submission. He contributed to the study design, data collection and processing, model development, results interpretation, and manuscript writing. The study is co-authored by Dr. Haniyeh Ghomi and Dr. Mohamed Hussein. Dr. Ghomi contributed to the study design, results interpretation, and manuscript writing. Dr. Hussein's contributions included supervision, funding, study conceptualization and design, and manuscript reviewing and editing.

2.2 Abstract

With the imminent widespread integration of Autonomous Vehicles (AVs) into our traffic ecosystem, understanding the factors that impact their safety is a vital research area. This study investigated the impact of a wide range of factors on the frequency of AV-road user conflicts, which is a well-established surrogate measure of safety. The study utilized the Woven prediction and validation dataset, which contains over 1000 hours of data collected around the Stanford University campus in California. The trajectories of AVs and other road users were analyzed to extract AV conflicts, which were then classified by location (intersections and road segments), type

(rear-end, angle, pedestrian, and cyclist conflicts), and severity (severe and non-severe conflicts). A list of potential contribution factors was prepared either directly from the dataset or using open street maps. Two Copula-based models were developed to investigate the contributing factors to the hourly rates of total and severe AV conflicts in road segments (model M1) and intersections (model M2). For road segments, the results show that the hourly rates of total and severe conflicts increased on large, major, and divided roads. The posted speed, presence of bus stops, and the presence of on-street parking were positively associated with the hourly rates of conflicts, but their impact on the rates of severe conflicts was not significant. The presence of bike lanes significantly reduced the hourly rates of both total and severe conflicts, while the density of access points was found to be positively associated with the hourly rates of severe conflicts. For intersections, the results show that intersection characteristics, mainly posted speed, presence of median, and presence of pedestrian crossing are the key contributing factors to the hourly conflict rates. The presence of traffic signals and bike lanes was shown to be associated with lower rates of severe AV-road user conflicts.

Keywords: Autonomous vehicles, Road safety, Conflict Analysis, Copula-based Models

2.3 Introduction

Transportation engineering is amidst a revolutionary change with the introduction of autonomous vehicles (AVs). Among the numerous anticipated changes, many believe that AVs will yield a significant reduction in road collisions by eliminating human error, which is often considered the key trigger of collisions. A survey conducted over two and a half years by the National Highway Traffic Safety Administration (NHTSA) concluded that 41 % of collisions occurred as a result of a driver recognition error (e.g., unawareness and loss of focus), 34 % were triggered from driver decision errors, and a further 10 % were caused by driver performance errors (Highway Traffic

Safety Administration, 2008). Several studies concluded that the introduction of AVs could eradicate collisions caused by these types of errors completely (Alsalhi et al., 2018; Chen et al., 2024; Pande et al., 2017). Other potential benefits of AVs include improving transportation equity (Fagnant & Kockelman, 2015), reducing emissions (Fagnant & Kockelman, 2015), and alleviating the financial pressure caused by traffic congestion and road collisions (Channamallu et al., 2023; Levin et al., 2019; Wang et al., 2020).

Although the commercial use of fully automated vehicles (i.e., Level 5 Automation with no human supervision) is still not permitted in the United States, testing of AVs is generally accepted on public roads provided that a trained driver is present onboard and can take control over the vehicle if needed (California Department of Motor Vehicles, 2022). This, coupled with AV collision reporting legislation, enables researchers to briefly glimpse into the suitability of AVs in our current transportation environment. Channamallu et al. (2023) analyzed traffic collisions from both conventional vehicles and AVs in the USA from July 2021 to May 2022. The study concluded that AVs substantially decrease the number of moderate and fatal injuries when compared to conventional vehicles, but they increase the number of rear-end collisions. Notably, this study suffered from the small sample size of AV collisions and lack of diverse weather conditions, limitations that are shared by several other studies in the literature (F. M. Favarò et al., 2017; Khattak et al., 2021). Elsewhere, a scoping review paper by Tafidis et al. reported that while it is expected that road safety would improve with the introduction of AVs, the scarcity of real-world AV data is a key limitation for conducting in-depth research to support this claim (Tafidis et al., 2022).

To overcome data limitations, several studies utilized a simulation-based approach to assess AV safety (Hammami & Borsos, 2024). Nevertheless, these studies suffer from several limitations,

including the inability to capture real-world conditions and the numerous assumptions used to manipulate car following models to represent AVs. Recently, large datasets were made available by AV manufacturers (e.g., Lyft Argoverse, and Waymo) have made it possible to extract traffic conflicts between AVs and other road users, thus allowing for more realistic assessments of AVs (Alozi & Hussein, 2022, 2023; Kamel et al., 2023). To date, the studies that utilized these datasets focused on predicting AV collisions rather than forming an understanding of how various factors influence the AV's ability to uphold safety standards.

This paper aims to mitigate existing gaps in the AV safety literature by utilizing real-world AV data and applying an appropriate modelling approach to evaluate the contributing factors that impact AV safety. To that end, the Woven prediction and validation dataset (Houston et al., 2020), formerly known as the Lyft Level 5 dataset was utilized. The data was collected by 20 AVs in Palo Alto, California near the Stanford University campus over a six-month period. The data consists of 150,000 scenes (25-second segments), providing detailed AV trajectories and the trajectories of road users detected by the AV, obtained by means of onboard AV sensors (Radar, LiDAR, and cameras). One of the benefits of this dataset is its location diversity as interactions between the AVs and road users were recorded while AVs traverse through both challenging residential and freeway environments. The provided trajectories were analyzed to extract traffic conflicts between AVs and road users, which were used as a surrogate for AV safety. Two Copula-based models were developed to investigate the contributing factors to the hourly rates of AV-road user conflicts across different severity levels at road segments (model M1) and intersections (model M2). The Copula-based modelling approach was utilized due to its ability to handle potential interdependency between the hourly rates of total and severe conflicts. The results of the study provide realistic insights into the impact of several factors (such as road characteristics, traffic parameters, and

built-environment factors) on AV safety. Such models represent safety planning tools that can be applied to assess AV safety before deployment and investigate the readiness of road infrastructure to integrate autonomous vehicles.

The rest of the paper is organized as follows: Section 2.4 presents a detailed review of the AV safety literature. Section 2.5 describes the data utilized in the study as well as the explanatory variables used in the developed models. A brief discussion of the modelling approach implemented in the study is presented in Section 2.6. Next, the results of the study are presented and discussed in Sections 2.7 and 2.8, respectively. Finally, Section 2.9 concludes with a summary of the findings and discloses the limitations of the study.

2.4 Literature Review

Previous studies that investigated AV safety can be classified into three categories based on the data used to measure safety: 1) AV collision-based studies; 2) simulation-based studies, and AV sensory-based studies. AV collision-based studies rely on analyzing AV collisions, which are considered the objective measure of safety, to assess the safety implications of AVs. Numerous studies that attempted to analyze AV collisions can be found in the literature. Earlier assessments were generally pessimistic about the safety performance of AVs compared to conventional vehicles. For instance, Banerjee et al. (2018) studied 42 AV-involved collisions in California between 2014 and 2016. The study reported that in terms of total miles driven, the safety performance of AVs could be substantially worse than human-driven vehicles. Similarly, Favarò et al. (2018) thoroughly reviewed disengagement data (i.e., incidents where the AVs conclude an event to be highly unsafe and relinquish control back to the human operator) provided by the California DMV between 2014 and 2017. The study concluded that even though the safety performance of the AVs was worse than conventional vehicles, it could be rapidly improved over

a short period of time. More recent assessments showed more promising results. For example, Pamidimukkala et al. (2023) analyzed 259 AV-involved collisions that occurred between 2014 and 2020 in California. Ultimately, the study found that weather conditions had no significant impact on collisions. The study also showed that AVs were considered to be at fault for a small portion of the collisions. Ashraf (2021) investigated the contributing factors to AV collisions based on collision data from the California DMV between 2016 and 2020. The study utilized a decision tree model and applied association rule methods to acquire a better understanding of pre-collision conditions. Overall, the study found that based on pre-collision data, most AV-involved collisions are a result of human-driven vehicle mistakes (e.g., poor reaction time). With the majority of reported collisions being rear-end collisions at intersections, the study observed that most of these collisions involved a human-driven vehicle colliding with an AV that is stopping at the intersection. While these studies reported useful insights regarding AV safety, they suffer from the limited number of AV collisions reported, which usually leads to inconclusive results and does not enable a comprehensive assessment of the factors affecting collision frequency and severity (Tafidis et al., 2022).

In order to circumnavigate the issues of limited data, several studies adopted a simulation-based approach to study AV safety (Hammami & Borsos, 2024). These studies typically utilize a simulated environment where the AV's driving behavior is simulated using a modified car-following model. The simulated trajectories are used to extract surrogate safety measurements (SSMs), such as traffic conflicts, which are used to assess AV safety. A wide range of indicators are used to quantify the severity of the resulting conflicts, most commonly used are Time-To-Collision (TTC) and Post-Encroachment Time (PET) (El-Hansali et al., 2021; Khashayarfard & Nassiri, 2021; Mousavi et al., 2021; Sekar et al., 2023). TTC is expressed as the time in seconds

remaining from a potential collision if road participants maintain their current speed and heading (Hyden, 1996) while PET is seen as the difference in time between when a road user exits an area of conflict and another road user arrives (Allen et al., 1978). For instance, Zhu & Tasic (2021) utilized a simulation-based approach to assess the safety of AVs on freeway on-ramps. The study reported that AVs can lead to a significant reduction in the frequency of merging conflicts. Morando et al. (2017) investigated the safety of signalized intersections and roundabouts for different AV penetration rates. The study found that increasing AV market share is associated with better overall safety and road efficiency of both intersections and roundabouts. Despite the limited body of research, simulation-based studies analyzing the impact of AVs on active road users can also be found in the literature. For example, Hammami & Borsos (2024) investigated the impact of AV behaviors (cautious, normal, and aggressive) on the frequency and severity of conflicts between AVs and cyclists at three-legged intersections using microsimulation. The study found that rear-end interactions constituted 95% of AV-cyclist conflicts, with a significant association between conflict severity and AV and cyclist behavior. While simulation-based studies have several merits, they mainly struggle to reflect real-world conditions, which impact the accuracy of the reported results.

Recently, with the publication of several open-source AV datasets, such as Lyft Level 5 (Houston et al., 2020), nuScenes (Caesar et al., 2019), ITE Vision Zero (City of Bellevue, 2020), Argoverse (Wilson et al., 2023), and Waymo (Sun et al., 2019), researchers have been able to conduct traffic conflict assessments using realistic traffic conflicts rather than simulated ones. For example, Alozi & Hussein (2022) utilized various open-source datasets to extract AV-pedestrian conflicts. The study developed an estimate of AV-pedestrian collisions using the Extreme Value Theory (EVT) technique. Alozi & Hussein (2022) utilized AV-road user conflicts to assess the safety of

pedestrians and cyclists in different interactions with AVs. Kamel et al. (2023) used the Lyft Level 5 dataset to conduct real-time safety of a road network using a Bayesian Hierarchical Extreme Value model. However, the focus of most of these studies has been to assess the interaction safety between road users or utilize traffic conflicts to predict future AV collision trends. To the best of the authors' knowledge, no studies attempted to investigate the contributing factors that affect AV conflicts, which we aim to mitigate in the current study.

2.5 Data

The dataset utilized in this paper was acquired from the Woven prediction and validation datasets, formerly known as the Lyft Level 5 datasets (Houston et al., 2020). The data consists of information collected by the onboard sensors (seven cameras, three LiDARs, and five radars) of a fleet of 20 AVs deployed along a fixed route in Palo Alto, California. The data was collected over a four-month period, primarily during daytime, between 8 AM and 4 PM. It comprises 150,000 scenes (segments) with each scene spanning approximately 25 seconds. Each scene provides detailed information about the subject AV and the detected road users within a 200-meter radius. The provided information includes a unique identifier, timestamps, 3-dimensional positioning in a local-coordinate system, and instantaneous speed of the AV and each road user. The resolution of the provided data is 10 frames per second. Furthermore, an in-house perception system designed by Woven Planet was used in tandem with the LiDAR data to classify road users that were manually validated by the developer before publishing the data.

Before extracting traffic conflicts, several pre-processing steps were conducted. First, the trajectory data of the AV and each road user was converted into a global coordinate system. Next, the trajectories underwent a rigorous review and filtering process to eliminate sporadic positional errors. AV trajectories were found to be very accurate with almost no errors in the trajectories.

However, several anomalies were uncovered for road user trajectories, mainly due to inaccurate LIDAR readings. To avoid any inaccuracies in conflict detection or the calculation of traffic conflict indicators, a smoothing algorithm was applied to eliminate the anomalies in road user trajectories. Specifically, the Basis Spline (B-Spline) technique was utilized to undertake this task as it is known for its exceptional flexibility for curve fitting and computational efficiency (Choi et al., 2023). Additionally, the Knot property of B-splines is appropriate for handling trajectory data as it allows for controlling trajectory smoothness and continuity (Eilers & Marx, 1996). Figure 2-1 provides an example of a road user trajectory before and after the smoothening process. Finally, the trajectories of objects that were stationary for the entire scene (e.g., pedestrian bystanders and parked vehicles) were removed to reduce the computational cost of traffic conflict calculations.

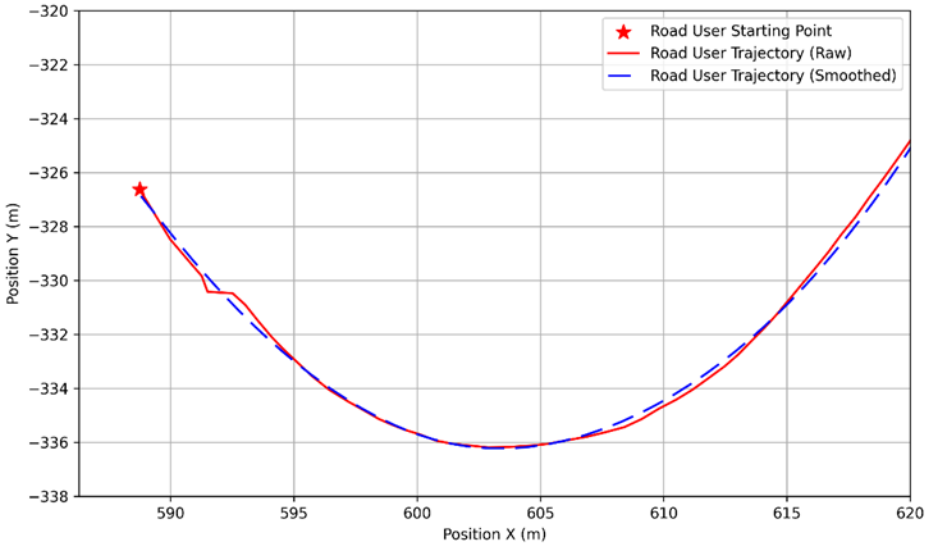

Figure 2-1: Example of a road user trajectory before and after smoothening

Road user trajectories were analyzed to extract conflicts between AVs and road users, using a Python-based code developed at McMaster University. AV conflicts with vehicles, pedestrians, and cyclists were considered in the analysis. TTC conflict indicator was utilized to measure the severity of AV-vehicle conflicts while PET was used to measure the severity of conflicts with

pedestrians and cyclists. TTC indicator is typically used to quantify AV-vehicle conflicts in the literature since it is highly accurate at conveying hazardous situations and relatively inexpensive computationally (Alozi & Hussein, 2024). This has made it a cornerstone in modern collision avoidance algorithms (Mahmud et al., 2017). However, given that TTC is computed by extrapolating trajectories into the future, a major drawback it suffers from is the assumption of a constant speed throughout the extrapolation period (Alozi & Hussein, 2022). Regardless, TTC is particularly seen as the primary indicator for rear-end vehicle conflicts (Arun et al., 2021). For conflicts with pedestrians and cyclists, the PET indicator is particularly useful since it does not require extrapolating trajectories and assuming constant speeds which neglect potential evasive actions. Rather, PET values depend on the outcome of the conflict (Alozi & Hussein, 2022). For crossing movements in particular, this allows PET to accurately convey the magnitude of the near-miss event (Arun et al., 2021; Mohamed & Saunier, 2017). A threshold of three seconds was used to distinguish between conflict scenarios and normal interactions. This threshold was selected based on the numerous published studies in the literature (Alozi & Hussein, 2022; Essa & Sayed, 2019; Sacchi & Sayed, 2016). Thus, only conflicts with TTC or PET below three seconds were considered in the analysis. Using this criterion, a total of 3471 conflicts were identified, of which 3363 (96.9%) were conflicts with vehicles, 44 (1.3%) involved pedestrians, and 64 (1.8%) involved cyclists. The majority of AV-vehicle conflicts (3047 conflicts) were found to be rear-end conflicts, while left-turn opposing conflicts (perpetrated by the AV or road user) and right angle conflicts accounted for 251 and 24 conflicts, respectively. As for conflict severity, several previous studies classified conflicts into high-, medium-, and low-severity conflicts based on the TTC or PET value. Conflicts with a conflict indicator value between 0 and 1 second are usually treated as high-severity conflicts. Conflicts ranging between 1 and 2 seconds are considered medium-

severity ones, while those between 2 and 3 seconds are considered low-severity conflicts. Due to the small number of observations of conflicts between 0 and 1 second (102 conflicts only), it was decided to classify conflicts into two categories only: Severe conflicts, involving conflicts with TTC or PET below 2 seconds, and non-severe conflicts, involving those with TTC or PET between 2 and 3 seconds.

Once identified, the conflicts were mapped using their global coordinates to the exact location where they occur and assigned to a specific intersection or road segment. Figure 2-2 shows the path of the AVs and the considered study area. The average hourly conflicts were calculated for each road segment and intersection and treated as the dependent variables in the developed models. It was observed that very few conflicts occur between 3 to 4 p.m. (only 26 conflicts across 26 road segments and 25 intersections), thus, this hour was removed from the analysis, and conflicts occurring between 8 a.m. and 3 p.m. only were considered.

Figure 2-2: Satellite map displaying the path of the AV (in blue) as it traverses through Palo Alto

Moreover, numerous potential contributing factors were obtained using Open Street Maps (OpenStreetMap, 2024). For road segments, the considered variables included road characteristics

(such as number of lanes and median type), traffic characteristics (such as posted speed), built environment factors (such as the presence of bike lanes and bus stops), and land use. For intersections, the considered factors included the type of traffic control device, land use, intersection geometry, and speed limit, among other factors. Tables 2-1 and 2-2 present the full list of potential contributing factors considered for road segments and intersections, respectively. It is worth mentioning that AADT information was not available in the study area. Accordingly, the hourly average number of detected road users by the AVs was used as a surrogate for exposure.

Table 2-1: Summary of variables used in road segment models (model M1)

Variable Name	Variable Description	Value
Average hourly detected road users	The average number of road users detected by the AVs on a road segment in an hour.	Min. = 114 Mean = 377 Max. = 671
Hourly conflict count	The average number of conflicts on a road segment in an hour.	Min. = 0 Mean = 11 Max. = 64
Hourly severe conflict count	The average number of severe conflicts (TTC or PET below 2 seconds) in an hour.	Min. = 0 Mean = 4 Max. = 31
Hourly non-severe conflict count	The average number of non-severe conflicts (TTC or PET between 2 and 3 seconds) in an hour.	Min. = 0 Mean = 7 Max. = 36
Direction	A binary variable representing whether the road is one-way (0) or two-way road (1).	0 = 102 1 = 2101
Number of lanes	A discrete variable representing the number of lanes on a road segment.	Min. = 1 Mean = 2.16 Max. = 3
Road Type	A binary variable representing whether the road is a major road (0) or a minor road (1).	0 = 1278 1 = 925

Speed Limit	A binary variable representing whether the posted speed limit is below 30 mph (0) or above 30 mph (1).	0 = 982 1 = 1221
Length (km)	A continuous variable representing the length of the road segment.	Min. = 0.05 Mean = 0.19 Max. =1.13
Access Point Density (per km)	A continuous variable representing the number of access points (e.g., driveways) per unit length of the road segment.	Min. =0 Mean = 15.22 Max. = 42.12
Presence of bus stops	A binary variable representing whether bus stops are present on the road segment (1) or not (0).	0 = 482 1 = 1721
Presence of median	A binary variable representing whether the road is divided (1) or undivided (0).	0 = 889 1 = 1314
Presence of Cycle Lane	A binary variable representing whether a cycle lane is present on the road segment (1) or not.	0 = 863 1 = 1340
Presence of on-street parking	A binary variable representing whether on-street parking is permitted on the road (1) or not (0).	0 = 1600 1 = 603
Land Use	A binary variable representing whether the dominant land use near the road segment is commercial (0) or other (1).	0 = 430 1 = 1773

Table 2-2: Summary of variables used in Intersection models (model M2)

Variable Name	Variable Description	Value
Average hourly detected Road Users	The average number of road users detected by the AVs on a road segment in an hour.	Min. = 100 Mean = 392 Max. = 660
Hourly conflict count	The average number of conflicts at an intersection in an hour.	Min. = 0 Mean = 6.5 Min. = 58
Hourly severe conflict count	The average number of severe conflicts (TTC or PET below 2 seconds) in an hour.	Min. = 0 Mean = 1 Max. = 11

Hourly non-severe conflict count	The average number of non-severe conflicts (TTC or PET between 2 and 3 seconds) in an hour.	Min. = 0 Mean = 5 Max. = 52
Traffic control device	A binary variable representing whether the type of traffic control device used at the intersection is Signalized (1) or not (0).	0 = 769 1 = 538
Speed Limit	A binary variable representing whether the posted speed limit is below 30 mph (0) or above 30 mph (1).	0 = 812 1 = 495
Presence of pedestrian crossing	A binary variable representing whether the pedestrian crossing at an intersection is present (1) or not (0).	0 = 471 1 = 836
Presence of cycle lane	A binary variable representing whether a cycle lane is present near the intersection (1) or not (0).	0 = 522 1 = 785
Presence of median	A binary variable representing whether the intersection is divided (1) or undivided (0).	0 = 857 1 = 450
Presence of bus stops	A binary variable representing whether bus stops are present near the intersection (1) or not (0).	0 = 316 1 = 991
Number of approaches	A binary variable representing whether the intersection is three-legged (0) or four legged (1)	0 = 611 1 = 696
Left turn phase	A binary variable representing whether the intersection has a Protected/Prohibited left turn phase (0) or Permissive (1).	0 = 565 1 = 742
Truck percentage	A binary variable representing whether the truck percentage at an intersection is greater than zero (1) or not (0).	1 = 785 2 = 522
Land Use	A binary variable representing whether the dominant land use near the intersection is residential (0) or other (1).	0 = 205 1 = 1102

2.6 Methodology

Two copula-based models were developed in order to evaluate the impact of different contributing factors on the hourly rate of AV conflicts on road segments (model M1) and intersections (model M2). Copulas are mathematical functions that provide the ability to capture the joint behavior of variables with different distributions. Copulas are particularly useful when developing a conflict prediction model as they help deal with the potential correlation amongst dependent variables. If left without proper treatment, correlation could introduce inaccuracies and biases into coefficient estimates (Wang et al., 2019; Washington et al., 2020).

By denoting $U_1, U_2, U_3, \dots, U_n$ as uniformly distributed random variables, a N-dimensional copula (C) with θ indicator can be represented through a joint cumulative distribution function as demonstrated in Equation 2-1:

$$C_\theta(u_1, u_2, u_3, \dots, u_n) = Pr(U_1 < u_1, U_2 < u_2, , U_3 < u_3, \dots, U_n < u_n) \quad (1)$$

To accommodate for the magnitude of correlation between parameters in the copula model, the association parameter (θ_u) is allowed to vary. Following Ghomi & Hussein (2021), the association parameter is derived using the frank model, as expressed in Equation 2-2:

$$C_{\theta_u} = \exp(bx_u) \quad (2)$$

Where, b is a coefficient vector that represents the copula parameters and x_u represents a set of explanatory variables. In this study a two-dimensional copula model was implemented to analyze the impact of various variables on the hourly count of both total and severe AV-road user conflicts, the joint distribution of the hourly count (i) and the jth level of severity can be represented in Equation 2-3:

$$Pr(f_i = i, s_i = j) = Pr\{[\gamma_{i-1} - zx_i < \epsilon_i < \gamma_i - zx_i], [\rho_{j-1} - qx_i < \sigma_i < \rho_j - qx_i]\} \quad (3)$$

Where, f and s represent the hourly rate of total and severe conflicts on road segment or intersection (i), respectively, γ_i and ρ_j are estimated thresholds, x_i refer to a vector of explanatory variables, z and q are coefficient estimates of explanatory variables and ϵ_i and σ_i are error terms. The model was implemented using the copula package available in RStudio software. Various model outputs were evaluated using AIC and Maximum Likelihood, and the model with the lowest AIC value was chosen.

2.7 Results

Two Capula-based models were developed as discussed earlier. First, a road segment model (model M1) was developed to assess the impact of different factors on both the hourly rate of total and severe conflicts. The scope of the datasets included 26 road segments, with a total number of conflicts of 2174. The frequency of severe conflicts that occurred on road segments was 819, while the remaining 1355 conflicts were non-severe ones. Second, an intersection model (model M2) was developed to investigate the impact of the different factors on AV conflicts at intersections. The data included 25 intersections that experienced 1297 conflicts, of which 279 were severe and 1018 were non-severe.

The estimated coefficients of the two models are presented in Tables 2-3 and 2-4, respectively. In both models, the signs of exposure parameters (average hourly road user count and road segment length in model M1, and average hourly road user count in model M2) were positive, indicating a direct association between conflict hourly rate and exposure as predicted. The log-likelihood of the two models were -166.97 and 137.62, respectively. The Root Mean Square Error (RMSE) for the two models were 0.27 and 0.16, respectively, indicating a strong model performance. It should be noted that the Copula-based model outperformed other models that were investigated during

the preliminary phase of the study, such as the Poisson lognormal model, and the negative binomial model, based on the value of the Akaike Information Criterion (AIC).

Table 2-3:Results of the road segment model (model M1)

Variables	Hourly count of conflicts			hourly count of severe conflicts		
	Estimate Coefficients	Standard Error	Significance	Estimate Coefficients	Standard Error	Significance
Constant - intercept	0.0392	0.085	0.645	0.1599	0.148	0.281
hourly count of non-severe conflicts	0.2948	0.159	0.064*	0.8515	0.207	0**
Hourly count of severe conflicts	0.189	0.102	0.064*	0.0217	0.041	0.596
Log(Average Hourly detected Road Users)	0.6862	0.067	0.199	0.5865	0.14	0**
Direction [Two-way]	0.4184	0.191	0.029**	0.4783	0.205	0.02**
Number of Lanes	0.3573	0.073	0**	0.0169	0.081	0.834
Road Type [Major]	0.0634	0.085	0.458	0.089	0.053	0.093*
Speed Limit [Greater than 30]	0.3932	0.206	0.057*	0.0392	0.085	0.645
Log(Length)	0.3046	0.07	0**	0.0217	0.041	0.596
Access Point Density	0.0217	0.041	0.596	0.089	0.053	0.093*
Presence of Bus Stop [Yes]	0.3562	0.073	0**	0.1383	0.179	0.44
Presence of median [Divided]	0.4783	0.205	0.02**	0.3562	0.073	0**
Presence of Cycle Lane [Yes]	-0.234	0.068	0.001**	-0.4843	0.275	0.079*
Presence of On-Street Parking [Yes]	0.195	0.753	0.014**	0.001	0.04	0.98
Land use [Residential]	0.226	0.148	0.755	0.133	0.08	0.249

** Significant at the 95% confidence level

* Significant at the 90 % confidence level

Table 2-4: Results of the intersection model (model M2)

Variables	Hourly count of conflicts			Hourly count of severe conflicts		
	Estimate Coefficients	Standard Error	Significance	Estimate Coefficients	Standard Error	Significance
Constant	0.0163	0.041	0.691	0.5268	0.225	0.019**
Log(Average Hourly detected Road Users)	0.4069	0.237	0.085*	0.0471	0.003	0**
Traffic Control Device [Signalized]	-0.0058	0.04	0.885	-0.2621	0.062	0**
Speed Limit [Greater than 30]	0.0001	0	0.579	0.6996	0.117	0**
Presence of Pedestrian Crossing [Yes]	0.0499	0.054	0.355	0.4508	0.111	0**
Presence of Cycle Lane [Yes]	-0.0862	0.067	0.199	-0.0485	0.131	0.067*
Presence of Median [Divided]	0.4184	0.191	0.029**	0.6047	0.184	0.001**
Presence of Bus Stop [Yes]	0.0163	0.041	0.691	0.052	0.124	0.675
Number of Approaches [4 Leg]	-0.0058	0.04	0.885	-0.3457	0.22	0.116
Left Turn Phase [Protected/Prohibited]	0.0001	0	0.579	0.0004	0.001	0.405
Truck Percentage [Greater than Zero]	0.0306	0.081	0.705	0.0963	0.013	0**
Land use [Residential]	0.0499	0.054	0.355	0.9544	0.278	0.001**

** Significant at the 95% confidence level

* Significant at the 90 % confidence level

2.8 Discussion

2.8.1 Road segment model (model M1)

The results presented in Table 2-3 show a general increase in the hourly rates of total and severe conflicts on large major roads. AVs travelling on two-way divided roads experienced higher rates of total and severe conflicts. AVs travelling on multi-lane roads and roads with higher posted speed limits experienced higher rates of conflicts, but no significant impact on the rates of severe conflicts was observed. These findings generally agree with previous studies in the safety literature that showed similar trends for conventional vehicles (Abdel-Aty & Radwan, 2000; Kononov et al., 2008; Milton & Mannering, 1998; Noland & Oh, 2004). AVs generally exhibit cautious driving behavior and strictly abide by posted speed limits. On larger multi-lane roads, this could potentially increase the number of lanes changing maneuvers attempted by human drivers to avoid the AVs, and therefore heavily influence the hourly conflict rate. An interesting finding is that the speed limit did not show a significant impact on the hourly rate of severe AV conflicts, which is not typical for conventional vehicles. A potential reason for this is that while human drivers tend to exceed speed limits in urban areas (Ewald and Wasserman LLC, 2019; Stephens et al., 2015), AVs never exceed the speed limit, which controls the severity of conflicts.

The presence of bus stops and on-street parking showed a strong positive association with AV hourly conflict rates, but their impact on severe conflicts was not statistically significant. Bus stops generate higher pedestrian activities on the road and increase the likelihood of pedestrian jaywalking (Ghomi & Hussein, 2022, 2023). With even a higher tendency of pedestrian jaywalking around AVs (Alozi & Hussein, 2023), a notable increase in AV-pedestrian conflicts is generally observed on these road segments. Additionally, the presence of bus stops typically leads to an increase in complex interactions (e.g. lane changing maneuvers and frequent speed changes),

which explains the higher rates of conflicts. The insignificant impact of bus stops on the rates of severe conflicts can be attributed to the reduction in vehicles' operating speed, which typically occurs near bus stop locations (Hamed, 2001; Yoneda et al., 2019). The impact of parking lanes on AV safety is somehow similar. While the frequency of complex interactions due to the presence of parking lanes can lead to increasing the hourly conflict count, their presence is usually associated with narrower lanes and reduced average vehicle speeds, which control the severe conflict rate.

The presence of bike lanes significantly reduced the hourly rates of both total and severe conflicts. Previous studies (e.g., Fowler & Koorey, 2006; Pu et al., 2017; Younes et al., 2024) showed that bike lanes reduce the operating speed of vehicles, which leads to significant safety benefits. Unfortunately, the frequency of AV-bike conflicts was very low in the analyzed data, which did not enable us to break down the results by road user class. Thus, it was not possible to assess whether the presence of bike lanes caused an increase in AV-bike conflicts or not. Nevertheless, previous studies (Alozi & Hussein, 2023) showed that AVs are generally cautious around bikes and can handle interactions with bikes on bike lanes very well. Finally, the density of access points was found to be positively associated with the hourly rates of AV severe conflicts. These results were expected since the density of access points leads to increased interactions between AVs and vehicles entering or leaving the road. The speed difference between the AV and the interacting vehicles typically led to a higher rates of severe conflicts.

2.8.2 Intersection model (model M2)

The results presented in Table 2-4 show that intersection characteristics, mainly posted speed, presence of median, and presence of pedestrian crossing have a significant impact on AV safety. The results show a positive association between higher posted speed limits and the hourly rates of

AV severe conflicts. The higher speeds, coupled with the complex interactions between AV and other road users at intersections seem to cause a high frequency of severe conflicts at intersections. The presence of medians is positively associated with the rates of total and severe conflicts. Medians are usually present at larger and more complex intersections, which experience a higher frequency of conflicts. Moreover, pedestrian crossings were found to be associated with a significant increase in the rates of severe conflicts. This can be attributed to the higher pedestrian presence at these intersections (i.e., higher AV-pedestrian conflicts) or the increase in AV stopping to yield to pedestrians on crosswalks, which increases the frequency of rear-end conflicts.

Signalized intersections experienced lower rates of severe conflicts compared to unsignalized ones. The presence of traffic signals provides orderly movements at intersections, which reduces the frequency of complex interactions between AVs and other road users. Surprisingly, protected left turn phases did not lead to a significant reduction in conflicts at intersections. This may be attributed to the limited number of left-turn opposing conflicts in the analyzed data. Further investigation is required to reach a conclusive conclusion regarding the influence of this factor on AV safety.

The presence of bike lanes was found to be associated with a reduction in the severe conflict rates at intersections. This can be attributed to lower operating speed as explained earlier in the previous model, particularly since previous studies showed that AVs can handle interactions with bikes safely (Alozi & Hussein, 2023). The results also show a positive association between truck percentage and severe conflict rates. A detailed review of AV interactions with trucks is needed to ensure AV safety in areas with higher truck presence.

2.9 Conclusion

Among the numerous expected benefits of AVs, improving road safety undoubtedly stands as one of the most sought advantages and is considered the main driver for large-scale adoption of AVs. Evaluating the safety performance of AVs is more crucial than ever to enable the full utilization of AVs and increase public trust in the technology. The objective of this study is to provide a comprehensive analysis to understand the impacts of various traffic-related and geometric factors on the safety performance of AVs at road segments and intersections. To that end, an open-source dataset provided by the Lyft Level 5 project was utilized to conduct the study. Using the data captured from AV sensors, the trajectories of the host AVs and nearby road users (human-driven vehicles, cyclists, and pedestrians) were extracted. Next, traffic conflicts between the host AVs and road users were identified and classified by type and location. The copula-based modelling approach was used to model the hourly rates of total and severe conflicts as functions in a wide range of potential contributing factors. Two models were developed, namely a road segment model (model M1) and an intersection model (model M2).

For road segments, results from the copula model indicated that road characteristics (direction, number of lanes, road type, speed limit, the presence of a dividing median) and infrastructure (presence of bus stops, presence of cycle lanes, and presence of on-street parking) have a significant impact on the hourly conflict rates. Regarding the rate of severe AV-road user conflicts, the hourly average of detected road users, road characteristics (direction, road type, access point density, the presence of a dividing median), and the presence of cycle lanes were identified as the most influential factors. For intersections, the hourly average of detected road users and the presence of a physical median were found to be variables that are positively associated with the hourly conflict rates, while the number of detected road users, intersection characteristics (posted

speed limit, presence of pedestrian crossing, presence of cycle lane, presence of a dividing median, and truck percentage), and the dominant land use at the intersection area were the most impactful variables on the severity of severe conflicts.

Nevertheless, the study encountered three main limitations that should be addressed in future studies. Firstly, the data lacks geographical diversity since the AVs travelled along the same path during the data collection period, which limits the scope of the study to 25 intersections and 26 road segments. Secondly, the dataset was collected between 8 a.m. and 4 p.m., which does not enable the assessment of AV conflicts during nighttime. There is a need to use larger and more diverse datasets in the future to mitigate those limitations. Finally, most of the detected conflicts were AV-vehicle conflicts, with AV-pedestrian and AV-cyclist conflicts being underrepresented. Future studies are recommended to consider larger conflict datasets and investigate other factors that are directly related to specific conflict types, including, for example, pedestrian network characteristics and bike infrastructure type.

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Chapter 3 Investigating the Contributing Factors Affecting the Severity of AV-related Conflicts

3.1 Preamble

As previously discussed in Chapter 1, this chapter presents a study that aimed at assessing the factors that impact the severity of AV-road user conflicts at intersections and road segments. The study primarily focuses on the third objective of the thesis while also contributing to the first, fourth, and fifth objectives. This study was submitted for publication in August 2024, as Gabaire, M., Ghomi, H., and Hussein, M. "Investigating the Contributing Factors Affecting the Severity of AV-related Conflicts". Mahdi Gabaire is the main contributor and the first author of this submission. In addition, Mahdi Gabaire's contributions include study design, data collection and processing, model development, results interpretation, and manuscript writing. The co-authors of this study are Dr. Haniyeh Ghomi and Dr. Mohamed Hussein. Dr. Ghomi's contributions include study design, results interpretation, and manuscript writing. Dr. Hussein contributed with supervision, funding, study conceptualization and design, and manuscript reviewing and editing.

3.2 Abstract

Autonomous Vehicles (AVs) have been advocated as a promising tool to enhance road safety and mobility, reduce greenhouse gas emissions, and improve transportation equity. Yet, studies that systematically analyzing the safety performance of AVs using reliable data are limited in the literature. This study proposes to use real-world AV sensory data to extract AV-road user conflicts and examine the impact of various contributing factors on the conflict outcome (i.e., the severity level of conflicts). The study utilized the open-source Lyft Level 5 dataset to conduct the analysis. AV-road user conflicts were extracted and classified into severe and non-severe conflicts. Two

modelling techniques were utilized to identify the key factors that impact the severity level of conflicts occurring on road segments and intersections, including the binary logistic regression and the ML multilayer perceptron model.

Results showed that the ML model outperformed the binary logistic model in terms of model accuracy and the ability to consider a larger set of factors. It was found that the average speed of vehicles around the AV, road user volume, the time of conflict, road segment length, land use, and road type are the key variables that determine conflict severity on road segments. At intersections, traffic control devices, road user volume, the presence of protected left turn phases, the average speed of vehicles around the AV, and land use were the most impactful factors. For both road segments and intersections, pedestrian volume was directly associated with higher conflict severity, while the presence of bus stops, bike lanes, and parking lanes led to less severe conflicts. The findings of the study suggest that severe AV- conflicts are less likely in residential areas, and factors like the density of access points, the presence of dividing medians, and cyclist volume are not likely to increase the severity of conflicts.

Keywords: Autonomous vehicles, Road safety, Conflict severity, Machine Learning, Multi-layered Perceptron model, binary logistic regression model

3.3 Introduction

The subject of road safety has been a priority for Canada since the publication of the first national road safety strategy in 1996 (Transport Canada, 1996). Numerous efforts have been made ever since to reduce the frequency of collisions and mitigate collision fatalities and serious injuries. Disruptive transportation technologies, such as Autonomous Vehicles (AVs), have been recently advocated as a promising tool to support these efforts and enhance road safety significantly. AVs

are expected to eliminate human-related factors that typically contribute to collisions, such as inattentiveness, fatigue, and speeding, thus, mitigating the majority of collisions on the roads. Additionally, numerous other benefits have been identified by integrating AVs into our traffic ecosystem. As highlighted by Fagnant & Kockelman (2015), AVs are expected to reduce congestion and greenhouse gas emissions by optimizing road capacity as well as enhance equity in transportation by providing the elderly and disabled with a convenient means of travel.

Research on AV technology has garnered a lot of attention as a result of these potential benefits. Nascimento et al. (2020) conducted a comprehensive review of the current literature published on AVs. The study revealed that the available literature is hyper-focus on the computational aspect of AVs and Artificial Intelligence (AI), with other critical issues such as assessing the impact of AVs on road user safety being understudied. While some safety studies have been undertaken using reported AV collisions to assess the potential benefits associated with the introduction of AVs (e.g., (Channamallu et al., 2023; Khattak et al., 2021)), collision data limitation has been an obstacle to developing in-depth evaluations of AV safety. To overcome data limitations, numerous AV safety studies relied on simulation-based approaches (e.g., Morando et al. (2017), El-Hansali et al. (2021), Sekar et al. (2023)). The majority of studies demonstrated that AVs would have a substantial positive influence on road safety, especially at higher penetration rates. Nevertheless, these types of studies suffer from several limitations, including the multiple assumptions implement to manipulate car following models in order to represent AVs and the unrealistic behaviour of road users interacting with AVs.

Recently, there has been a rapid growth in AV testing on public roads in many areas of the world. Through field testing, developers have been collecting valuable data to assess AV operations in real-world conditions. Several developers have published portions of the collected data to foster

innovation in AV research. Examples of published data include Lyft Level 5 (Houston et al., 2020), nuScenes (Caesar et al., 2019), ITE Vision Zero (City of Bellevue, 2020), Argoverse (Wilson et al., 2023), and Waymo (Sun et al., 2019). As the data captures interactions between AV and road users, it has become feasible to conduct proactive AV safety assessments using AV-road user conflicts (Alozi & Hussein, 2022, 2023, 2024) and study AV-road user interactions using realistic data (Alozi & Hussein, 2024; Lanzaro et al., 2023; Shoman et al., 2024). Most of the studies focused on analyzing the dynamics of AV-road user interactions as opposed to investigating the contributing factors influencing the frequency and severity of observed conflicts.

This study aims to utilize rich AV sensory data to extract AV-road user conflicts and examine the contributing factors that influence the conflict outcome (i.e., the severity level of conflicts). The study utilized the Woven prediction and validation datasets (Houston et al., 2020), previously branded as the Lyft Level 5 datasets, to extract traffic conflicts and conduct the analysis. The data was captured in Palo Alto, California between October 2019 and March 2020. The data includes high-resolution AV trajectory data as well as the trajectories of all road users within a 200-meter radius of the AVs. The severity of conflicts was quantified using two traffic conflict indicators, namely Time-to-Collision (TTC), used to measure the severity of rear-end conflicts, and Post-Encroachment Time (PET) for other conflict types. The observed conflicts were classified into two classes, severe and non-severe, based on the value of the traffic conflict indicator. Two modelling approaches were then utilized to study the impact of various contributing factors on conflict severity level, including binary logistic regression, a well-established traditional statistical model that is well-suited to address classification problems, and an advanced machine learning model, known as the multilayer perceptron model. The machine learning model was selected as it is less sensitive to correlation between explanatory variables, which enables a more accurate assessment

of their impact on conflict severity. For each modelling approach, two models were developed, one for conflicts occurring at intersections and another for those occurring in road sections. Ultimately, the results from this study intend to aid in understanding contributing factors that affect serious conflicts involving AVs. Furthermore, these models aid in providing safety planning tools to legislators and city planners to easily identify areas that could be at risk under current conditions before the widespread deployment of AVs. Hence, proactively assisting in achieving fewer injuries and loss of life as per the goals outlined in the national road safety strategy.

The structure paper will be as follows: Section 3.4 provides a summary of the literature review. Section 3.5 presents the methodology used to undertake the analysis. Section 3.6 addresses the study data and the explanatory variables used in the developed models. The results of the study are presented and discussed in Section 3.7 Finally, Section 3.8 concludes with a summary of the findings and recommendations for future studies.

3.4 Literature Review

Existing studies that investigated the safety implication caused by the introduction of AVs utilized three distinctive approaches, namely the statistical analysis of collision data (e.g., (F. M. Favarò et al., 2017; Khattak et al., 2021; Channamallu et al., 2023)), computer simulations (e.g., (Morando et al., 2017; Virdi et al., 2019; Zhu & Tasic, 2021; Hammami & Borsos, 2024)), and analysis of traffic conflicts extracted from AV sensor data (e.g., (Alozi & Hussein, 2022, 2023)). Most of these studies focused on predicting AV safety trends and assessing the safety benefits that could be attained by adopting AV technology.

A review of the published studies that investigated the factors that impact the outcome of AV-road user collisions (or conflicts) illustrates a lack of comprehensive analysis. For example, Ren et al.

(2021) investigated the contributing factors influencing the severity of AV collisions using official collision reports provided by the California Department of Motor Vehicles (DMV) Database collected between May 2018 and March 2021. Overall, 180 AV-involved collisions were retrieved, of which 96 occurred under autonomous driving mode while the remaining collisions occurred during the standard driving mode. The study found that collision severity was greatly influenced by the presence of dividing medians, mixed land uses, and the number of lanes on roadways. Notably, the study suffers from the lack of diverse environmental conditions and a relatively small size of collision data. Elsewhere, F. Favarò et al. (2018) investigated the factors contributing to AV collisions utilizing a unique surrogate measure of safety to overcome collision data limitations. More specifically, the study used the reported disengagement data, defined as instances where the AV relinquishes complete control back to the human operator, as a surrogate of collisions. The study analyzed 5325 disengagement cases across eight manufacturers, over the span of 2 years between September 2014 to December 2016. Findings from the investigation indicate no association between the frequency of disengagements and environmental conditions or location characteristics.

Simulation-based studies have been also used to investigate the factors that impact AV safety, with a focus on the AV market penetration rate. For instance, Sekar et al. (2023) examined the safety impact associated with the introduction of AVs across different market penetration rates using PTV Vissim microsimulation software. The study found that highway safety performance increased as the market penetration rate of AVs increased. Results also indicated significant improvement in safety performance in addition to substantial decreases in overall travel time. Similar findings were also reported by Sinha et al. (2020). Nevertheless, the main limitation of these studies was the

several assumptions implemented to represent the behaviour of the AV, which is not seen to encapsulate the uncertain nature of the real world precisely.

More recently, assessments using AV perception data have been gaining attention for their easily accessible high-quality data. For instance, Kamel et al. (2023) proposed a novel framework to assess the safety performance of AVs on a large-scale network. The main source of data the study used was the Lyft Level 5 dataset. Utilizing a Bayesian hierarchical extreme value model, the proposed framework would be capable of conducting real-time safety assessment, where collision-prone locations could be identified, and countermeasures would be recommended over a short period of time. Elsewhere, Alozi & Hussein (2024) applied a subset of the Lyft Level 5 perception dataset to develop a machine learning model that can predict conflict occurrence in real time. The study incorporated a version of long short-term memory (LSTM) to predict the likelihood and severity of potential future conflicts within a three-second window. The study considered all types of road users (e.g., pedestrians, cyclists, and human-driven vehicles). While these studies establish the framework for proactive safety assessments of AV safety using conflict data, analyzing the influential factors impacting the outcome of AV conflicts remains an untouched area in the literature.

3.5 Methodology

To identify the contributing factors that affect the outcomes of AV-road user conflicts, two approaches were applied. First, using a frequentist approach, the binary logistic regression model was developed. This assisted in establishing a relationship between various contributing factors (e.g., geometric and traffic characteristics) and the severity level of conflicts involving AVs. Two logistic regression models were developed, namely (model M1) for conflicts occurring in road segments and (model M2) for those occurring at intersections. Second, two machine learning (ML)

multilayer perceptron models were applied, namely, (model M3) and (model M4) for road segment and intersection conflicts, respectively. The ML models were applied to investigate whether they could enhance the prediction accuracy of conflict outcomes and to enable a comprehensive analysis of explanatory variables without prior assumptions of the impact of correlation among variables on the results. The following section provides a breakdown of the fundamental principles of each approach.

3.5.1 Logistic regression

In safety studies, the logistic regression approach is a well-established method for investigating the relationship between influential factors and the likelihood of different levels of collision/conflict severity (Ahmed et al., 2018; Torrão, 2014; Xu et al., 2013). In this study, the binary logistic regression modelling approach was developed to examine the influences of various explanatory variables on the likelihood of different AV conflict severity levels. The logit function was the preferred link function used to limit the outcome of the model to range between 1 and 0, which represented severe and non-severe outcomes respectively. By denoting P as the probability of the outcome, the log transformation used in the logistic regression model can be represented according to Equation 3-1 as follows:

$$log(P) = log\left(\frac{P}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_j x_k \qquad (1)$$

Where, $log\left(\frac{P}{1-p}\right)$ is the log of the odds, $\beta_0, \beta_1, \beta_2, \ldots, \beta_j$ are the estimated coefficients of the predictors obtained through the maximum likelihood estimation method, and $x_1, x_2, \ldots, x_k$ represent the set predictors employed in the model. For simplicity, Equation 1 can be rearranged to compute probability directly as shown in Equation 3-2:

$$P = \frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_k x_k}}{1+e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_k x_k}} = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_k x_k)}} \quad (2)$$

Lastly, in order to ensure model robustness, the 10-fold cross-validation method was employed, with 90% of the data selected randomly to train the model and 10% used for model validation in each fold.

3.5.2 Multilayer Perceptron model

The multilayer perceptron model is an ML model that has been recently utilized in several road safety studies for its broad versatility and potential to capture complex relationship in datasets (e.g., (Ruangkanjanases et al., 2024; Yan et al., 2023)). The multilayer perceptron model is an advancement of the perceptron model introduced by Rosenblatt in the 1950s (Rosenblatt, 1958). Perceptron machines are effective at addressing linearly separable problems involving simple logic operations like "and," "or," and "not." However, the perceptron has a single layer of functional neurons, limiting its capability to solve non-linearly separable problems. The multilayer perceptron addresses this limitation by incorporating multiple layers of functional neurons between the input and output layers. As illustrated in Figure 3-1, each layer in a multilayer perceptron is entirely connected to the next layer, without any same-layer or cross-layer connections between neurons. The input layer lacks functional neurons and merely acts as a structural unit to receive information. The neurons in the hidden and output layers process the signals from the input layer, with the final results emerging from the output layer.

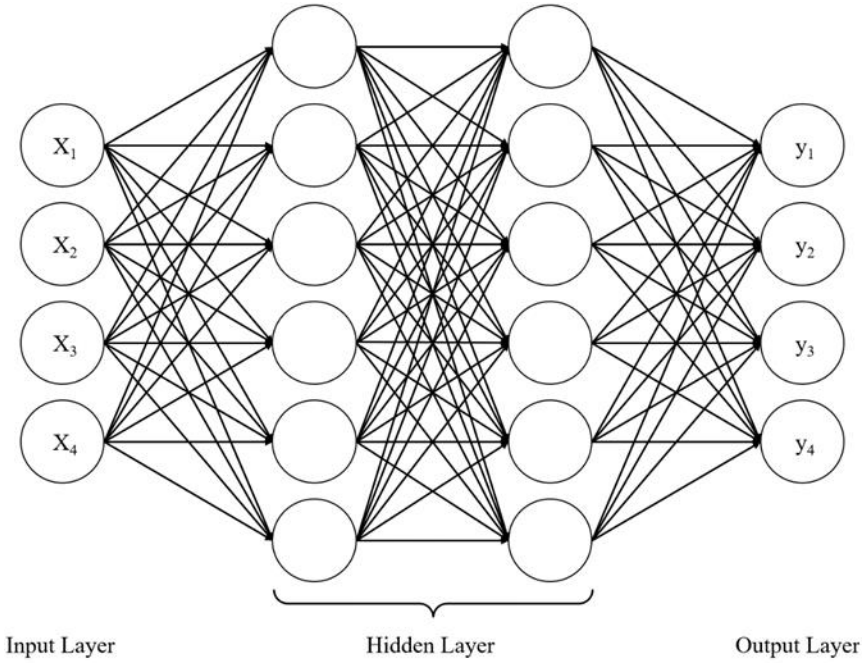

Figure 3-1: Overview of the multilayer perceptron model

A multi-layer perceptron artificial neural network (ANN) customarily consists of three distinct types of layers: the input layer, the output layer, and one or more hidden layers. The input layer is responsible for receiving the values derived from the explanatory variables, serving as the input data. The total number of neurons constituting the input layer is determined by the total number of independent variables being studied. The hidden layer, which comprises 'm' neurons, accumulates the weighted input values from these explanatory variables and is instrumental in computing complex associative patterns. The number of hidden layers can range from 1 to 2 which are known as shallow neural networks. These are best for simple classification problems. With more complex high dimensional data, additional hidden layers could be implemented. These are generally known as “Deep Neural Networks (DNNs)”.

Given the training set $D = \{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$ where N is the number of locations (i.e., intersections or road segments), the input layer contains J neurons (equal to the number of explanatory variables and the output is a l-dimensional vector (i.e., the severity of collisions).

Assume there is a single hidden layer with q neurons. The threshold for the j^{th} neuron in the output layer at location (i) is ξ_{ij}, and for the h^{th} neuron in the hidden layer, it is λ_{ih}. The weight between the j^{th} input neuron and the h^{th} hidden neuron is v_{jh}, and the weight between the h^{th} hidden neuron and the k^{th} output neuron is w_{hk}. The Rectified Linear Unit (ReLU) function is utilized as the activation function. And the relevant calculations are as Equations (3-5):

$$\alpha_{ih} = \sum_{j=1}^{J} v_{ijh} x_{ij} \quad (3)$$

$$\beta_{ij} = \sum_{k=1}^{K} \omega_{hij} b_{ih} \quad (4)$$

$$y_{ij} = f\left(\sum_{h=1}^{q} \omega_{hij} \cdot b_{ih} + \zeta_{ij}\right) \quad (5)$$

Where α_{ih} represents the input to the h^{th} hidden neuron at location i, β_j represents the input to the k^{th} output neuron at location i, and y_{ij} represents the severity level at location i.

A multilayer perceptron uses an error back-propagation algorithm to optimize the weighting factors. Over an iterative process, training data is feed into the neutral network and passed through the multiple hidden layers until an output is formed. This output is then assessed through evaluating the error. This algorithm aims to minimize the overall error on the training set. The mean-square error for the n^{th} sample is summarized in equation 3-6. Based on the results, the weight between the layers are readjusted.

$$E_n = \frac{1}{2} \sum_{j=1}^{l} \left(y_j^n - \hat{y}_j^n\right)^2 \quad (6)$$

3.6 Data

The prediction and validation dataset from the Lyft Level 5 project (currently rebranded as the Woven datasets under Toyota) was utilized to undertake the analysis. The data was collected by a

fleet of 20 AVs from an urban corridor in Palo Alto, California over six months (October 2019 to March 2020). The 20 AVs were mainly driving on the El Camino Real corridor in Palo Alto from the intersection of El Camino Real and California Avenue to the intersection of El Camino Real and Wells Avenue, spanning a total length of 5.2 km and covering 26 road segments and 25 intersections. The data covers nearly 1000 hours of driving time, arranged in the form of small segments (scenes), 25 seconds each. The variables provided by the dataset consisted of unique identifiers, timestamps, size, heading, and local trajectory coordinates of the AV and any road user detected by the AV within a 200-meter radius. Using an in-house perception system, the developer classified the detected road users by type into cars, pedestrians, cyclists, trucks, buses, and emergency vehicles, among other classes. The current study focused on cars, cyclists, and pedestrians due to the limited number of other road user types.

As depicted in Figure 3-2, data pre-processing started with the trajectory evaluation and filtering process. With the host's (AV) trajectories, minimal errors were detected since it was measured using highly accurate GPS instruments. On the other hand, road user trajectories were measured using AV LiDAR, which impacted trajectory accuracy and introduced sporadic positional errors. To offset these issues, trajectories were smoothened using the Basis Spline (B-Spline) technique. The B-Spline is a well-established approach for trajectory smoothing while also not being computationally costly (Choi et al., 2023).

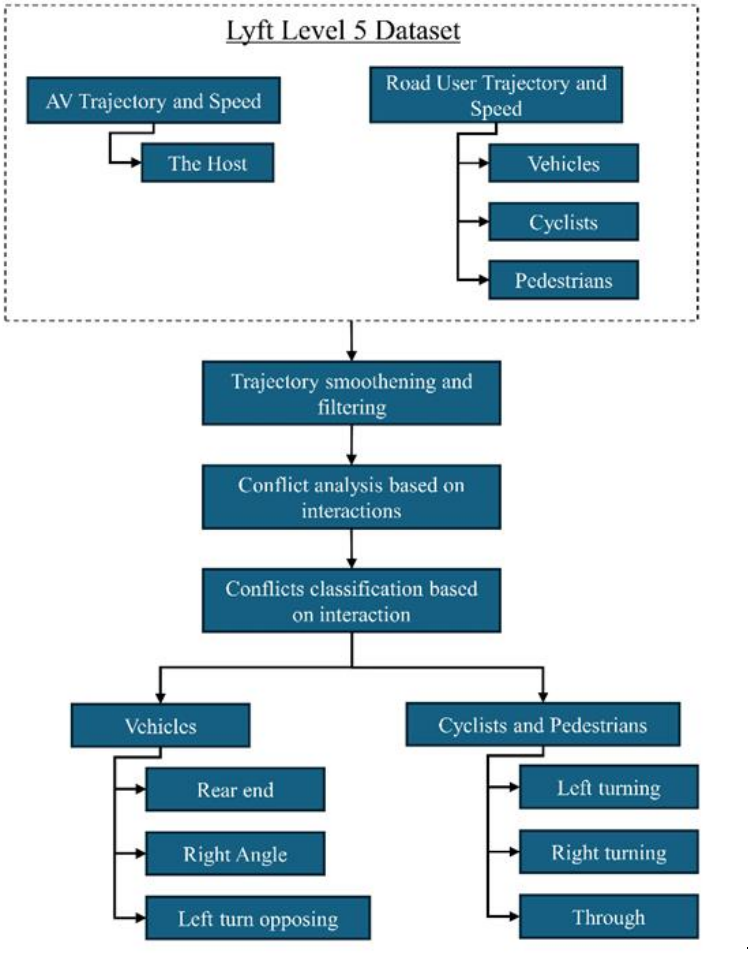

Figure 3-2: Framework for extracting and classifying AV-road user conflicts

Next, the trajectories of both the AV and road users in each scene were extracted. A Python-based framework developed at McMaster University was utilized to extract AV-road user conflicts. The Time-To-Collision (TTC) indicator was employed to measure the severity of rear-end conflicts between AVs and vehicles. Post-Encroachment Time (PET) indicator was utilized to quantify the risk associated with AV conflicts with pedestrians and cyclists, as well as angle and turning conflicts with cars. In this study, a three-second threshold of both TTC and PET indicators was utilized to define conflicts. The same threshold has been used in numerous studies in the literature (Sacchi & Sayed, 2016; Essa & Sayed, 2019; Alozi & Hussein, 2022; Lanzaro et al., 2023; Shoman

et al., 2024). In total, 3510 AV-road user conflicts were detected across 25 intersections and 26 road segments.

Ideally, the target was to classify the severity of conflicts into three groups: the high severity conflicts, with the conflict indicator ranging between 0 and 1 seconds, medium severity conflicts, with the conflict indicator ranging between 1 and 2 seconds, and low severity conflicts, with the conflict indicator ranging between 2 and 3 seconds. However, due to the limited occurrences of conflicts in the 0-1 second category (78 conflicts on road segments and 26 at intersections), it was decided to classify conflicts into two categories: severe conflicts that have a conflict indicator between 0-2 seconds and non-severe conflicts, with conflict indicator ranging between 2 and 3 seconds. Table 3-1 shows a breakdown of the detected conflicts by location and type.

Table 3-1: Detailed breakdown of detected conflicts

Conflict Type	Intersections		Road segments		Total	
	Severe	Non-severe	Severe	Non-severe	Severe	Non-severe
Rear-end conflicts	253	800	802	1273	1055	2073
Other AV-vehicle conflicts	15	183	9	70	24	253
AV-pedestrian conflicts	6	18	5	11	11	29
AV-cyclist conflicts	9	23	17	16	26	39
Total	283	1024	833	1370	1116	2394

Lastly, a comprehensive list of potential contribution factors that could impact the outcome of AV-road user conflicts was extracted. Several factors were extracted directly from the dataset, such as average vehicle speed, the number of detected road users at the time of conflict, the percentage of pedestrians and cyclists at the time of conflict, and the time and season of the conflict. Other factors related to land use, built environment, and road and intersection characteristics were extracted

using Open Street Maps (OpenStreetMap contributors, 2024). Tables 3-2 and 3-3 provide a detailed description of the potential contributing factors utilized in this study for road segments and intersections, respectively.

Table 3-2: Summary of explanatory variables used in road segment models (model M1 & M3)

Variable Name	Variable Description	Value
Average speed of vehicles (m/s)	The average speed of vehicles surrounding the AV within a 200-meter radius at the time of conflict.	Min. = 1.561 Mean = 9.641 Max. =18.284
Detected Road Users	The average number of road users detected by the AVs within a 200-meter radius at the time of conflict.	Min. = 20 Mean = 386 Max. = 1299
Percentage of Cyclists	A discrete variable representing the proportion of cyclists of the detected road users	Min. = 0 Mean = 1.27 Max. = 22.79
Percentage of Pedestrians	A discrete variable representing the proportion of pedestrians of the detected road users	Min. = 0 Mean = 12.577 Max. =76.65
Season	A categorical variable representing whether the conflict occurs in the Fall (0), Spring (1), or Winter (2).	0 = 597 1 = 212 2 = 1394
Time of Day	A categorical variable representing whether the time of day at which the conflict occurred is Off Peak (0), Morning Peak (1), or Evening Peak (2).	0 = 1380 1 = 556 2 = 267
Weekday	A binary variable representing whether the conflict occurred during a weekend (1) or not (0).	0 = 24 1 = 2179
Direction	A binary variable representing whether the road is one-way (0) or two-way road (1)	0 = 102 1 = 2101
Number of lanes	A discrete variable representing the number of lanes on the road segment where the conflict occurred.	Min. = 1 Mean = 2.16 Max. = 3

Road Type	A binary variable representing whether the road where the conflict occurred is a minor road (0) or a major road (1).	0 = 925 1 = 1278
Speed Limit	A binary variable representing whether the posted speed limit at conflict location is below 30 mph (0) or above 30 mph (1).	0 = 982 1 = 1221
Length (km)	A continuous variable representing the length of the road segment where the conflict occurred.	Min. = 0.05 Mean = 0.19 Max. =1.13
Access Point Density (per km)	A continuous variable representing the number of access points (e.g., driveways) per unit length of the road segment where the conflict occurred.	Min. =0 Mean = 15.22 Max. = 42.12
Presence of bus stops	A binary variable representing whether bus stops are present on the road segment where the conflict occurred (1) or not (0).	0 = 482 1 = 1721
Presence of median	A binary variable representing whether the road where the conflict occurred is divided (1) or undivided (0).	0 = 889 1 = 1314
Presence of cycle lane	A binary variable representing whether a cycle lane is present on the road segment where the conflict occurred (1) or not (0).	0 = 863 1 = 1340
Presence of on-street parking	A binary variable representing whether on-street parking is permitted on the road segment where the conflict occurred (1) or not (0).	0 = 1600 1 = 603
Land Use	A binary variable representing whether the dominant land use at the conflict location is residential (0) or other (1).	0 = 430 1 = 1773

Table 3-3: Summary of explanatory variables used in Intersection models (model M2 & M4)

Variable Name	Variable Description	Value
Average speed of vehicles (m/s)	The average speed of vehicles surrounding the AV within a 200-meter radius at the time of conflict.	Min. = 0 Mean = 7.24 Max. =17.75

Detected Road Users	The average number of road users detected by the AVs within a 200-meter radius at the time of conflict.	Min. = 15 Mean = 390 Max. =1259
Percentage of Cyclists	A discrete variable representing the proportion of cyclists of the detected road users.	Min. = 0 Mean = 1.30 Max. =44.83
Percentage of Pedestrians	A discrete variable representing the proportion of pedestrians of the detected road users.	Min. = 0 Mean = 12.81 Max. =93.83
Season	A categorical variable representing whether the conflict occurs in the Fall (0), Spring (1), or Winter (2).	0 = 341 1 = 119 2 = 847
Time of Day	A categorical variable representing whether the time of day at which the conflict occurred is Off Peak (0), Morning Peak (1), or Evening Peak (2).	0 = 805 1 = 348 2 = 154
Weekday	A categorical variable representing whether the conflict occurred during a weekend (1) or not (0).	0 = 9 1 = 1298
Traffic control device	A binary variable representing whether the type of traffic control device used in the intersection is Signalized (1) or not (0).	0 = 769 1 = 538
Speed Limit	A binary variable representing whether the posted speed limit at conflict location is below 30 mph (0) or above 30 mph (1).	0 = 812 1 = 495
Presence of pedestrian crossing	A binary variable representing whether the pedestrian crossing at an intersection is present (1) or not (0).	0 = 471 1 = 836
Presence of cycle lane	A binary variable representing whether a cycle lane is present at the intersection where the conflict occurred (1) or not (0).	0 = 522 1 = 785
Presence of median	A binary variable representing whether the intersection where the conflict occurred is divided (1) or undivided (0).	0 = 857 1 = 450
Presence of bus stops	A binary variable representing whether bus stops are present at the intersection where the conflict occurred (1) or not (0).	0 = 316 1 = 991

Number of approaches	A binary variable representing whether the intersection is three-legged (0) or four legged (1)	0 = 611 1 = 696
Left turn phase	A binary variable representing whether the intersection has a Protected/Prohibited (0) left turn phase or Permissive (1).	0 = 565 1 = 742
Truck percentage	A binary variable representing whether the truck percentage at an intersection is greater than zero (1) or not (0).	1 = 785 2 = 522
Land Use	A binary variable representing whether the dominant land use at the conflict location is residential (0) or other (1).	0 = 205 1 = 1102

3.7 Results and Discussion

3.7.1 Logistic regression

Before developing the logistic regression models, it was necessary to conduct a correlation analysis among the potential contribution factors listed in Tables 3-2 and 3-3. The Cramer's V approach (Cramer, 1946) was utilized to undertake the correlation analysis because of its compatibility with the current data and simple interpretability. The results of Cramer's V test range from 0 to 1, with values greater than 0.7 suggesting a very high correlation between variables (D. K. Lee, 2016). The results indicated a high correlation between some variable pairs, leading to the elimination of five variables from the road segment model (model M1), namely road type, speed limit, presence of median, presence of a cycle lane, and land use. Similarly, five variables (left turn phase, speed limit, presence of a cycle lane, presence of median, and land use) were discarded from the intersection model (model M2). The backward stepwise regression approach was then utilized to select the final variable list in the two models. Tables 3-4 and 3-5 show the final list of variables considered in the two models, as well as the estimated model coefficients and significance levels.

All variables were found to be statistically significant in the road segment model (model M1), while all but the presence of bus stops were found to be statistically significant in the intersection model (model M2).

Table 3-4: Road segment model results (model M1)

Variables Names	Estimated Coefficients	Significance
Constant	-0.5959	0.0107**
Number of detected road users	-0.0004	0.0462**
Average speed of vehicles	0.0563	0.0004**
Season [Spring]	-0.3091	0.0957*
Season [Winter]	-0.1289	0.2349
Access point density	-0.0126	0.0202**

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

Table 3-5: Intersection model (model M2)

Variables Names	Estimated Coefficients	Significance
Constant	-0.8961	0.0211**
Number of detected road users	-0.00101	0.0398**
Average speed of vehicles	0.0695	0.0126**
Season [Spring]	0.4962	0.0735*
Season [Winter]	0.1211	0.4948
Presence of bus stop [Yes]	-0.2514	0.1667
Truck Percentage [Zero]	-0.8449	0.0002**

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

Moreover, in order to assess the performance of the two models, the confusion matrices of the two models were developed (shown in Tables 3-6 and 3-7, respectively). The reported misclassification error produced was 36.6% for model M1 and 37.3% for model M2. Understandably with more non-severe observations present in the training data, both models show great capability in predicting non-severe conflicts compared to severe conflicts. This was concluded from the

sensitivity of non-severe conflicts, which were approximately 69.9% for model M1 and 86.9% for model M2.

Table 3-6: Confusion matrix for road segment model (model M1)

	Predicted severe	Predicted non-severe
Observed Severe	457 (47.9 %)	498 (52.1 %)
Observed non-severe	376 (30.1 %)	872 (69.9 %)

Table 3-7:Confusion matrix for intersection model (model M2)

	Predicted severe	Predicted non-severe
Observed severe	188 (32.4 %)	393 (67.6 %)
Observed non-severe	95 (13.1 %)	631 (86.9%)

The results presented in Tables 3-4 and 3-5 suggest that for both the road segment and intersection models, the number of road users detected by the AV within a 200-meter radius is negatively associated with the likelihood of a severe conflict outcome. The number of road users detected by the AV represents a surrogate for the exposure parameter. As exposure increases, average vehicle speeds are expected to drop, which could reduce the severity of conflicts. This hypothesis is further confirmed by the strong positive association between the average speed of vehicles around AVs and the severity of the observed conflicts in the two models. The results suggest that as the average speed of vehicles around the AV increases, it is more likely that AV-road user conflicts are more severe.

Moreover, the results of the road segment model (model M1) suggest that a higher density of access points (e.g., driveways) leads to reducing the probability of a higher severity of conflicts. This finding seems to contradict the consensus of past safety studies that show an increase in

collision frequency and severity of conventional vehicles with the increase in the number of access points per kilometer (e.g., (Elvik, 2017), (Schultz et al., 2009), (Gattis et al., 2005)). The explanation of this finding is not straightforward, but potential reasons could include the conservative behavior of AVs in residential areas, which was highlighted in previous studies (e.g., (Chen et al., 2020)). The results also suggest that severe AV conflicts are more likely in the Fall compared to Spring and Winter. Geographically, Palo Alto is situated in Northern California which is known for its low-temperature winters but lack of snowfall that typically leads to increasing collision severity. During the Fall season, the region experiences an increase in precipitation. The negative impact of rain and fog on the AV perception sensors (e.g., Radar, LiDAR, and cameras) of the AV could be a contributing factor to such a finding, as highlighted in Sezgin et al. (2023). The wet surface conditions also increase the severity of many types of conflicts, such as rear-end conflicts, which constitute the majority of conflicts in this study.

For the intersection model (model M2), the presence of bus stops and the truck percentage were found to have a negative association with the likelihood of a conflict being of high severity. The impact of the two factors could be explained by the lower operating speed of vehicles at intersections where bus stops and trucks are present. This agrees with findings from previous studies in safety literature. For example, Ghomi and Hussein (2021, 2022) showed that although more collisions are expected at intersections where bus stops are present, the resulting collisions are likely not severe due to the overall lower operating speed of vehicles. Finally, the impact of season on conflict severity showed an opposite trend to the road segment model. According to the estimated coefficients shown in Table 3-5, the likelihood of severe outcomes of AV conflicts increases in the Spring season compared to the Fall and Winter. One potential explanation for this is the increased pedestrian and cyclist activities in the Spring, which ultimately increases the

frequency of their interactions with AVs. The frequent decelerations due to such interactions potentially increase the frequency of rear-end conflicts at intersections.

3.7.2 Multilayer perceptron model

The binary logistic regression models did not enable the investigation of the impact of several factors due to the high correlation among them. Additionally, the prediction accuracy of the two models (models M1 and M2) was not high. To mitigate these issues, a machine learning approach was utilized. Two Multilayer perceptron models were developed to predict the outcome of conflicts occurring in road segments (model M3) and intersections (model M4). The AIC values for the two models were 1025.9 and 543.9, respectively. In terms of predictive capabilities, the misclassification errors for the two models were 27.7% and 30.5%, respectively, indicating a substantial improvement in accuracy over the logistic regression model. Through analyzing the confusion matrices presented on Tables 3-8 and 3-9, the models demonstrate to be highly effective at identifying the non-severe conflict cases in road segments and intersections. While for severe conflict cases, the road segment model (model M3) predicted severe conflicts with relatively good accuracy at 70.5 % while in the intersection model (model M4) a low true value rate (recall) was experienced for severe conflicts **(**40.2 %). Other key performance indicators suggest that both models perform moderately well with F1 scores of 0.63 for the road segment model (model M3) and 0.51 for the intersection model (model M4). Figures 3-3 and 3-4 illustrate the incremental change in model accuracy and loss over four epochs. For both models, the predictive performance of the models with unseen data (test data), steadily increases with each iteration. In contrast, the model loss for the road segment (model M3) and intersection model (model M4) experience a decreasing trend with each epoch.

Table 3-8: Confusion matrix for road segment model (model M3)

	Predicted severe	Predicted non-severe
Observed severe	518 (70.5 %)	217 (29.5 %)
Observed non-severe	392 (26.7 %)	1075 (73.3 %)

Table 3-9: Confusion matrix for intersection model (model M4)

	Predicted severe	Predicted non-severe
Observed severe	209 (40.2 %)	311 (59.8 %)
Observed non-severe	88 (11.2 %)	699 (88.8 %)

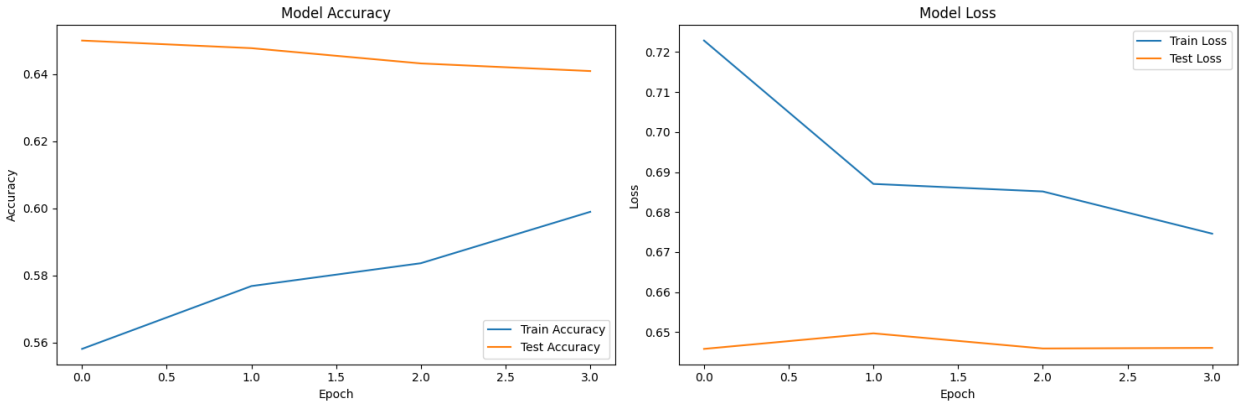

Figure 3-3: Training and testing metrics for the road segment multilayer perceptron model (model M3).

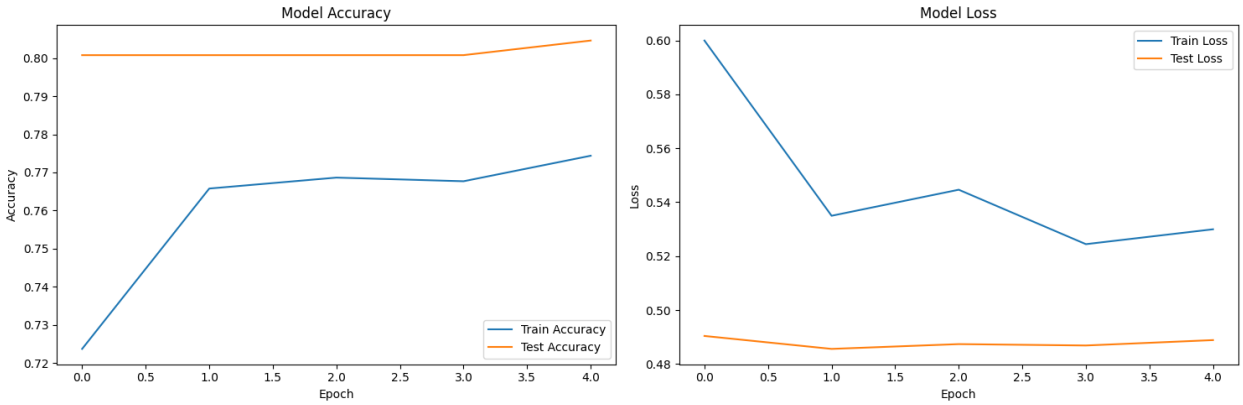

Figure 3-4:Training and testing metrics for the intersection multilayer perceptron model (model M4).

To enhance the interpretability of the results, the SHapley Additive EXplanation (SHAP) approach was utilized**.** More specifically, a 'beeswarm' plot was developed for each model (Figures 3-3 and 3-4) to organize variables in descending order (y-axis), with the variables on the top being the most impactful when predicting conflict outcome (severity level) and the subsequent variables exhibiting a lesser impact. The x-axis of the plot conveys the SHAP value, which indicates the influence of the variable on a single model prediction (whether the variable is positively or negatively associated with conflict severity). The feature value of categorical variables corresponds to the variable values presented in Tables 3-2 and 3-3. For example, time of day was modeled as a categorical variable that takes 0 for the off-peak period, 1 for the morning peak period, and 2 for the evening peak. Thus, values displayed in red in Figures 3-3 and 3-4 represent the higher value of this variable (2, or the evening peak), values in purple correspond to the middle value (1, or morning peak), and those displayed in blue represent the lower value of the variable (0, or the off-peak period). As shown in Figure 3-3 the average speed of the vehicles surrounding the AV and the number of detected road users are the most influential factors in determining conflict severity on road segments (model M3). For intersections (model M4), traffic control devices and the number of detected road users were found to be the most significant variables. For both models, the weekend variable was deemed to be the least impactful variable.

Figure 3-5: SHAP plot for the road segment multilayer perceptron model (model M3).

Figure 3-6: SHAP plot for the intersection multilayer perceptron model (model M4)

The results of the road segment model (shown in Figure 3-3) suggest that the average speed of vehicles and the number of detected road users by the AV are the most important factors in determining the severity of conflicts. The SHAP plot suggests a positive association between speed and the severity of conflicts and a negative association between the number of road users detected by the AV and conflict severity, which are the same trends resulting from the binary logistic regression model (model M1). The time of the day, road segment length, land use, and road type were also identified as important factors in determining the severity of conflicts according to Figure 3-3. The results show that conflicts occurring as AVs travel during the afternoon peak hours, on longer road major roads, and in non-residential areas segments are more likely to be severe. The results show that roads with on-street parking lanes and a higher number of bus stops are less

likely to experience severe conflicts, potentially due to the lower speed of vehicles on such roads. Similar to the logistic regression model, access point density seems to be negatively associated with conflict severity, although it was not found to be a particularly important factor in determining conflict severity. The results also suggest that AV conflicts are more likely to be severe as the percentage of pedestrians increases, while the percentage of cyclists does not seem to be an important factor in determining AV-road user conflict outcomes. This aligns with the results of (Alozi & Hussein, 2023) which indicated that AVs could handle interactions with cyclists well but raised concerns over interactions with pedestrians, especially as AVs are making right turns. Notably, weekday, the presence of dividing medians, the presence of bike lanes, access point density, and the number of lanes were not found to have a significant impact on AV conflict severity on road segments.

As for the intersection model (model M4), the results presented in Figure 3-4 show that the type of traffic control device, road user volume detected by the AV, the presence of protected left-turn phases at signalized intersections, and average vehicle speed around the AVs are the most important factors that determine the severity outcome of conflicts. More severe conflicts were found to be more likely at signalized intersections, especially if they do not have a protected left-turn phase. Signalized intersections typically experience a high frequency of rear-end conflicts, which is the most common conflict type in the study. Most unsignalized intersections in the studied corridor are minor intersections that do not experience a high frequency of conflicts. Also, the absence of protected left-turn phases increases the probability of observing severe left-turn opposing conflicts, especially at higher speeds. Similar to the road segment model, the number of road users detected by the AV was found to be negatively associated with severe conflicts while average vehicle speed was directly associated with more severe conflicts.

Following those five variables, land use, the presence of bus stops at the intersection, truck percentage, number of approaches, presence of bike lanes, and the percentage of cyclists and pedestrians at the intersections were shown to have an average significance in determining the outcome of AV conflicts. The presence of bus stops seems to be negatively associated with conflict severity, potentially because of the lower average vehicle speed at these intersections. Cyclist activities at the intersections (represented by the presence of bike lanes and a higher percentage of cyclists) seem to reduce the severity of AV conflicts. The presence of bike lanes typically leads to decreasing road width and is typically associated with better safety performance. Also, previous studies (Alozi & Hussein, 2023) showed that AVs are generally conservative around cyclists, which can explain the lower severity of conflicts. On the contrary, higher pedestrian activities were found to be positively associated with conflict severity. Increasing pedestrian activities are typically associated with frequent stops for turning vehicles, which leads to more rear-end conflicts. Notably, weekday, time of the day, the presence of dividing medians, season, and the presence of marked pedestrian crosswalks were not found to have a significant impact on AV conflict severity at intersections.

3.8 Conclusion

With the presence of AV on roads set to increase rapidly in the upcoming years, fully comprehending the factors impacting the safety of AV-road user interactions is vital for increasing public trust and promoting large-scale adoption. This study strives to evaluate the relationship between various factors and the outcome of AV-road user conflicts (i.e., AV-road user conflict severity level). The primary source of data in this study was the open-source Lyft Level 5 dataset, which provides the trajectories of AVs and nearby road users over a span of 1000 hours of travel time. Using the provided trajectories, AV-road user conflicts were extracted and classified into

severe and non-severe conflicts. Two modelling techniques were utilized to determine the key factors that impact the severity level of conflicts occurring on road segments and intersections, including the binary logistic regression and the ML multilayer perceptron model.

Results showed that the ML multilayer perceptron model outperformed the binary logistic regression model in terms of model accuracy and the ability to consider a larger set of potential contributing factors. It was found that the average speed of vehicles around the AV, the number of detected road users, the time of day, road segment length, land use, and road type are the key variables that determine the severity outcome of AV-road user conflicts on road segments. At intersections, traffic control devices, the number of detected road users, the presence of protected left turn phases, the average speed of vehicles around the AV, and land use were determined to be the most impactful factors on conflict severity. For both road segments and intersections, the presence of pedestrians contributed to was associated with higher severity of conflicts, while the presence of bus stops, bike lanes, and on-street parking lanes led to less severe conflicts. The findings of the study also suggest that severe AV-road user conflicts are less likely in residential areas, and factors like the density of access points, the presence of dividing medians, and cyclist volume are not likely to increase the severity of conflicts.

The results of the study can be very helpful for planners and engineers to assess the impact of infrastructure, traffic conditions, and built-environment factors on AV safety before large-scale deployment. Nevertheless, the study has several limitations that future studies are encouraged to address. First, most conflicts extracted from the available dataset used in this study were rear-end AV-vehicle conflicts. Other types of conflicts were underrepresented in the study, which makes it difficult to assess the impact of contributing factors on specific conflict types. Second, the data was collected between 8 a.m. and 4 p.m., which did not enable the investigation of night-time

conflicts. Future studies are recommended to utilize other datasets to mitigate those limitations and investigate the impact of other factors, such as location and road user behaviour on the results. Additionally, extracted conflicts did not include an adequate number of very severe conflicts (i.e., conflicts with PET or TTC ranging between 0 and 1 seconds) which restricted a comprehensive investigation into those high severity conflicts. This could be the result of the assumption that the threshold for the employed safety indicators (PET and TTC) would hold constant between traditional conflicts and AV conflicts. With AVs having been recorded to have less perception time and reaction time, for future study it is strongly recommended to revisit what would best represent a severe conflicts value from the perspective of the AV. Finally, future studies should investigate other conflict indicators other than those utilized in the study and explore the most appropriate indicator for different conflict types in more detail.

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Chapter 4 Conclusion

As the prospect of AVs operating in our traffic environment is set to become feasible in the upcoming years, the work presented in this thesis aims to analyse the factors that may affect the safety performance of AVs. To that end, two studies were conducted using AV-road user conflicts as a surrogate measure of AV safety. The first study examined the potential impact of various traffic-related and geometric factors on the frequency of AV-road user conflicts at road segments and intersections. AV-road user conflicts were extracted by analyzing the trajectories of AVs and road users provided in the Woven perception and predictions dataset (formerly known as the Lyft level 5 dataset). Conflicts were quantified using two traffic conflict indicators, namely Time-To-Collision (TTC) for rear-end conflicts and Post Encroachment Time (PET) for other conflict types. A total of 3510 conflicts were considered in the analysis, of which 1116 conflicts were classified as severe conflicts (with conflict indicator ranging from 0 to 2 seconds) and 2394 conflicts were not severe (with conflict indicator ranging from 2 to 3 seconds).

A copula-based model was developed to analyze the assess the impact of a wide range of contributing factors and the hourly rates of total and severe conflicts in 26 road segments and 25 intersections. The results of the road segment model indicated that the hourly rates of total and severe conflicts increased on large, major, and divided roads. The posted speed, presence of bus stops, and presence of on-street parking were positively associated with the hourly rates of conflicts, but their impact on the rates of severe conflicts was not significant. The presence of bike lanes significantly reduced the hourly rates of both total and severe conflicts, while the density of access points was found to be positively associated with the hourly rates of severe conflicts. For intersections, the results showed that road user volume and the presence of a physical median are positively associated with the hourly rates of total and severe conflicts. Posted speed limit, the

presence of pedestrian crossing, and truck percentage are specifically increasing the hourly count of severe conflicts. The presence of traffic signals and bike lanes at the intersection seemed to reduce the hourly count of severe conflicts.

The second study applied two modelling approaches, namely a logistic regression and ML multi-layer perceptron modeling approaches to identify the key factors that impact the outcome (severity level) of AV-road user conflicts. Results showed that the ML multilayer perceptron model outperformed the binary logistic regression model in terms of model accuracy and the ability to consider a larger set of potential contributing factors. It was found that the average speed of vehicles around the AV, road user volume, the time of day, road segment length, land use, and road type are the key variables that determine the severity outcome of AV-road user conflicts on road segments. At intersections, traffic control devices, the number of detected road users, the presence of protected left turn phases, the average speed of vehicles around the AV, and land use were determined to be the most impactful factors on conflict severity. For both road segments and intersections, the presence of pedestrians contributed to was associated with higher severity of conflicts, while the presence of bus stops, bike lanes, and on-street parking lanes led to less severe conflicts. The findings of the study also suggest that severe AV-road user conflicts are less likely in residential areas, and factors like the density of access points, the presence of dividing medians, and cyclist volume are not likely to increase the severity of conflicts. Tables 4-1 and 4-2 provide a comprehensive summary of the results of the two studies outlined in this thesis.

Table 4-1: Summary of road segment results

Factor Names	Impact on the frequency of conflicts	Impact on conflict severity
Road Users Volume	Inconclusive/Insignificant	Negative

Average Speed of Road Users	NA	Positive
Percentage of Cyclists	NA	Inconclusive/Insignificant
Percentage of Pedestrians	NA	Positive
Season - Winter	NA	Positive
Time of Day - Evening Peak	NA	Positive
Weekday - Yes	NA	Inconclusive/Insignificant
Direction - Two way	Positive	Inconclusive/Insignificant
Number of lanes	Positive	Inconclusive/Insignificant
Road Type - Major	Inconclusive/Insignificant	Positive
Speed Limit - Over 30 mph	Positive	Inconclusive/Insignificant
Length (km)	Positive	Positive
Access Point Density (per km)	Inconclusive/Insignificant	Negative
Presence of bus stops/High No. of bus stops	Positive	Negative
Presence of median - Divided	Positive	Inconclusive/Insignificant
Presence of Cycle Lane	Negative	Inconclusive/Insignificant
Presence of on-street parking	Positive	Negative
Land Use - Non-residential	Inconclusive/Insignificant	Positive

Table 4-2: Summary of intersection results

Factor Names	Impact on the frequency of conflicts	Impact on conflict severity
Road Users Volume	Positive	Negative
Average Speed of Road Users	NA	Positive

Percentage of Cyclists	NA	Negative
Percentage of Pedestrians	NA	Positively
Season - Winter	NA	Inconclusive/Insignificant
Time of Day - Evening Peak	NA	Inconclusive/Insignificant
Weekday - Yes	NA	Inconclusive/Insignificant
Traffic Control Device - Signalized	Inconclusive/Insignificant	Positive
Speed Limit - Over 30 mph	Inconclusive/Insignificant	Inconclusive/Insignificant
Presence of pedestrian crossing	Inconclusive/Insignificant	Inconclusive/Insignificant
Presence of cycle lane	Inconclusive/Insignificant	Negative
Presence of median - Divided	Positive	Inconclusive/Insignificant
Presence of bus stops	Inconclusive/Insignificant	Negative
Number of approaches - Four	Inconclusive/Insignificant	Inconclusive/Insignificant
Left turn phase – Permissive	Inconclusive/Insignificant	Positive
Truck percentage	Inconclusive/Insignificant	Positive
Land Use - Non-residential	Inconclusive/Insignificant	Positive

Since AV safety studies utilizing real data are limited in the current literature, the results from these studies provide a unique perspective and aid in reevaluating our expectations about the impact of traffic conditions, road characteristics, and built-environment factors on the safety performance of AVs. In terms of urban planning and transportation management in particular, the results allow city officials to assess the current state of our infrastructure and promote better decision-making for future development projects. Traffic authorities could utilize the results of this thesis to plan AV routes and make necessary modifications to road infrastructure to prepare it for the widespread

deployment of AVs. AV developers could benefit from the results as well by tuning AV-driving algorithms to better cope factors that elevate safety risks. This could include enhancing the interaction behaviour with pedestrians and revising AV behaviour around bus stops.

4.1 Limitations:

These studies encountered several limitations that should be addressed in future studies. First, the data lacks geographical diversity since the AVs travelled along the same path during the data collection period, which limits the scope of the study to 25 intersections and 26 road segments. Second, the dataset was collected between 8 a.m. and 4 p.m., which does not enable the assessment of AV conflicts during nighttime. There is a need to use larger and more diverse datasets in the future to mitigate those limitations. Third, it was observed that most conflicts extracted from the available dataset used in this study were rear-end AV-vehicle conflicts. Other types of conflicts were underrepresented in the study, which makes it difficult to assess the impact of contributing factors on specific conflict types.

4.2 Recommendations for future work:

Future studies are recommended to consider larger conflict datasets and investigate other factors that are directly related to specific conflict types, including, for example, pedestrian network characteristics and bike infrastructure type. Moreover, extracted conflicts did not include an adequate number of very severe conflicts (i.e., conflicts with PET or TTC ranging between 0 and 1 seconds). While this is to be expected as AVs tend to have advanced sensors and can quickly adjust to avoid a highly hazardous interaction, future studies are recommended to investigate those high-severity conflicts using additional data. Finally, the study relied on two conflict indicators (TTC for rear-end conflicts and PET for other conflict types). Future studies should investigate

other conflict indicators and explore the most appropriate indicator for different conflict types in more detail.