

Safety and Operations of Autonomous Traffic at Highway Bottlenecks

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Abstract

Safety and Operations of Autonomous Traffic at Highway Bottlenecks

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A reduction of the available travel lane, commonly referred to as a lane drop, may occur on freeways due to road design, incidents or road maintenance. Lane drops lead to merging and mandatory lane-changing, resulting in various traffic problems, including delays, congestion and safety risks. In mixed traffic environments, the interactions between autonomous vehicles and human-driven vehicles add complexity and alter traffic dynamics in uncertain ways. Understanding the performance of autonomous vehicles is essential for planning and developing a control framework. This study investigates AV performance at a lane-drop bottleneck under varying traffic demands and AV penetration rates, and explores the sensitivity of car-following and lane-changing behavioural parameters. Using PTV VISSIM-COM for microsimulation, three AV driving logics (i.e. cautious, normal, and aggressive) were modelled across four traffic demand levels. Safety performance was assessed using the Surrogate Safety Assessment Model (SSAM) based on surrogate conflicts indicators such as Time-to-Collision (TTC) and Post-Encroachment Time (PET). The results show trade-offs between safety and efficiency across driving logics. Cautious AVs enhance safety and flow stability at low penetration rates but lead to increased delays as penetration rises. Aggressive AVs reduce delays at high penetration rates but increase risk due to higher speed and more changeable behaviour. Normal AVs provide balanced performance across most conditions, particularly in moderate penetration scenarios. The findings emphasize the need for adaptive AV behaviour strategies that respond to real-time traffic composition, AV share and roadway complexity which is a key to achieving safe and efficient traffic systems.

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List of Abbreviations

AVs: Autonomous Vehicles
CVs: Connected Vehicles
CAVs: Connected Autonomous Vehicles
MPRs: Market Penetration Rates
HVs: Human-driven Vehicles
SSAM: Surrogate Safety Assessment Model
TTC: Time-to-Collision
PET: Post-Encroachment Time
MaxS: Maximum Speed
DeltaS: Deceleration Rate
MaxD: Maximum Deceleration
ML: Machine Learning
TL: Temporal Logic
LTL: Linear Temporal Logic
CTL: Computation Tree Logic
STL: Signal Temporal Logic
GM: the General Motors Model
OVM: Optimal Velocity Model
FVDM: Full Velocity Difference Model
EOVM: the Extended Optimal Velocity Model
SOVM: the Stochastic Optimal Velocity Model
MA-OVM: the Multi-anticipative Optimal Velocity Model
AOVM: the Adaptive Optimal Velocity Model
IDM: Intelligent Driver Model
ACC: Adaptive Cruise Control
CACC: Cooperative Adaptive Cruise Control
SUMO: the Simulation of Urban Mobility
AIMSUN: Advanced Interactive Microscopic Simulation for Urban and Non-urban Network
CORSIM: the Corridor Simulation
GUI: Graphical User Interface
FHWA: Federal Highway Administration
TSIS: Traffic Software Integrated System
API: Application Programming Interface
LOS: Level of Service
EB: Empirical Bayes
NN: Neural Network

Chapter 1 Introduction

1.1 Background

Autonomous vehicles (AVs) are known as self-driving or robotic vehicles, using a combination of sensors, controllers, and onboard computers, along with sophisticated software, which allows the vehicle to control at least some driving functions instead of a human driver (such as steering, breaking and acceleration). However, it is also important to understand the difference between autonomous vehicles, connected vehicles (CVs) and connected autonomous vehicles (CAVs). Transport Canada defines connected vehicles as “the vehicle may be able to communicate with its occupants, with other vehicles and road users, with the surrounding transportation infrastructure and equip with internet-based applications and other entities” [1]. Thus, a connected autonomous vehicle is the vehicle that is capable of fulfilling the operational functions of a conventional vehicle and is able to communicate with nearby cars and infrastructures for safer and more efficient driving [2].

According to the Society of Automotive Engineers International, AV can be defined as six levels, from Level 0 (no automation) to Level 5 (full automation) [3]. Each level represents a gradual increase in automation capabilities, from basic driver assistance to fully autonomous operation. To reach autonomous driving by itself, AV relies on the sensors to detect the objects surrounding it, identify the obstacles on the road and perform safety and efficiency with the built-in software functionality and algorithms. As the first step to collect the surrounding environment data, sensors play an important role in AVs, and its characteristics are further influencing the decision-making process. Basically, sensors can be divided into two categories, passive and active sensors. Passive sensors, such as cameras, gain information from the environment and provide output; active sensors, such as LiDAR (light detection and range) and Radar (radio detection and range) emit information into the environment and detect the environmental response to provide output [4].

As a relatively new type of vehicle, autonomous vehicles have various benefits for users and other people. From internal impact, using autonomous vehicles can reduce the drivers’ stress and increase productivity. From external impact, using autonomous vehicles may reduce crash risks and energy consumption, and also increase road capacity [5]. The Market Penetration Rates (MPRs) of AVs have been predicted by many researchers. A survey released that the level 4 robotic taxi will become commercially available on a large scale by 2030, and fully autonomous trucks will be viable between 2028 and 2031 [6]. According to the report from the Victoria Transport Policy Institute, autonomous vehicles will become reliable and safe for common use by 2025 and by at least 2045 half of new vehicles are autonomous considering both operating costs and labour costs. The potential gains will occur even AVs are expensive and rare, but more benefits will be significant when AVs are affordable and common [7]. During this transit period, AVs will share the road with human-driven vehicles (HVs), creating a complex and dynamic traffic environment. In scenarios where AVs operate without lateral moving or interference of HVs, their full capabilities can be utilized, leading to improve traffic efficiency. But in mixed traffic conditions, due to the differences in driving behaviour and decision-making between AVs and HVs, might cause disruptions, reducing traffic efficiency and compromising safety in certain conditions.

To evaluate the performance of AV, simulation software is commonly used for modelling its driving behaviour. Given the limited availability of real-world AV datasets, simulation studies have been conducted

using driving parameters from existing literature. The European Union's CoExist project provides valuable data on driving behaviour and their impact in mixed traffic environments [8]. Using this data, VISSIM provides three driving logics of AV: cautious, normal and aggressive. Each driving logic is modelled by a car-following model and lane-changing behaviour, allowing for a more comprehensive understanding of how AVs interact in various traffic conditions. As a state-of-art simulation tool, VISSIM offers a detailed performance of AVs, capturing metrics such as vehicle delay, travel time, and stop delay. Additionally, to better understand the safety impacts of AVs, the Surrogate Safety Assessment Model (SSAM) is widely used to investigate the crash severity, conflict types and conduct risk analysis. SSAM provides statistical values and measures such as Time to Collision (TTC), Post Encroachment Time (PET), maximum speed (MaxS), deceleration rate (DeltaS) and maximum deceleration (MaxD), which help to determine the type and severity of conflicts [9].

1.2 Problem statement

A reduction in the lane number, commonly referred to a lane drop, is a typical situation on a freeway due to road design, incidents or road maintenance. Lane drops can lead to unexpected merging and mandatory lane-changing, resulting in various traffic problems, including oscillations, congestion and safety risks [10]. Previous research has demonstrated that congestion at bottlenecks leads to a reduction in the number of vehicles able to pass through, a phenomenon known as "capacity drop" [11]. The discharge flow at bottlenecks is approximately 10% lower than the prevailing flow observed prior to queue formation [12]. Although AVs have their capabilities of real-time communication and precise motion control, HV in mixed traffic environments may interfere with AV decision-making. As the AVs tend to maintain larger headways compared to HVs due to conservative behaviour, their gradual introduction will influence traffic flow in the future[2].

Numerous studies have explored AV impacts under different scenarios, but much of the research has focused on homogeneous traffic conditions, investigating communication stability [13], longitudinal dynamics [14] and operations like platoon merging and splitting [15]. However, fewer studies have addressed AVs behaviour in heterogeneous conditions, representing vehicles with varying static and dynamic characteristics. Some studies consider scenarios such as considering the use of a dedicated lane on a ramp, highway or roundabout for AVs [16], [17], [18] or modelling the behaviour of AVs [19], [20]. Despite these efforts, research on AVs often assumes one type of AVs with HVs interact and there are still lots of uncertainties to be able to clearly state to what extent.

Key questions remain about AV performance at lane drop bottlenecks and the potential impact of different AV driving logics. For example, should AVs adopt a more aggressive approach, with reduced headways to increase road capacity, or a more cautious approach to enhance safety? To what extent would different AV driving logics affect performance under these conditions? How might varying AV penetration rates influence traffic dynamics, and would increasing AV MPR significantly improve conditions, even under different traffic demands? Moreover, we will discuss which specific parameters in AV driving models will affect traffic flow and whether an optimal balance between AV and HV proportions in mixed traffic. These questions still need further research to determine optimal AV driving strategies and integration approaches for enhanced performance in complex traffic environments.

1.3 Research objectives

This thesis aims to assess the efficiency and safety impacts of AVs with varying MPRs and different driving

logics in mixed-traffic environment with HVs. The objective is to investigate how AVs with different MPRs perform in mixed traffic scenarios, particularly at lane drop bottlenecks, to describe the relationship between MPR and traffic flow efficiency. Additionally, the research will compare the performance differences among various AV driving logics, such as cautious, normal, and aggressive driving modes, focusing on their interaction with HVs and how these differences influence traffic flow, and overall operation. Lastly, the study will conduct a sensitivity analysis of driving behaviour parameters to examine how variations in model parameters affect traffic performance, enabling us to understand how the model behaves under different conditions and determine which parameters should be prioritized for calibration, ensuring the model's reliability and accuracy.

1.4 Thesis organization

This thesis is organized into five chapters. The first chapter introduces the background related to autonomous vehicles and indicates the problem for AV under mixed traffic environments at a lane drop bottleneck. The second chapter provides the literature related to autonomous vehicles at the merging section, lane-changing models, traffic simulation and traffic safety analysis. The third chapter provides the details of the methodology using simulation software and evaluation. The fourth chapter describes the scenario of the simulation and results. It includes the operational efficiency and traffic safety evaluation, along with a parameter study to identify driving behaviour parameters that influence traffic performance. The last chapter summarizes the work developed in this study and provides the conclusion and recommendations for future research work.

Chapter 2 Literature review

Researchers have conducted extensive studies to analyse the heterogeneous traffic flow with AV. To better understand how AVs influence in such environments, this literature reviews both the technologies developed for AVs and simulation models. Firstly, it introduces the technology and operation of AVs, with a focus on the scenario of merging. Afterward, some novel models used for AV, such as car-following models and lane changing models which address how AVs interact with HVs and each other in mixed traffic environments, will be presented. Lastly, we will review literature that utilizes VISSIM and SSAM and see how the simulations contribute to understanding traffic flow and safety.

2.1 AV related research

Research in autonomous vehicles has gained significant attention from the technology to the application. In this section, it explored key research areas relevant to the operation and behaviour of AVs within traffic system. First, it reviewed the general operational capabilities of AVs, highlighting advancements in sensing control and decision-making technologies that enable AVs to navigate complex driving environments. The review then focused on the concept of driving logics with distinct impacts on traffic efficiency and safety. These behavioural models reflect different priorities, such as improving decision-making uncertainty and safety navigation. Lastly, the review introduced studies on merging scenarios, highlighting how AV operations vary under different conditions, such as mixed traffic, fully autonomous scenarios and multi-lane merging environments, emphasizing the need for further analysis of AV performance across diverse traffic settings.

2.1.1 Operation of AV

Normally, autonomous vehicles operate based on three stages: sense, planning and act. AV relies on numerous sensors to sense its surroundings and determine the vehicle's relative and absolute position such as cameras, LiDAR, radar and GPS.

However, both AV and CV technologies have inherent shortcomings, for example, the line of sight sensing limitation of AV sensors and the dependency on the high penetration rate of CVs [21], lagged response to the control input. Studies focus on sensor fusion to improve environmental awareness and reduce the error rates in object detection and tracking. Ramzi [22] proposed an adaptive optimal controller with relies on bidirectional platoon communication and deals with parameter uncertainties. Zheng [23] studied the influence of information flow topology on the closed-loop stability of homogeneous vehicular platoons moving in a rigid formation. In a mixed platoon with CAVs, AVs, and HVs, under spatial continuous communication interruption, communication degradation can lead to an increased risk of rear-end collisions. He [24] improved the cooperative adaptive cruise control model by considering the relative speed and distance of the vehicles using MATLAB/Simulink and TruckSim co-simulation. Also, the study by Yu [25] presents an interesting finding: in a mixed platoon with communication degradation, HVs can contribute to a stabilizing platoon by reducing the backward extension of speed fluctuation and lowering rear-end collision risk.

Path planning for AVs involves creating safe and efficient routes from the current location to the destination, and motion control ensures the vehicle follows the path. Many research studies address problems like obstacle avoidance, trajectory prediction [26], [27] and dynamic route adjustments [28] in response to real-time changes. According to the semantics used to define motion and risk, the existing methods for motion prediction and risk assessment for AVs are classified into three levels: physics-based models, manoeuvre-based

models and interaction-aware models [29]. The physics-based model only considers the motion of vehicles based on basic physical laws, such as constant velocity or constant acceleration. Kinematic and dynamic models extend physic-based models by considering the kinematics or dynamics of a vehicle, such as the longitudinal and lateral tire forces [30]. Considering the physical limitations of a vehicle, Vinicius [31] analyses the influence of occlusion caused by a lack of visibility and predicts the motion using Markov Chains with more realistic manner inputs. Manoeuvre-based models predict motion by estimating the intention or goal of the other road users, and interaction-aware models consider the vehicles' manoeuvres inter-dependencies, for example, Wang [32], Zhang [33] and Zhou [34] enhanced existing models for AV path planning by predicting the lateral positions of the surrounding vehicles and contributed to safer and optimal path planning. However, trajectory prototype methods focus on the individual vehicle's past motion patterns, and inter-vehicle influences cannot be considered. To address this problem, Mohammad [35] proposed two layers of reinforcement learning-based decision-making architecture for learning left-turn policies at unsignalized intersections, by adopting soft actor-critic principles to learn driving behaviour and using a predictive control framework to ensure left-turn manoeuvre. This model combines physics-based and machine learning (ML) techniques which better model complex patterns in motion and have better accuracy and adaptability. Zhang [36] applied a scenario-based model predictive control approach for decision-making and control systems and demonstrated the capability of the proposed control architecture to perform safe manoeuvres by testing the result with the HighD dataset. Similarly, Lu [37] proposed a framework for keyframe-based trajectory prediction by extracting the features from the scene and encoding them as context.

AVs have varying performance under different scenarios which prompts researchers to establish specialized models to simulate and analyse these conditions. Platoon formation is an important strategy for traffic flow in a connected environment and some of the relevant elements of platoons have been widely discussed, including platoon policy, platoon-based models and platoon size [38]. Tian [39] proposed a model based on cellular automaton to explain the space-gap-speed relation of AV on a circular road and an open road with an on-ramp. Zhou [40] simulated the varied maximum platoon size and the result shows that a smaller platoon size can improve traffic stability and a larger size can increase capacity. For intersection scenarios, AV can considerably enhance the operational efficiency of urban traffic and reduce signal delays in intersections [41]. Remin [42] develops a novel mixed-integer non-linear program to control the trajectory through signalized intersections. For dedicated lane setting for AV, Ye [43] using a fundamental diagram approach discussed the impact of setting dedicated lanes for AV in heterogeneous traffic flow. Davis [44] optimized the merging position for AV into a high-speed dedicated lane considering the deviation of the headway and velocity differences. Instead of taking into account the merging point and merging impact in a dedicated lane, Reza [45] developed a model for the different arrangements of AV and HV with four possible lane-allocation policies, including "dedicated-dedicated lane", "mixed-mixed lane", "mixed-AV dedicated lane" and "HV dedicated lane-mixed lane".

2.1.2 Driving logic of AV

The operation of AV relies on three core components: perception, decision-making and control. These are the autonomous driving logic, enabling the vehicle to perceive their surroundings and collect the data about the environment, including the presence of other vehicles, pedestrians and obstacles, and decide on the appropriate actions and execute them accurately.

According to the PTV VISSIM group [46], the driving logic of AVs is defined by its behavioural profile, which

determines how the vehicle handles different situations on the road. The driving logic is categorized into cautious, normal and aggressive, with distinct characteristics resulting to different driving styles and risk tolerance [47]. Cautious drivers tend to maintain larger safety margins, such as longer time headways and greater distances from other vehicles [48], [49]. Azam simulated the cautious AVs at four-leg intersections and validated them using field data at MPRs from 25% to 100% [50]. The result shows that cautious AVs exhibit conservative driving patterns, which can lead to smoother traffic flow but may also result in longer delays and higher emissions due to their conservative nature. While promoting safety, cautious driving can negatively affect traffic performance, especially at higher demand levels, leading to increased delays and reduced speed [51]. Aggressive drivers often engage in risky behaviours such as rapid acceleration, close following and frequent lane changes. This style is associated with higher speeds and more abrupt manoeuvres [52], [53]. Aggressive driving significantly increased the risk of accidents, with aggressive drivers having 35 times the odds of crashing compared to non-aggressive drivers [54]. However, in terms of traffic flow, aggressive driving can reduce delays and improve efficiency, especially in high-demand scenarios [48]. Normal driving represents a balanced approach, avoiding the extremes of cautious and aggressive behaviours. It involves moderate acceleration and deceleration, maintaining reasonable safety margins without being overly conservative [55], [56]. Normal driving trends offer a balance between safety and efficiency, performing better than cautious driving in high-demand scenarios but not as efficiently as aggressive driving [51].

There are also various logical frameworks and decision-making models employed in AVs operation such as non-monotonic logic, formal method, configuration logic and bounded multi-dimensional modal logic. Traditional logical systems often struggle to handle the inherent uncertainties and exceptions encountered in real-world scenarios. Non-monotonic logic provides a solution by enabling systems to adapt to new information and exceptions. This approach allows multiple factors to be combine into more accurate and robust driver models, improving decision-making under uncertainty [57]. Formal methods are a branch of computer science focused on checking the correctness of digital circuits and computer programs. In autonomous driving, formal methods are increasingly applied to ensure system safety and reliability, such as Temporal Logics (TL), Linear Temporal Logic (LTL), Computation Tree Logic (CTL) and Signal Temporal Logic (STL) [58]. TL is a tool for reasoning about time-dependent behaviours, LTL is used for ensuring long-term behaviours like staying in a lane which specifies properties over sequences of states in time, and CTL is a branching-time logic that models different potential outcomes of actions. STL is an important tool for formalized driving tasks and safety specifications based on traffic regulations which can be used for path planning and ensuring compliance with road rules, particularly in urban environments [59]. Research by Mehdipour et al. [60] demonstrates how formal methods and temporal logic are employed to ensure safety and efficiency in diverse traffic scenarios. These methods help AVs manage complex interactions, such as navigating intersections or merging lanes, with a system-level approach. Configuration logic is a multilevel semantic framework that models the physical environment and traffic rules, ensuring geometric consistency and safe navigation. Bozga et al. [61] illustrate how configuration logic can be used to specify traffic rules and characterize sequences of scenes like intersections, roundabouts and merging roads. This framework helps AVs understand the structure of traffic situations and make informed decisions. Bounded multi-dimensional modal logic focuses on traffic situations with spatio-temporal properties. This framework proposed by Xu et al. [62] enables AVs to make real-time decision-making by predicting the actions of surrounding vehicles and ensures AVs can react quickly and appropriately to changes.

2.1.3 AV merging related

Based on AV technology, some studies started to explore the optimal control strategies of merging control aiming to increase traffic efficiency and improve traffic conditions at traffic bottlenecks. For example, Scholte et al. [63] propose a control strategy for single vehicle to merging into platoon at highway on-ramp. Xue and Ding [64] present a platoon-based hierarchical merging control algorithm for on-ramp vehicles with connected autonomous vehicle technology. However, most previous studies of ramp merging focused on the lower-level design of vehicle operation, and a few studies addressed the mixed traffic conditions on multi-lane freeway systems. Many existing strategies on proposed solutions in discrete decision space and the longitudinal and lateral directions of traffic flow level should be further investigated.

A large number of studies have investigated the highway merging operation differently from the assumptions presented: the level of technology requested (human-driven vehicle, connected vehicle, autonomous vehicle, connected and autonomous vehicle), the lane number of mainline in merging area considered (signal lane, multi lanes), the control logic (centralized, decentralized), the range of control area (ramp, mainline or both [65]), the merging strategy level (operation control, tactical control or both [66]). The existing strategies for on-ramp merging summarised here are divided into three categories: considered AV exclusive merging control, mixed traffic merging control on signal mainline and multiline merging strategies. Marinescu and Jan et al. [67] were one of the first researchers who tried to study the merging strategy. In their research, they expended the merging algorithm from freeway to on-ramp merging traffic for two phases—gap selection and moving into gap.

To simply the traffic situation, without considering the interpreter of uncertain human-driven behaviour, Xu et al. [68] assumed all the vehicles are AVs and connected by wireless technology with other vehicles and roadside units and they used a genetic approach to calculate the merging manoeuvres and their merging sequence to minimization of travel time of mainline vehicles and maximization of the number of merging vehicles. However, Shi and Qi et al. [69] used an algorithm to determine the number of roadside units and control the merging process of traffic flow. Ding et al. [70] address the problem of two strings of vehicles in a longitudinal direction using a rule-based adjusting algorithm to improve the throughput, and reduce the delay, computational cost, and fuel consumption by comparing with the other two control strategies. Scholte et al. [63] proposed a strategy to address differences initial positions and velocities, which is satisfactory considering safety, efficiency and passenger comfort, while this work does not address the mixed traffic situation. Similarly, Zhou et al. [71] presented a vehicle trajectory planning method using real-world leading vehicle trajectory and considered different traffic demand levels. Unlike applied fixed planning horizon length, the planning time varies. Especially in heavy traffic, Xue and Zhang et al. [72] proposed a platoon-based cooperative optimal control algorithm to adapt to time-varying traffic volume. Meng et al. [73] consider the collision-free control strategy under nonlinear vehicle dynamics, and the simulation result shows that all vehicles achieve safety for on-ramp merging with a smooth control input. To determine the sequence of merging, Nishi and Doshi et al. [74] present a multipolicy decision-making method with a reinforcement learning technique to decide the merging point and achieve safe merging. Chen and Arem et al. [27] use a third-order vehicle dynamics model and test 135 scenarios with different initial conditions to optimize desired accelerations for AV.

The following studies address the merging operation strategies in mixed traffic with connected and autonomous vehicles and human-driven vehicles. Depending on the level of AV, the merging strategies can be divided into operational control and tactical control. The operational control focuses on the real-time actions

of vehicles, such as position, speed and acceleration to safely merge into traffic. Tactical control, it focuses on the broader strategy and planning, requiring for successful merging and addresses the upper-level decisions, such merging sequence and gap. M. Karimi et al. [75] developed a lower-level control framework for cooperative AV trajectory optimization considering six scenarios with different combinations of AVs and conventional vehicles at the merging point. Venkatesh et al. [76] validated the framework using real-world data to predict the behaviour of HV in mixed traffic and generated the merging interactions between HV and AV. A typical control problem for AV on-ramp merging is to predict the motion of HV and guide AV into the mainline. To address this problem, Kherroubi [77] proposed an artificial neural network using field data to predict the passing intentions of HV drivers. According to the control logic, we can define centralized protocol and decentralized protocol for AV merging strategies. A centralized protocol relies on a centralized control system, such as a roadside infrastructure unit, traffic management server, or cloud-based system. The task for all AVs is decided by the central controller, for example, the best merging positions, speeds and timings for each AV based on traffic conditions and vehicle dynamics. In decentralized approaches, there is not a global controller, more relies on local decision-making by individual vehicles. Each vehicle communicates with its closest vehicles and manages its merging actions [78]. Na Chen [79] proposed a hierarchical cooperative merging control approach and optimal dynamic vehicle sequence by minimizing predicted traffic disturbances. The results are compared with the first-in-first-out rule which shows a decreased disturbance. Jing [80] presented a hierarchical and decentralized cooperative coordination framework for merging control considering both upper and lower levels. However, these models were tested in simplified scenarios which only considered one main lane and one on-ramp lane.

For the multi-lane merging scenario, some researchers have considered approaches to achieve smooth collaborative merging. Subraveti et al. [81] used an incentive-based lane-specific traffic flow model for testing the performance of individual control measures and the performance of combined control. The result shows that the individual control led to high delays compared to the combined control, which balance the delays on mainline and on-ramp. Hu and Sun [82] proposed a cooperative lane changing control optimization model and time discrete linear cooperative merging control system to ensure the safe and smooth lane changing execution, which optimizes both main lane and on-ramp vehicles' trajectories with AV only. Karbalaieali and Osman [83] considered the merging manoeuvres with different alternatives on a one-mile freeway segment and established an optimization model with the objective function of minimizing the travel time through a merging junction. Han and Xu [84] proposed a simulation framework for platooning merging operations including upper-level and lower-level, using same-lane platooning, multi-lane joining and on-ramp merging modules. However, limited studies have been conducted on optimal operation control for multi-lane mainstream and single-lane on-ramps under connected environments with mixed traffic (HVs and AVs), which also consider balancing the traffic density of main lanes before and after merging.

2.2 Modelling approach for AV merging

Car-following model and lane-changing models are extended by many studies to simulate AV sensing, decision-making and acting. In the longitudinal direction, a vehicle would follow the preceding vehicle with appropriate gap acceptance, speed adoption and desired acceleration or deceleration. In the lateral direction, the vehicle needs to find and decide a proper time for lane changing, merging or diverging and overtaking [85].

These models explain how AVs adjust speed, acceleration and position in response to nearby vehicles during merging. Here, we summarize these models and their use for better understanding AV modelling.

2.2.1 Car following model

Car-following models are essential in understanding and simulating the longitudinal behaviour of vehicles. According to their utilized logic and developing process, car following models can be divided into stimulus-response models, safety distance models, physiology-psychology models, artificial intelligence models, optimal-velocity models and intelligent driving models.

In stimulus-response models, vehicle behaviour is changed refer to the external movement changes in preceding vehicles. The General Motors (GM) model is the first stimulus-response model by using the acceleration/deceleration as a stimulus [86]. Unlike the GM models that describe the relationship between stimulus and response, the safety distance models focus on maintaining a minimum gap with following and preceding vehicles. The first general acceleration model was developed by Gipps [87], [88] where each vehicle follows a set of rules ensuring safe acceleration and deceleration. This model captures realistic driver behaviour by including safety constraints, but it is less flexible in adapting to varying traffic conditions, so this model has numeral extensions, calibrations and modifications by various researchers [89], [90], [91], [92]. Later, considering the results of driver's physiology and psychology characteristics, Michaels [93] proposed the first physiology-psychology model and use a "perceptual threshold" for space headway and relative speed for following vehicles. The famous traffic flow simulation software VISSIM is also used by physiology-psychology model, the Wiedemann 74 and Wiedemann 99 model. The first artificial intelligence model was proposed by Kikuchi [94], using fuzzy sets and fuzzy rules to represent the uncertainties in driving behaviour. Since then, many car following models using artificial intelligence combined with different methods have been constructed [95], [96], [97].

At the same time, based on the theory and method of statistical physics, Bando et al. [98] established the first optimal velocity model (OVM), which defines a vehicle's acceleration based on its current speed and the distance to the vehicle ahead. Since its development, researchers have extended OV model in various ways to improve traffic stability and incorporate more realistic driving behaviours. For example, Helbing et al. [99] introduced the negative velocity difference into OVM and formed the generalized force (GF) model. Jiang et al. [100] introduced the full velocity difference model (FVDM) by further integrating the positive velocity difference and demonstrating its improvements in traffic stability over the traditional OVM. These three models represent the foundational approaches within the optimal velocity model family, each contributing to enhanced realism and stability in traffic modelling. Expect these, several additional changes have been applied to address various aspects of driver behaviour and traffic conditions. For example, the extended optimal velocity model (EOVM) [101], [102] which incorporates factors like driver reaction time, the stochastic optimal velocity model (SOVM) [103], [104], [105] which considers the unpredictable of driver behaviour and applies randomness, the multi-anticipative optimal velocity model (MA-OVM) [106], [107] where each vehicle considers the behaviour of multiple vehicles ahead, the adaptive optimal velocity model (AOVM) [108], [109] which dynamically adjusts the optimal speed based on road conditions, and the fuzzy logic-based optimal velocity model which uses fuzzy rules to simulate human-like driving responses.

Inspired by OVM principles, the intelligent driver model (IDM) was established by Treiber and Helbing [110], [111]. IDM is a widely used car-following model and it combines desired velocity and safety distance in a single framework, which is easily adopted for simulating AV and HV interactions [112]. Adaptive cruise control (ACC)

and cooperative adaptive cruise control (CACC) models are two important models used to simulate AV, and both models help maintain safety distance and consistent speeds [113]. ACC adjusts the vehicles speed and maintains a safe gap based on real-time feedback, typically from sensors such as camera, radar or LiDAR. CACC extends ACC by incorporating vehicle-to-vehicle communications, allowing a network of vehicles to coordinate their movements. Van defines ACC/CACC as focusing on the impact of AV on traffic flow characteristics and simulates the vehicles using automated longitudinal control combined with intervehicle communications [114]. Zhao et al. [115] constructed simulation framework of CACC platoon and studied the lane capacity considering different manoeuvres, such as forming, splitting, dismissing and joining in a platoon. However, the concept of ACC and CACC is in the development stage and there is no consensus or definition of the model categories is fixed at this stage.

2.2.2 Lane changing model

Lane-changing behaviour refers to the actions and decisions made by drivers to switch from one lane to another while driving on a multi-lane road or highway. These manoeuvres are commonly divided into two categories: mandatory lane changing and discrete lane changing by Gipps [87]. For the mandatory lane change process, the vehicles are required to leave the current lane, for example, drivers prepare for upcoming exits or turns. Whereas in discretionary lane changing, drivers wish to get better driving conditions and perform to overtake slower vehicles, adjust their position, and shorten travel time. Another well-known lane-changing model is proposed by Sparmann [116], which categorizes the behaviour as slower-to-faster and faster-to-slower. These behaviours are influenced by the vehicle's speed, the traffic conditions and the driver's objectives.

Table 1 Categories of Sparmann lane-changing model

Type of lane changing	Slower-to-faster	Faster-to-slower
Motivation	To increase speed and avoid congestion	To avoid upcoming congestion, prepare for an exit or avoid obstacles
Speed change	Vehicle moves to a faster lane to speed up	Vehicle moves to a slow lane, reducing speed
Key factors	Gap acceptance, speed difference, traffic density and safety distance	Gap acceptance, anticipating merging points or exits, safety distance
Typical scenario	Overtaking slower vehicles on a highway or road	Preparing for a turn or avoiding congestion in the fast lane
Autonomous behaviour	More frequent in autonomous systems aiming to maximize efficiency	Less frequent, but may occur in anticipation of upcoming traffic scenarios

In the existing lane-changing research, some scholars have considered smooth lane-changing behaviour to help drivers perform the process without collision with other vehicles. Wei et al. [117] carried out a simulation of three-lane roadways applying different velocity limits lane changing behaviour using the optimal velocity model, considering the headway difference, velocity difference, safety distance of the subjective vehicle and adjacent vehicles and the probability of lane changing. The result is analysed by a fundamental diagram and compares the effect of lane changing and unchangeable lanes with different headway and velocity in different lanes. Moreover, Williams and Wu et al. [118] provide an algorithm for vehicle detection, motion

prediction and delaying information. Iwamura et al. [119] were concerned the driver's decision-making process and established a complex system of traffic flow under different demands with game theory. Nagalur [120] presented a first-order lane-level traffic flow model to balance the lane flow distribution and help to reduce the congestion. Nassim et al. [121] developed a lane-changing model based on the real-world data and compared the TTC and number of lane changing with the Simulation of Urban Mobility (SUMO) simulation result, which successfully executed lane-changing manoeuvres in unseen traffic situations.

Numerical results reveal the social dilemma which appeared in a middle traffic density or a jam phase. At present, there are many studies on lane-changing behaviour of a single autonomous vehicle and most of the research studies used data-driven and simulation methods. There are fewer studies on the influence of lane-changing behaviour on density and the relationship between individual lanes. The research carried out by Han and Zhu [122] mainly adopts empirical, simulation methods to analyse the relationship between lane changing behaviour and density, the rate of changing in or out of the lane under different penetration rate of CACC vehicles for the four ring-shaped expressway. The result shows that the density of single lane decreases with the AVs, the rate of changing into lanes and the linear relationship between density and the rate of changing lanes appears.

2.3 Micro-simulation modelling tools for AVs

There is numerous micro-simulation software used in the evaluation, testing and optimization of vehicle behaviour in various traffic conditions. Each of these applies different car-following behaviours, lane-changing and gap-acceptance models, as we mentioned in previous sections. Here we will introduce some popular micro-simulation modelling tools commonly used for AV research, including Simulation of Urban Mobility (SUMO), Advanced Interactive Microscopic Simulation for Urban and Non-urban Network (AIMSUN), the Corridor Simulation (CORSIM) and VISSIM.

2.3.1 Micro-simulation modelling software

SUMO is an open-source micro-simulation tool developed by the German Aerospace Centre (DLR) and is known for its flexibility and cost-effectiveness [123]. It provides several car-following and lane-changing models that define the interaction of vehicles on the road. The Krauss model is the default car-following model in SUMO, which is based on the Safe Speed Model [124]. It defines a safe following distance by calculating the maximum safe deceleration and speed of the following vehicles and includes a stochastic component, which allows for some randomness in driver behaviour. A Graphical User Interface (GUI) is provided for the user to control the simulation and easily access the value of the attribute [125]. SUMO can import road networks from real-world maps, such as OpenStreetMap, and supports large-scale traffic networks for simulating urban environments, freeway systems, or complex intersections.

AIMSUN was developed by Barcelo and is widely used for examining traffic-responsive signal control and priority control for transit vehicles [126]. It has many sub-models to simulate the behaviour, such as the car-following model, lane-changing model, gap acceptance model for lane-changing or yielding, overtaking, on-ramp or off-ramp and look-ahead distance [127]. The car-following model implemented in AIMSUN is based on Gipps' safety distance model. However, the Gipps model is a one-dimensional model that only considers the vehicle and its leader, the model in AIMSUN also considers the influence of adjacent lanes. The lane-changing model in AIMSUN was also developed by Gipps and is defined as a decision process. The gap-acceptance model in AIMSUN takes into account the distance of vehicles to the collision point, their speed and acceleration rates

[128]. These more sophisticated models result in fewer problems in modelling multi-lane traffic in congestion networks [129].

The CORSIM software was developed by the US Federal Highway Administration (FHWA), combining two microscopic models, NETSIM and FRESIM. It also introduces the Traffic Software Integrated System (TSIS) to provide an integrated, user-friendly interface [130] and can simultaneously simulate traffic operation on surface streets and freeways in an integrated fashion [131]. In CORSIM, each driver will try to maintain their desired headway with other vehicles while also travelling as fast as possible with his desired speed [132]. The lane-changing model of CORSIM is divided into three types: mandatory lane changes, discretionary lane changes and positioning lane changes. It allows users to modify selected parameters to calibrate lane-changing behaviour in the real world, such as maximum deceleration rates, average time/distance, minimum acceptable gap in an adjacent traffic stream, look-ahead distance, and desire and thresholds for making discretionary lane changes [133]. The strength of this software is to simulate varied scenarios from signalized intersections to arterial and freeway corridors, and one of the most well-documented simulation software available.

PTV VISSIM is the leading microscopic simulation software for modelling transport operations and allows to analysis the performance of traffic, which was developed by the German company PTV Vision in 1992. VISSIM traffic flow model is a stochastic, time step based, microscopic model. VISSIM uses the psycho-physical perception model developed by Wiedemann, which contains a psycho-physical car-following model for longitudinal vehicle movement and a rule-based algorithm for lateral vehicle movement [46]. In order to simulate multi-traffic flow, this software provides a variety of transit options, such as pedestrians, bicyclists, motorcycles, cars, trucks, buses, light and heavy rail to customized vehicle types [134]. VISSIM is an effective tool for evaluating capacity and safety, using application programming interfaces (API) integration for external driver models and using graphic user-interfaces for visualization. The models of VISSIM and the application of that in recent years will be presented in the next section.

2.3.2 Models in VISSIM

As we mentioned before, the car-following in VISSIM is Wiedemann's traffic flow model, which defines four different driving states for the driver--free driving, approaching, following, and braking.

In the free driving state, the driver is not influenced by preceding vehicles and aims to reach and maintain his desired speed. During the approaching driving state, the driver decelerates to match the speed ahead; once the desired safety distance is achieved, the driver will maintain the same speed as the preceding vehicle. In the following state, the driver keeps a consistent distance from the preceding vehicle without consciously decelerating or accelerating. During the braking state, the driver will apply medium to high deceleration rates when the distance to the preceding vehicles falls below the desired safety threshold. Drivers will switch from one state to another once they reach a certain threshold like the difference of speed and distance. Figure 1 shows a graphical representation of the Wiedemann car-following model, and the thresholds are shown with a certain shape [135].

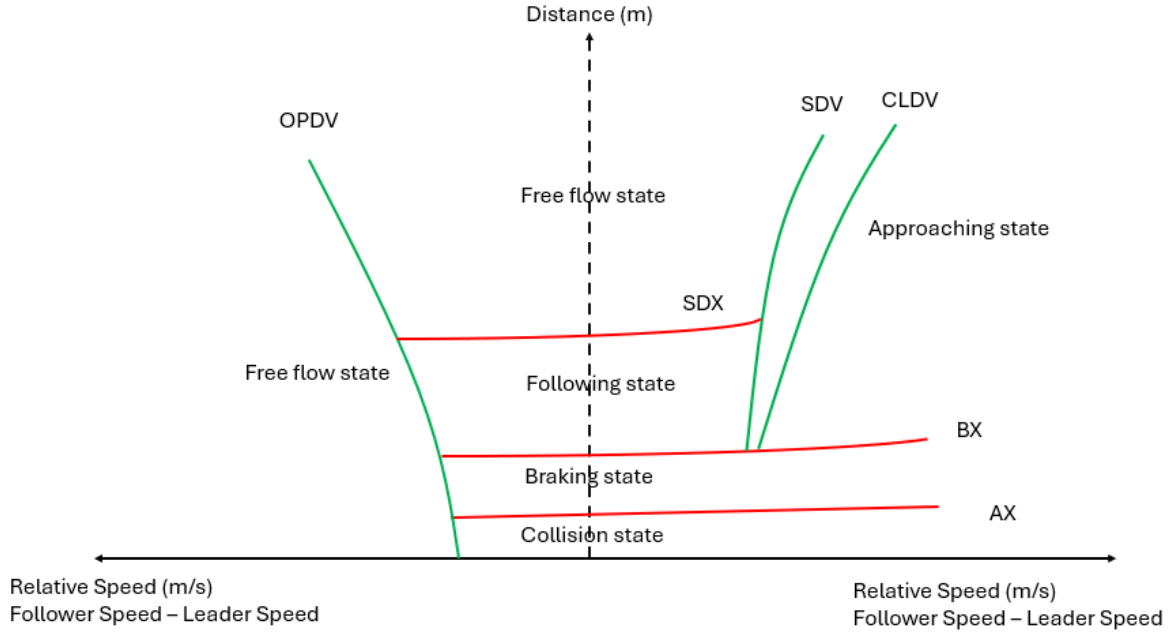


Figure 1 Schematic of Wiedemann model with various driving regimes and thresholds

VISSIM uses two different models for defining the car following behaviour for drivers, including the Wiedemann 99 and the Wiedemann 74 model. Since the Wiedemann 74 is used for urban traffic, the Wiedemann 99 is mainly for interurban traffic which we will use for simulation in this study [136]. According to Wiedemann model [137] and VISSIM parameters setting, there are ten parameters ($CC0$ - $CC9$) and the relation between the parameters and the thresholds are defined as:

The desired distance between two vehicles AX is represented by the length of the front vehicle L and the desired front -to near distance $CC0$. This threshold is mathematically defined as:

$$AX = L + CC0 \quad (0.1)$$

The minimum following distance between two vehicles BX is a function of desired distance AX , gap time distribution $CC1$, and the speed of the vehicle v :

$$BX = AX + CC1 \times v \quad (0.2)$$

In addition, the perception threshold SDX , models the maximum following distance and relates to BX and “following” distance oscillation $CC2$. This is about 1.5-2.5 times of BX [138].

$$SDX = BX + CC2 \quad (0.3)$$

The action point SDV occurs when the driver observes that he approaches the slower leading vehicle. This distance is linked to the space headway difference ΔX , “threshold for entering ‘braking state’” $CC3$ and “negative speed difference” $CC4$.

$$SDV = -\frac{\Delta X - SDX}{CC3} - CC4 \quad (0.4)$$

Similarly, the acceleration action point $OPDV$ occurs when the following vehicle driver notices that he is slower than the leading vehicle and starts to accelerate. This distance is related to “positive speed difference” $CC5$ and “distance impact on oscillation” $CC6$.

$$OPDV = -\frac{CC6}{1700} \times (\Delta X - L)^2 - \delta \cdot CC5 \quad (0.5)$$

Here, $CC6$ represents the extent to which distance affects oscillations, where it can either have no impact or increase with increasing distance.

Finally, δ is a variable which is equal to 1 when the subject vehicle speed is greater than $CC5$, otherwise the value is equal to 0.

The decreasing speed difference $CLDV$, similar to SDV , models the perception of small speed differences at short and decreasing distances [139].

$$CLDV = \frac{CC6}{1700} \times (\Delta X - L)^2 - CC4 \quad (0.6)$$

“Oscillation acceleration” $CC7$ is to describe the acceleration oscillation during the following state; $CC8$ is “acceleration from standstill” to define the acceleration when starting from standstill condition and is limited by the desired and maximum acceleration functions assigned to the vehicle type; $CC9$ is the acceleration at the speed of 80 km/h. Below is the description of Wiedemann 99 car-following parameters.

Table 2 Wiedemann 99 parameters

Parameters	Description	Unit
CC0	Standstill distance: the desired gap between two vehicles.	m
CC1	Gap time distribution: addition time gap for driver to maintain following state	s
CC2	Following distance oscillation: maximum additional distance beyond the desired safety distance accepted by a following driver	m
CC3	Threshold for entering “braking state”: time between the beginning of the deceleration process and reaching the maximum safety distance	s
CC4	Negative speed difference: speed difference of subject vehicle and leading vehicle (negative value)	m/s
CC5	Positive speed difference: relative speed limit compared to faster leading vehicle during closing state (positive value)	m/s
CC6	Distance impact on oscillation: influence of distance on speed oscillation during the following condition	1/m/s
CC7	Oscillation acceleration: actual acceleration during oscillation during following state	m/s ²
CC8	Acceleration from standstill: desired acceleration when vehicles starting from the standstill condition and is limited by the desired and maximum acceleration functions	m/s ²
CC9	Acceleration at 80 km/h: acceleration at 80 km/h and is limited by the desired and maximum acceleration functions	m/s ²

In VISSIM, lane-changing behaviour is categorized into two types: necessary lane changing and free lane changing. Necessary lane-changing occurs when a vehicle must switch lanes due to mandatory conditions such as an upcoming exit or merging. In this case, the driving behaviour parameters contain the maximum acceptable deceleration for the lane changing vehicle and its leading vehicle in the target lane. Free lane-changing, on the other hand, occurs when a vehicle voluntarily changes lanes with enough space in the adjacent lane. VISSIM evaluates if there is enough space in the new lane and determines if lane changes can be performed.

Several parameters influence lane-changing behaviour in VISSIM, including the look-ahead distance, minimum headway, safety distance reduction factor, and maximum deceleration for cooperative braking. The look-ahead distance will affect the vehicle's movement when approaching a stationary obstacle. With the shorter look-ahead distance for overtaking it, the less chance of being able to overtake. If the look-ahead distance is 0, the vehicle will rely on the number of interaction objects to decide whether to overtake. The number of interaction objects refers to any network objects that may influence the vehicle's movement, such as preceding vehicles, red signal heads, reduced speed areas, priority rules for cases and downstream conflict areas. The number of preceding vehicles is the vehicle perceives along its route or path to react to them. In the case of autonomous vehicles, even if the number of interactive vehicles is limited to one whose sensors are not able to detect vehicles through the front vehicle, they are still able to detect all traffic signs with the help of V2X communication. Another important parameter is the safety distance reduction factor, which modifies the desired safety distance during lane change. This factor determines how much the safety distance is reduced to carry out a lane change. During the lane changing, the safety distance is temporarily reduced to a fraction of the original distance, determined by multiplying the original safety distance by the safety-distance reduction factor. The maximum deceleration for cooperative braking is another parameter, reflecting the extent to which a trailing vehicle is braking cooperatively in order to allow the preceding vehicle in the adjacent lane to merge into its own lane [140].

2.3.3 Applications of VISSIM

Testing autonomous vehicles in real-world environments can be expensive or unsafe due to the need for specialized infrastructure and vehicles, as well as challenges such as extreme weather and critical traffic scenarios. Simulation software is an essential tool for rapidly testing AVs and controlling every variable in the environment, from traffic density and road conditions to the behaviour of other road users. VISSIM offers a wide range of applications, including traffic flow analysis, signal optimization, safety evaluation and autonomous vehicle simulation. The topics related to VISSIM could be summarised as VISSIM calibration, driving-behaviour simulation, incident simulation and heterogeneous traffic simulation [141].

The accuracy of model parameters is highly influenced by the accuracy of the vehicle's movements in the network, so the calibration is a primary concern for real world simulation users. It may lead to inaccurate results and unreliable conclusions under improper calibration [142], so it is necessary to consider specific traffic scenarios and define the characteristics based on that.

Genetic algorithm (GA) is the most used methodology for calibration, by finding optimal or near-optimal solutions to complex problems. For example, Zhang et al. [143] used a modified GA model optimal multi-objective function and the mean absolute percent error in the Wiedemann 74 model to obtain realistic results. Gunarathne [144] also used the GA optimization tool in MATLAB to calibrate the driving behaviour, considering average standstill distance, additive part of safety distance, look ahead distance, standing distance and driving distance. Similarly, U.Gazder [145] and Kang [146] calibrated a traffic micro-simulation model with minimum headway, stand still distance, lateral minimum distance and number of observed vehicles. Different from calibrating the Wiedemann 74, Abdeen [147] looked at the Wiedemann 99 model and used traffic volume and travel speed for calibration and average travel time to validate the results. Li et al. [148] calibrated the parameters in VISSIM by travel time and number of stops distribution at signalized intersections. Claude et al. [149] identified how the driving behaviour parameters will influence the lane flow distribution and found CC1 is the most relevant parameter for the calibration of freeway capacity. Anuj et al. [150] focused on the

calibration and validation of driving behaviour parameters to effectively merging traffic, looking at the impacts such as capacity and speed differences under different traffic flow conditions. Muhammad [151] calibrated and validated the models based on the traffic volumes and average speed and calculated the difference of VISSIM model average passing sight distance with Glennon's model, which presents the passing distances for passenger cars overtaking truck platoons.

VISSIM can simulate the performance of intersections, roundabouts, and urban freeways. It helps in optimizing traffic signal timings, analysing queue lengths, and evaluating the effectiveness of intersection designs. Novera and Qidun [152] applied a step-by-step procedure using an integrated VISSIM and MATLAB approach to simulate the intersection dynamics. They considered the total number of vehicles entering and exiting the intersection and evaluated the queue length on each road. Additionally, VISSIM is used to assess the effectiveness of roundabouts, including capacity, delay, and conflict analysis, which allows planners to evaluate alternative designs. Fang et al. [153] extracted the data from videos collected at four roundabouts with vehicle circulation speed, critical gap, follow-up headway, travel time and vehicle queue length. They compared the VISSIM simulation roundabouts with measured in the field and found the critical gap is the most effective calibration variable. Lee [16] examined the efficiency of dedicated lanes of AVs in a roundabout with an unbalanced traffic flow and selected the travel time, delay time, speed of vehicles and the queue of vehicles as measurements. The results revealed that at lower AV penetration rates, the impact of traffic imbalance is higher and a dedicated lane for AV only improves the traffic conditions when the penetration rate of AV is higher. Studies have used VISSIM to compare the performance of signalized versus unsignalized roundabouts, showing improvements in delay and level of service (LOS) when signalized roundabouts are optimized [154], [155]. Furthermore, VISSIM models complex freeway and urban traffic conditions, including lane changing, merging behaviour, and bottleneck formations, helping to identify congestion points and optimize traffic flow [156], [157], [158].

VISSIM can model heterogeneous traffic conditions that include HVs and AVs, allowing researchers to evaluate the impacts of various levels of AV penetration on traffic flow, safety, and infrastructure. The behaviour of AV communicating with the leading vehicle can be reproduced well in VISSIM by comparing the data from real-world scenarios [159]. M. Azam et al. [50] quantify the impacts of varying penetrations of AV when introduced in mixed traffic conditions at four-leg signalized intersections. Zhou [160] investigates how the utilization of AV affects the road capacity after traffic accidents and the scenario is set as a one-way double lane, tested with filed data in Singapore. The result shows that increasing the proportion of automated vehicles on roads can effectively improve the traffic capacity of urban expressways.

VISSIM integrates with environment modelling tools to evaluate the impact of traffic conditions on emissions and fuel consumption. By simulating different traffic management strategies, it helps in reducing the environmental footprint of transport systems. VISSIM can simulate the impact of adverse weather conditions, such as fog, on fuel consumption. Studies have shown that vehicles consume more fuel under foggy conditions due to changes in driving behaviour [161]. Additionally, VISSIM's emission calculations allow for comparative analysis of different roadway designs and their impact on fuel consumption and emissions. For example, studies comparing different interchange designs found the certain designs resulted in lower fuel consumption and emissions [162].

2.4 Road safety evaluation

2.4.1 Statistical analysis

Methodologically, the following methods of statistical analysis were used to assess road safety: relationship analysis [163], time series analysis [164], Bayesian methods [165], Poisson and negative binomial regression [166] and machine learning [167].

Relationship analysis uses correlation, regression, and variance analysis to explore relationships between variables and road safety outcomes, Singh, D. et al. consider various variables such as vehicle characteristics, driver attributes, roadway design elements, crash-related factors and environmental influences [163]. Time series analysis employs dynamic models and forecasting to predict future safety trends based on historical data. Joanna et al. used structural time-series modelling to forecast and monitor road safety at the regional level in Poland and they explored the relationship between road accidents/injuries, road traffic exposure and other risk determinants and assessing impacts of road safety interventions [168]. Techniques like the empirical Bayes (EB) method control for confounding factors and provide robust estimates of treatment effects. Reyad, P. et al compared the effectiveness of two improvement projects in the city of Edmonton using a conflicted based before-and-after study and the EB methods [165]. Poisson and negative binomial regression models are foundational for analysing crash data, especially when dealing with rare events. Mao et al. apply a bias-correction procedure to the parameter estimation of Poisson and negative binomial regression and demonstrate the finite sample bias associated with a small sample of crashes [166]. The first approach within machine learning was concerned with Neural Network (NN) applications, which can model complex nonlinear relationships and improve prediction accuracy. Abdel-Aty utilized a probabilistic neural network (PNN) to classify the data into either crasher or non-crashes and demonstrated the training speed of PNN is much faster than multilayer feed-forward networks [169].

2.4.2 Applications of SSAM

According to Das et al. [170], the surrogate safety measures used in mixed traffic safety assessment can be divided into two classes: individual SSMs (surrogate safety measures) and SSM-based models. They further divide the individual SSMs into five categories and the SSM-based models into six categories. Table 3 shows the individual SSMs, their focus and key measurements.

Table 3 Categories of individual SSMs

Category	Focus	Key measures
Time-based SSMs (TSSMs)	Use the temporal proximity between two vehicles to flag a traffic interaction as traffic conflict	TTC, PET
Deceleration-based SSMs (DeSSMs)	Use the rate of deceleration applied in response to a sudden event	Deceleration rate to avoid crash (DRAC), Max Deceleration
Combined SSMs (CSSMs)	Develop to overcome the limitations of single SSMs	Driving volatility (DV), average damping ratio (ADR), maximum speed of the vehicle (MaxS)
Distance-based SSMs	Depend on the vehicles safe	Safe stopping distance (which depends on

(DSSMs)	stooping distance computation	response time, initial speed and pavement condition)
Energy-based SSMs (ESSMs)	Describe the influence of speed on kinetic energy involved in collisions	The amount of energy dissipated during a collision (which depends on the speeds and the mass of vehicle pairs, and the angle of approaching vehicle)

Tanmay Das considers surrogate safety models as combining multiple SSMs or using data-driven probabilistic estimation methods, the summary of six categories of surrogate safety models is shown in Table 4.

Table 4 Categories of surrogate safety models

Category	Focus	Key measures
Uncertainty model	Build a probabilistic model using available data to present probability density function of random variables for prediction	Steering rate, braking rate, and road geometry
Extreme value theory	Model the stochastic behaviour and estimate rare, unsafe traffic interactions or conflicts	
Causal and counterfactual model	Calculate the probability of an encounter yielding a traffic conflict	Initial condition and evasive action
Surrogate safety assessment model (SSAM)	Use vehicle trajectory to define, classify and analyse traffic conflicts by combining multiple independent SSMs	TTC, PET, MaxS, MaxD, DR
Deep learning and machine learning based surrogate safety model	Report the real-time traffic conflict by using detailed information on crashes, driver behaviour and vehicular movements	
Fuzzy logic-based surrogate safety model	Avoid rigid thresholds and consider system uncertainties	

SSAM (Surrogate Safety Assessment Model) is a tool used in traffic safety analysis to evaluate the safety performance of road designs and traffic operations. It uses traffic simulation data to identify and analyse potential conflicts between vehicles, which are surrogate measures of safety.

SSAM are adapted to evaluate the safety performance of AVs, although traditional SSMs may not capture the unique behaviour of these vehicles. SSAM can be employed to conduct before-and-after evaluations of safety treatments, and this involves analysing traffic conflicts before and after implementing safety measures to determine their effectiveness [171]. With the advent of connected vehicle data, SSMs can incorporate real-time data to enhance predictive accuracy. Chen et al. analysed the signalised-T intersection and identified the conflicts using SSAM with the indicators TTC and crash index, and the model was introduced to analyse the temporal and spatial distribution of conflict frequencies during a signal cycle [172].

However, there are still some limitations to SSAM. For example, validating SSMs is resource-intensive and often relies on relative validation methods rather than absolute crash data [173]. And the potential sampling and measurement errors can affect the reliability of SSMs [174]. Moreover, existing SSMs may not fully account

for the severity of potential collisions or the complexity of mixed traffic environments [175]. Recent research has focused on improving SSAM by developing new indicators, considering machine learning integration [176].

SSAM and traditional statistical analysis of traffic conflicts differ in their approach, data usage, and application in road safety studies. SSAM relies on vehicle trajectory data, whether simulated or observed, to assess interactions and identify potential risks before crashes occur. It uses surrogate safety measures such as time-to-collision and post-encroachment time to evaluate road safety proactively. This makes SSAM particularly useful in road design and planning, as it allows engineers to assess safety implications before implementing changes.

In contrast, traditional statistical analysis of conflicts depends on historical crash data to evaluate safety. It applies statistical methods to determine the significance of geometric and traffic factors in past accidents. However, this approach is reactive, as it only assesses risk based on past crashes, making it less effective in predicting future conflicts, especially for new road designs. Additionally, statistical analysis often struggles with small sample sizes, limiting its effectiveness in scenarios when lack of crash data.

Overall, both traffic surrogate safety assessment and statistical analysis have their unique strengths and limitations. Surrogate safety measures offer a flexible approach and frequent data collection for real-time safety assessments, whereas traditional statistical analysis provides well-established methods for understanding and predicting road safety based on past crash trends but may be less adaptable to new or modified road conditions.

Chapter 3 Methodology

The aim of this study was to simulate and compare the performance of different driving logic of autonomous vehicles in the merging section. To observe this, we built up a merging section using VISSIM. The method involves two parts, including developing a traffic network and analysing simulation output. The first part of the study applies the VISSIM software to create mixed traffic scenarios and develops a simulation model of a lane-drop merging section. Different scenarios were generated based on different Market Penetration Rates (MPRs) of AVs and HVs. The second part analyses the simulation output, focusing on efficiency and safety performance measures. These results demonstrate the impacts of varying AVs and MPRs on these performance indicators.

3.1 Microsimulation modelling of traffic network using VISSIM

3.1.1 Modelling of driving behaviour

In VISSIM, AVs can be modelled using different driving behaviours, typically categorized as cautious, normal, and aggressive. These behaviours define how an AV interacts with other vehicles, the road environment, and its decision making. The default driving behaviour parameters for three categories of AVs and HVs in VISSIM, including the car-following model, lane-changing acceleration and deceleration are provided in Table 5, Table 6, Table 7 and Table 8 the values of their parameters were adopted from the CoEXist project [8].

Table 5 Recommended settings for autonomous vehicles

Parameter	Cautious	Normal	Aggressive
Max look-ahead distance(m)	250	250	300
Number of interaction objects	2	2	10
Number of interaction vehicles	1	1	8

The values of parameters show that aggressive AVs are capable of perceiving information on a higher number of objects and vehicles and longer look-ahead distance as compared to other AV driving logics. According to the CoEXist database, standstill distances (CC0), following behaviour in the course of time (CC2-CC6) and mean queue discharge headway of AVs were obtained.

Table 6 Parameters value of car-following model of AV and HV

Parameter	Units	Cautious	Normal	Aggressive	Human-driven
CC0	m	1.5	1.5	1	1.5
CC1	s	1.5	0.9	0.6	0.9
CC2	m	0	0	0	4
CC3	s	-10	-8	-6	-8
CC4	m/s	-0.1	-0.1	-0.1	-0.35
CC5	m/s	0.1	0.1	0.1	0.35
CC6	1/ (m.s)	0	0	0	11.44
CC7	m/s ²	0.1	0.1	0.1	0.25
CC8	m/s ²	3	3.5	4	3.5

CC9	m/s ²	1.2	1.5	2	1.5
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Table 7 Parameters value of lane-changing of AV and HV

Parameter	Cautious		Normal		Aggressive		Human-driven	
	Own	Trailing vehicle	Own	Trailing vehicle	Own	Trailing vehicle	Own	Trailing vehicle
Maximum deceleration	-3.5	-2.5	-4	-3	-4	-4	-4	-3
-1 m/s per distance	80	80	100	100	100	100	200	200
Accepted deceleration	-1	-1	-1	-1	-1	-1.5	-1	-0.5

From Table 8 we can find that cautious AVs apply less aggressive braking and less speed changing; aggressive AVs will decelerate rapidly, allowing them to stop quickly when necessary; normal AVs can decelerate more aggressively than cautious AVs, though not to the same extent as aggressive AVs.

Table 8 Behavioural functionality value of AV and HDV

Behavioural functionality	Cautious	Normal	Aggressive	Human-driven
Min. headway	1	0.5	0.5	0.5
Safety distance reduction factor	1	0.6	0.5	0.6
Max. deceleration for cooperative braking	-2.5	-3	-6	-3

The values of parameters show that cautious AVs maintain a greater headway with the vehicle ahead to ensure they have enough time to react to suddenly braking or changing. Normal AVs maintain a reasonable headway time between vehicles, allowing them to follow closely enough to maintain traffic flow while ensuring the distance for stopping. Aggressive AVs will follow other vehicles closely, reducing the headway time to allow themselves quicker movement through congested areas.

Cooperative lane change is another driving behaviour parameter setting for AVs. It defines how vehicles cooperate to facilitate smoother traffic flow during lane changing. For example, when vehicle A observes that a leading vehicle B on the adjacent lane intends to merge into its lane, vehicle A will try to change lanes to create space for vehicle B. However, this manoeuvre depends on new route compatibility, relative speed with vehicle B and collision time thresholds. In this study, we will analyse how cooperative lane-change behaviour affects traffic efficiency and compare it with non-cooperative lane-change behaviour.

3.1.2 Modelling of geometry and vehicle input

In this study, we used a hypothetical 650-meter-long two-lane merging model VISSIM, as illustrated in Figure 2. According to the Manual on Uniform Traffic Control Devices, for roadways having a posted speed limit of 70 km/h (45mph) or greater, the transition taper length for a lane reduction should be computed by the formula $L = 0.62 WS$ for speeds in km/h ($L = WS$ for speeds in mph). For roadways having a posted speed limit is less than 70 km/h (45 mph), the formula $L = WS^2/155$ for speeds in km/h ($L = WS^2/60$ for speeds

in mph) should be used to compute taper length. Under both formulas, L equals the taper length in meters (feet), W is the width offset distance in meters (feet), and S equals the 85th-percentile speed or the posted or statutory speed limit. In this case, the taper of the merging section is suggested at 155 m.

The scenarios were prepared under varying demand levels, the MPRs of AVs and HVs, and the category of AVs. The values of size, speed, and lateral distances for AVs were adopted from the values for HVs. The lanes in the model are defined as “free lane selection”, which allows vehicles to overtake on each lane. Additionally, the speed for all the vehicles was uniformly set as 70 ± 2 km/h to simulate consistent flow conditions in the network.

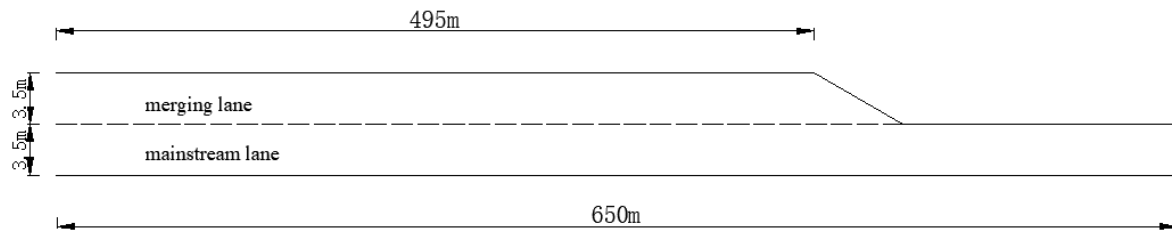


Figure 2 Network used for an extended merging

3.2 Simulation output

Each simulation scenario runs 10 times to collect output on various performance measures. Each simulation run lasted a total of 3900 seconds, including a warm-up period of 300 seconds to ensure steady state conditions were reached before recording. The results will reflect system performance using VISSIM, traffic safety indicators from SSAM and parameter sensitivity analysis.

3.2.1 Analysing vehicle efficiency using VISSIM

VISSIM is a traffic simulation software used to generate delay and travel time measurements. In VISSIM, vehicle delay refers to the average delay of all vehicles, calculated as the difference between the ideal travel time and the actual travel time. The ideal of travel time is the travel time which can be achieved under free flow conditions, without interference from other vehicles, signal controls or other reasons for stops. Stop delay refers to the time a vehicle spends at a complete standstill when its speed is zero [177].

3.2.2 Analysing vehicle conflict using SSAM

The Surrogate Safety Assessment Model (SSAM) is a software application used to analyse traffic conflicts by directly processing vehicle trajectory data. By importing the trajectory data from VISSIM, SSAM obtains detailed information about vehicle positions and dimensions approximately every tenth of a second, enabling it to assess the traffic conditions. SSAM analyses vehicle-to-vehicle interactions to identify conflict events and catalogues all events found, providing output that includes the number, type, severity and locations of simulated conflicts [178].

SSAM utilizes five surrogate safety measures to evaluate the likelihood and severity of simulated conflicts, including time to collision (TTC), post encroachment time (PET), deceleration rate (DR), maximum speed (MaxS) and difference in vehicle speeds (DeltaS). It also provides statistical data regarding the minimum, maximum, mean and variance of each of these measures.

TTC, PET and DR are intended to reflect the severity of the conflict event itself, specifically the likelihood of a collision resulting from the conflict. TTC indicates the minimum time observed during a conflict before a

potential collision occurs, based on the current vehicle position, speeds, and trajectories. It serves as a critical indicator of collision risk, where lower TTC values indicate a higher probability of a crash. PET is defined as the minimum time interval between when the first vehicle last occupied a position, and the second vehicle subsequently arrived at the same position. Smaller PET values suggest a greater chance of collision. A higher DR indicates a higher probability of collision, as it reflects the reactive braking efforts of the second vehicle to avoid an impact. Higher deceleration typically signals a more urgent or severe response to an imminent collision risk.

MaxS and DeltaS indicate the potential severity of a collision, should the conflict event result in an impact rather than a near-miss. Higher MaxS values reflect a higher likely severity of the resulting collision, as vehicles traveling at higher speeds carry more kinetic energy, potentially leading to more destructive impacts. A higher DeltaS indicates a higher severity of the resulting collision. A larger difference in vehicle speeds at the time of minimum TTC (t_{MinTTC}) suggests a more forceful collision, as the momentum would not be synchronized, leading to a more violent crash. MaxS and DeltaS can also be combined with the mass of the vehicles involved to calculate momentum, providing a better estimate of potential collision severity.

These measurements are widely used in TSSM and CSSMS for mixed traffic safety assessment. However, there are some limitations. For example, TTC can only report the number of conflicts rather than the severity of conflicts and assumes constant vehicle speeds without considering the acceleration and deceleration. Similarly, PET does not consider the vehicle pairs' speed differences or distance and assumes a fixed spatial collision point, ignoring the spatial dynamics. Given these limitations, it is important to combine multiple surrogate measurements to obtain a comprehensive safety assessment.

It is important to determine the chance of conflicts and the potential severity of resulting collisions when analysing traffic safety. If a location that experiences frequent conflicts with high severity in terms of TTC, PET, and DR but low MaxS and DeltaS may not be concerned for safety improvements because the resulting crashes are more likely to result in minor property damage rather than severe injuries or fatalities. On the other hand, locations with fewer conflicts but much higher MaxS and DeltaS values present a higher risk of serious injury or fatality in the collision, having greater prioritizing for safety upgrades.

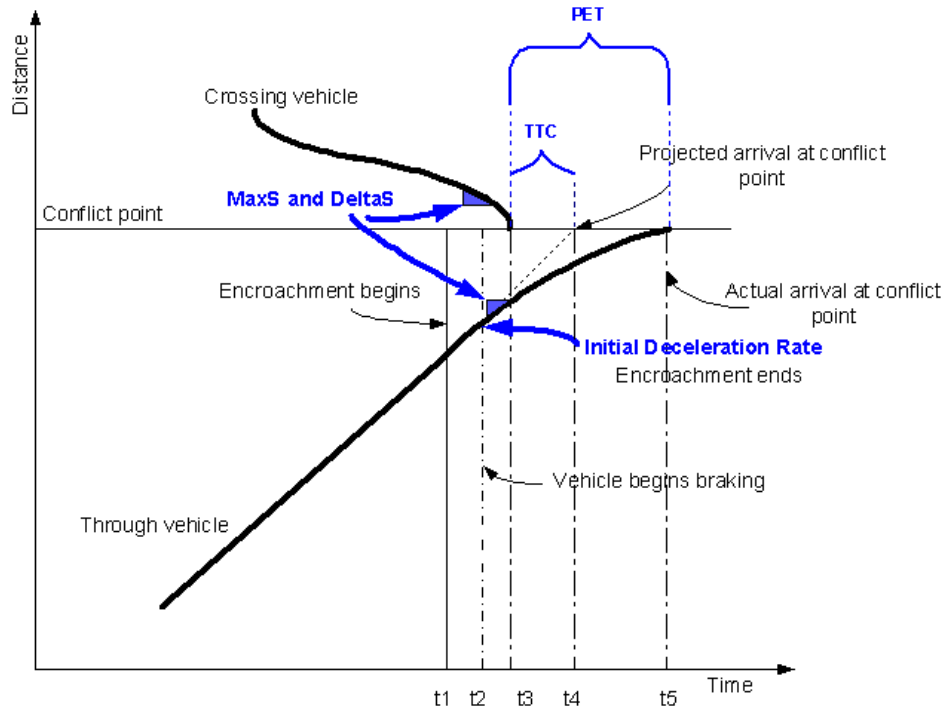


Figure 3 Surrogate measures on conflict point diagram [178]

Conflicts in SSAM are categorized into four types: unclassified, crossing, rear-end and lane-change, based on the conflict angle, which is calculated for each pair of conflicting vehicles or determined by link and lane information. If the link and lane information are unavailable for both vehicles, the conflict angles are used to classify the conflict. If the $|\text{conflict angle}| > 85^\circ$ the conflict is classified as a crossing. If $|\text{conflict angle}| < 30^\circ$, it is classified as rear-end. If $30^\circ < |\text{conflict angle}| < 85^\circ$, it is considered as a lane-change. If the conflict angle is unknown, the conflict is labelled as unclassified. However, when the link and lane information are available, it is used to classify conflicts more precisely based on vehicle positions throughout the event. If both vehicles occupy the same lane (on the same link) at the start or end of the conflict event, classification follows these rules. If the vehicles occupy the same lane at both the start and end of the event, the conflict is classified as a rear-end. If either vehicle changes lanes during the event but remains on the same link, the event is classified as a lane-change. If either vehicle changes links during the event, the conflict angle is used to determine the classification as described earlier [179]. SSAM provide the default value of TTC of 1.5 seconds, suggested by a previous study [180].

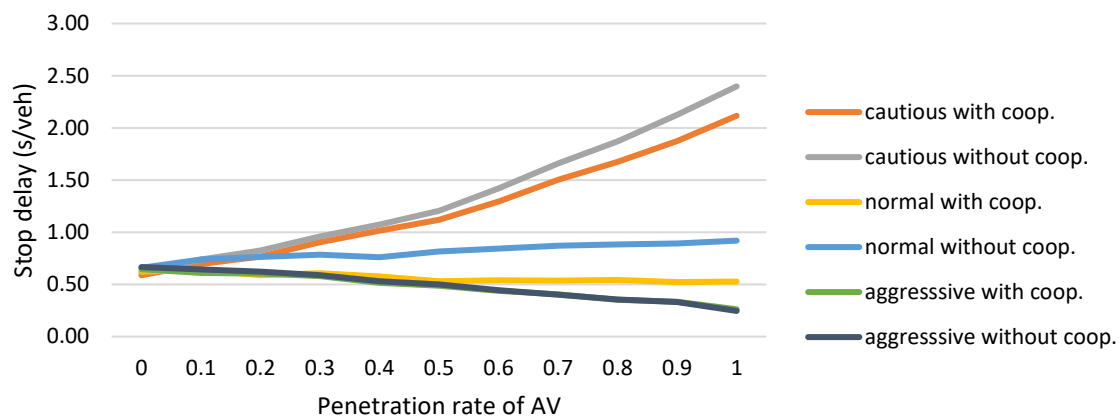
Chapter 4 Simulation and result

This chapter presents the results of the microsimulation analysis, focusing on the operational performance, traffic safety, and sensitivity of key behavioural parameters for autonomous vehicles under varying penetration rates and traffic demand levels. This chapter is structured into four main sections: analysis of traffic efficiency including stop delay and vehicle delay; sensitivity analysis of car-following and lane-changing model parameters on traffic efficiency; evaluation of safety outcomes using surrogate measures; assessment of lane-changing parameters influences on safety performance.

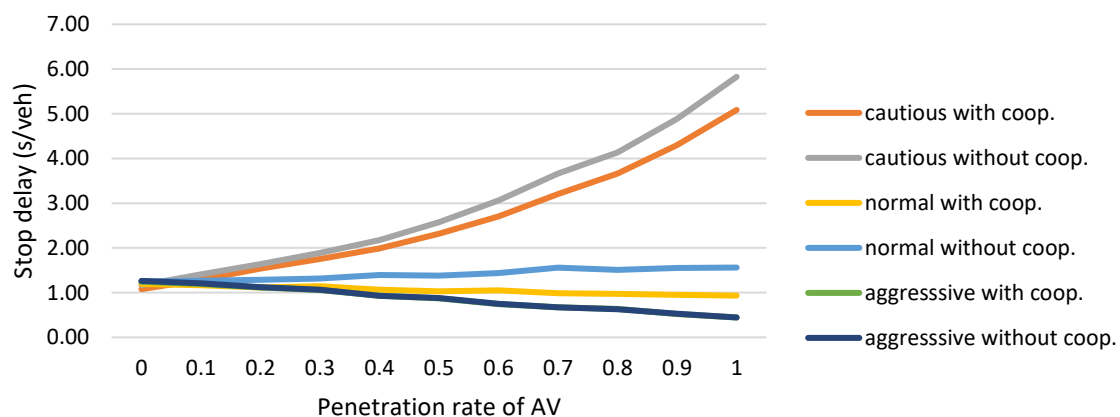
4.1 Operation performance

For operation performance assessment, the scenarios were created based on the following three factors: demand level, MPRs of AVs and category of AVs. The vehicle input for the simulation varied with four different scenarios: 1500 veh/h, 1650 veh/h, 1800 veh/h and 1950 veh/h. For each scenario, the MPRs of AV were adjusted from 0% to 100% in 10% increments, with the remaining percentage of vehicles being HV. The categories of AVs include cautious AVs with cooperative lane-change (referred to as *with coop.* in the results shown below), cautious AVs without cooperative lane-change (referred to as *without coop.* in the results shown below), normal AVs with coop., normal AVs without coop., aggressive AVs with coop. and aggressive AVs without coop.. A total of 264 simulation scenarios were conducted by combining four demand levels, eleven proportion levels of AVs and six driving logics. With the help of delay measurement and network evaluation, the data on stop delays and vehicle delays are shown below.

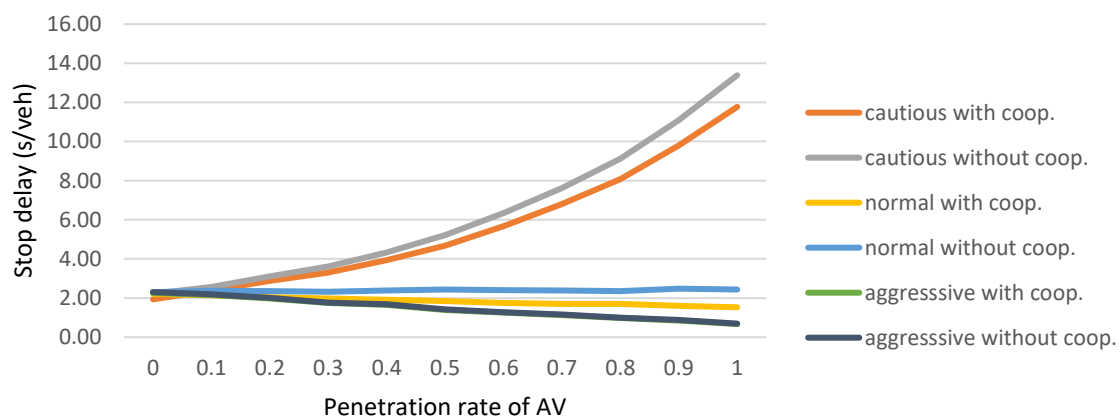
Figure 4 shows the stop delay of AVs at four demand levels, where the X-axis represents the MPRs of AVs, ranging from 0 to 1 and the Y-axis represents stop delay. For all demand levels, stop delay increases for cautious AVs as the penetration rate rises, while normal and aggressive AVs (especially with cooperative lane-change) maintain relatively low stop delays. At full penetration rate and demand in 1950 veh/h, delays for cautious AVs reach over 25 s/veh, while normal AVs rise steadily, reaching only 4 s/veh. Cautious driving logic performs worst at higher penetration rates of AVs, and cooperation helps but does not eliminate inefficiencies completely, especially at higher demands. Aggressive AV with or without cooperative lane-change performs similarly at all demand levels and is the best overall which continues to minimize delays under higher AV penetration. Normal AVs provide a balanced performance but tend to increase slightly in delay at higher penetration rates without cooperation.



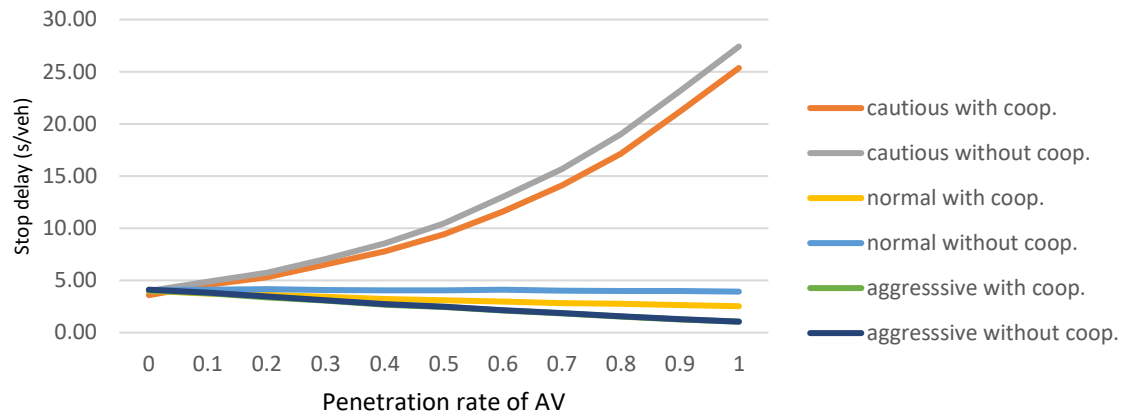
(a) demand in 1500 veh/h



(b) demand in 1650 veh/h



(c) demand in 1800 veh/h



(d) demand in 1950 veh/h

Figure 4 Stop delay for different driving logic under varying demand

Figures 5-8 illustrate the effect on vehicle delay under all the tested scenarios. The X-axis represents the MPRs of AVs, ranging from 0 to 1; the Y-axis represents vehicle delay, negative values indicate improvement (reduced delay), and positive values indicate worsening delays.

Cautious AVs show the most significant fluctuations with increasing demand. At low demand (1500 veh/h), the delay increase is less than 150%, while from Figure 8, we can see that at higher demand level, cautious AVs delays increase progressively with higher AV penetration, and at 100% AV the vehicle delay increment is above 320% compared to all HVs. Normal AVs with cooperative lane-change show decreasing delay as AV penetration increases and at full AV penetration, delay decreases by 30% approximately compared with all HVs. While, for the normal AVs without cooperation, the delay remains relatively stable under varying AVs MPR. For aggressive behaviour, with cooperations results in the most significant reductions among all logics, and without cooperation has similar reductions although slightly less than with cooperation.

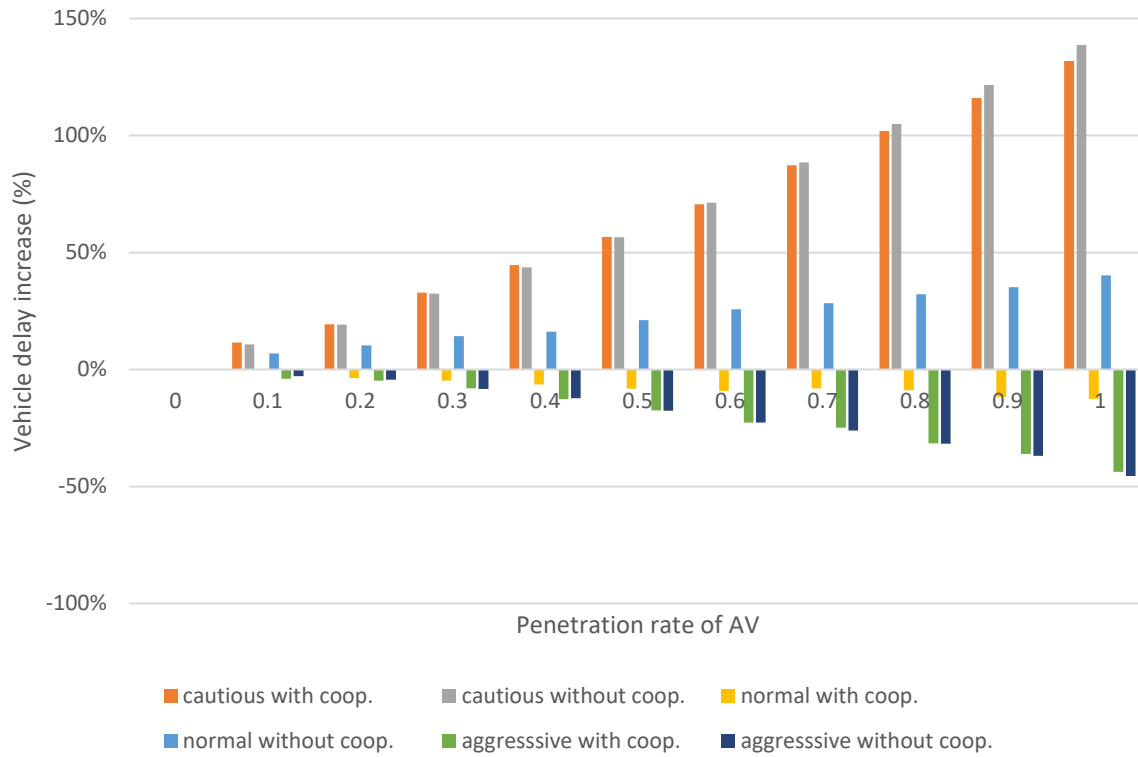


Figure 5 Vehicle delay increment compared with all HVs demand in 1500 veh/h

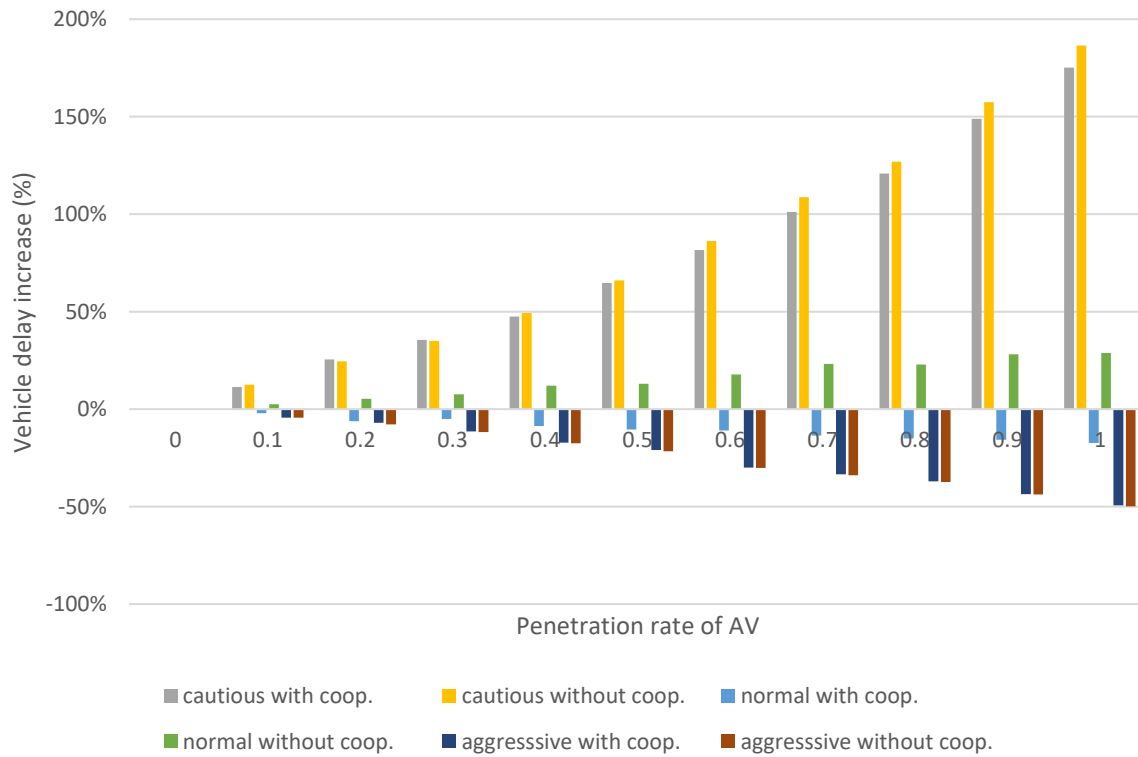


Figure 6 Vehicle delay increment compared with all HVs demand in 1650 veh/h

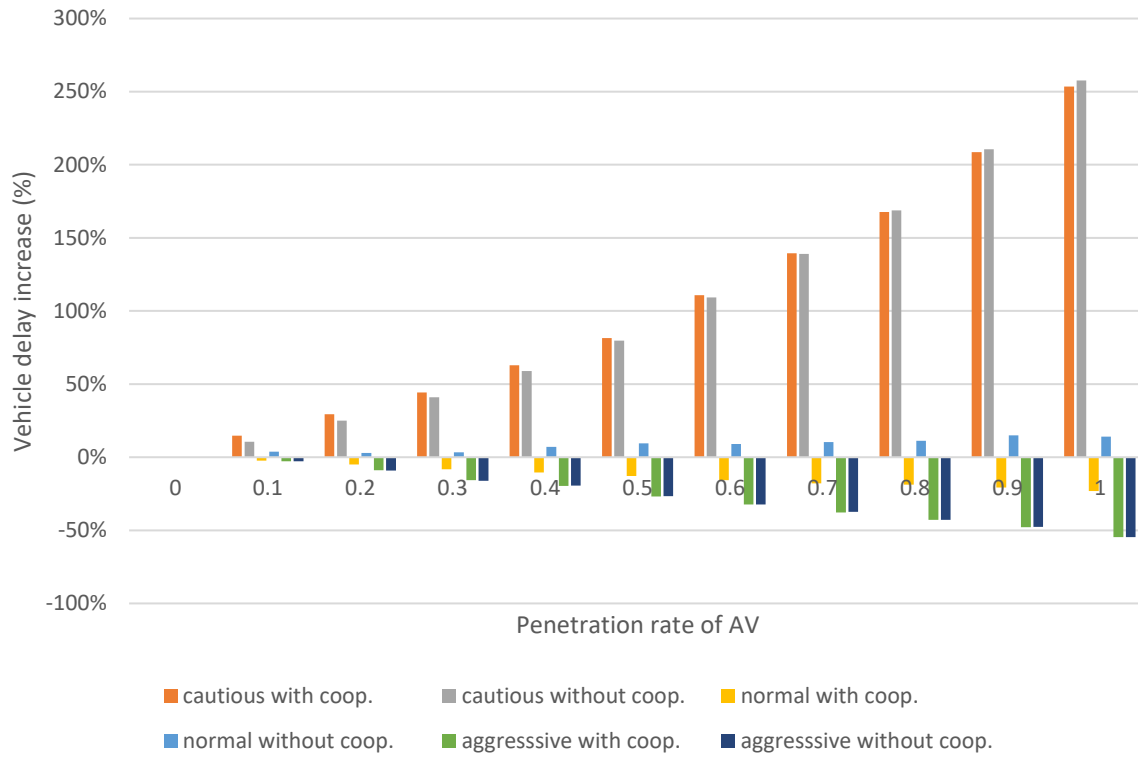


Figure 7 Vehicle delay increment compared with all HVs demand in 1800 veh/h

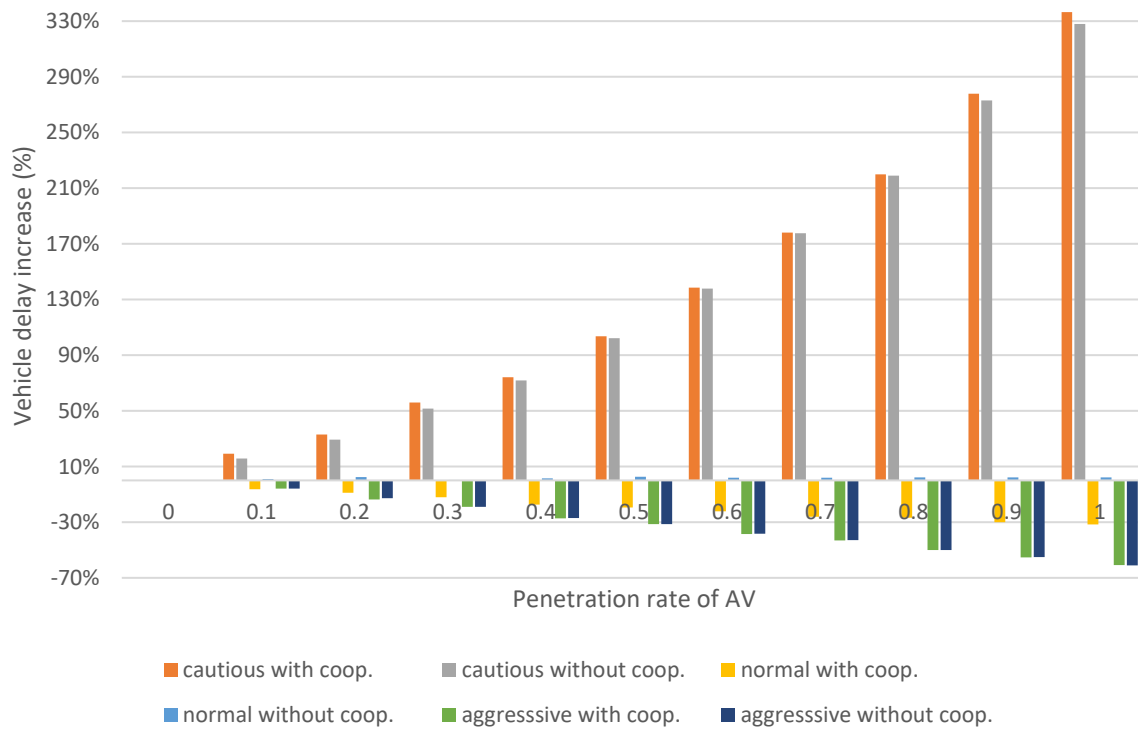


Figure 8 Vehicle delay increment compared with all HVs demand in 1950 veh/h

These results show the effectiveness of AV driving behaviour across varying penetration levels. Cautious AVs lead to increased delays as their penetration grows. In contrast, aggressive AVs show decreasing delays with higher penetration rates. Normal AVs maintain stable performance across all penetration levels. Additionally, cooperation improves performance for all driving logics, consistently reducing delays, even though the extent of improvement may vary depending on the AV behaviour type.

4.2 Parameters influencing operational impact

We conducted a sensitivity study to determine the influence of car following parameters (Wiedeman 99) and lane changing parameters, all parameters are performed for human-driven vehicles only. Based on VISSIM default values, we chose an increment of 10% of the initial value and simulated with 42 random seeds, 15 runs, 3600 simulation second intervals and 15 mins warm-up period. The vehicle input for the simulation varied with four different scenarios: 1500 veh/h, 1800 veh/h and 2100 veh/h.

Table 9 Testing parameters value

Parameter		Units	70%	80%	90%	Default value	110%	120%	130%
Wiedeman 99 parameters	CC0	m	1.05	1.20	1.35	1.50	1.65	1.80	1.95
	CC2	m	2.8	3.2	3.6	4.0	4.4	4.8	5.2
	CC3	s	-5.6	-6.4	-7.2	-8.0	-8.8	-9.6	-10.4
	CC4	m/s	-0.24	-0.28	-0.32	-0.35	-0.39	-0.42	-0.46
	CC5	m/s	0.24	0.28	0.32	0.35	0.39	0.42	0.46
	CC6	1/(m.s)	8.01	9.15	10.30	11.44	12.58	13.73	14.87
	CC7	m/s ²	0.17	0.20	0.23	0.25	0.28	0.30	0.33
	CC8	m/s ²	2.45	2.80	3.15	3.50	3.85	4.20	4.55
	CC9	m/s ²	1.05	1.20	1.35	1.50	1.65	1.80	1.95
Lane changing parameters	min. headway (front/rear)	m	0.35	0.4	0.45	0.5	0.55	0.6	0.65
	to slower lane	s	7.7	8.8	9.9	11	12.1	13.2	14.3
	safety distance reduction factor		0.42	0.48	0.54	0.6	0.66	0.72	0.78
	maximum deceleration	m/s ²	-2.1	-2.4	-2.7	-3	-3.3	-3.6	-3.9

The tables below show the deviation between the stop delay, stops, vehicle delays, vehicle amount, queue delays and acceleration compared to initial value. For each input demand, the average deviation for the evaluated measurement is determined. If the average deviation for the parameter is larger than the others, the

parameter has a relevant influence on the traffic operation.

According to PTV VISSIM, *stop delay* refers to the average delay experienced by each vehicle in seconds due to stops, excluding stops at public transit stops and in parking lots. *Vehicle delay*, on the other hand, represents the average delay experienced by all vehicles in the segment. *Stops* indicate the average number of stops per vehicle, excluding stops at public transit stops and in parking lots. The term "vehicles" refers to the total number of vehicles in the segment, and "Acc" refers to the acceleration of vehicles. *Queue delay* refers to the additional time a vehicle spends specifically in a queue, which usually means slow speeds or waiting to pass through a bottleneck.

Table 10 Resulting average deviation under traffic input 1500 veh/h

		Stop delay	Stops	Vehicle delay	Vehicles	Acc	Queue delay
Wiedemann99	CC0	17.72%	20.53%	13.25%	0.06%	-2.90%	111.84%
	CC2	16.56%	10.11%	8.70%	0.29%	-2.43%	38.44%
	CC3	5.66%	15.51%	7.51%	0.10%	-2.01%	99.28%
	CC4	17.57%	13.89%	8.17%	0.04%	-2.84%	100.00%
	CC5	17.57%	13.89%	8.17%	0.04%	-2.84%	100.00%
	CC6	20.16%	11.50%	5.68%	0.10%	-2.16%	24.61%
	CC7	15.07%	17.23%	9.18%	0.02%	-2.67%	89.66%
	CC8	1.60%	14.80%	7.54%	0.00%	-0.40%	103.05%
	CC9	2.40%	2.30%	1.42%	0.00%	-0.46%	16.84%
Lane-changing	min. headway (front/rear)	7.88%	14.38%	6.62%	0.00%	-0.79%	87.79%
	safety distance reduction factor	14.78%	9.72%	5.00%	0.02%	-1.85%	49.84%
	maximum deceleration for cooperative braking	6.30%	17.19%	9.98%	0.02%	-1.23%	117.14%

Table 11 Resulting average deviation under traffic input 1800 veh/h

		Stop delay	Stops	Vehicle delay	Vehicles	Acc	Queue delay
Wiedemann99	CC0	18.18%	29.48%	25.83%	1.86%	-18.60%	34.01%
	CC2	9.92%	12.70%	11.12%	0.72%	-10.31%	13.90%
	CC3	3.69%	5.68%	5.51%	0.44%	-5.47%	6.89%

	CC4	4.16%	5.57%	5.65%	0.34%	-6.21%	7.33%
	CC5	4.16%	5.57%	5.65%	0.34%	-6.21%	7.33%
	CC6	7.13%	5.59%	4.25%	0.26%	-7.01%	5.75%
	CC7	3.77%	4.28%	3.41%	0.31%	-8.02%	5.39%
	CC8	5.47%	6.23%	5.44%	0.24%	-3.55%	7.42%
	CC9	3.10%	8.52%	6.81%	0.41%	-2.24%	9.83%
Lane-changing	min. headway (front/rear)	5.56%	6.94%	5.51%	0.39%	-4.46%	7.33%
	safety distance reduction factor	5.36%	8.41%	7.17%	0.49%	-4.82%	9.54%
	maximum deceleration for cooperative braking	6.48%	4.93%	4.52%	0.29%	-3.44%	6.00%

Table 12 Resulting average deviation under traffic input 2100 veh/h

		Stop delay	Stops	Vehicle delay	Vehicles	Acc	Queue delay
Wiedemann99	CC0	2.76%	3.17%	5.18%	2.14%	-32.17%	5.16%
	CC2	3.39%	6.57%	5.57%	1.58%	-12.29%	6.69%
	CC3	6.71%	2.37%	2.26%	0.39%	-23.68%	2.20%
	CC4	3.56%	0.88%	0.53%	0.31%	-23.04%	0.88%
	CC5	3.56%	0.88%	0.53%	0.31%	-23.04%	0.88%
	CC6	2.84%	1.45%	1.73%	0.51%	-7.30%	2.01%
	CC7	3.77%	4.45%	1.49%	0.54%	-9.83%	1.85%
	CC8	2.83%	2.29%	1.84%	0.61%	-6.44%	2.32%
	CC9	1.84%	1.41%	1.29%	0.29%	-4.52%	1.57%
Lane-changing	min. headway (front/rear)	6.37%	1.98%	1.42%	0.41%	-16.16%	1.36%
	safety distance reduction factor	3.79%	2.27%	1.82%	0.44%	-18.19%	2.07%
	maximum	5.77%	2.71%	2.91%	0.80%	-6.56%	3.35%

	deceleration for cooperative braking						
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These results show that the standstill distance CC0 is one of the most relevant parameters in the Wiedemann 99 car-following model to calibrate safety distance. With increasing CC0, the safety distance increases and lane capacity decreases. Similarly, the modification of the following variation CC2 for Wiedemann 99 leads to comparable changes as CC0, affecting the following variation. The higher CC2 is set, the more distance for vehicles is kept.

On the other hand, CC9 for Wiedemann 99 has a relatively minor influence on operation under all demand levels. This parameter, which presents the acceleration at 80 km/h, does not apply to this scenario. Other parameters within Wiedemann 99 (CC3 to CC8) only affect the operational aspect under low traffic demand conditions. As demand increases, these parameter changes have less effect compared to CC0 and CC2.

For the lane-changing parameters, variations in their values significantly impact the operational outcomes, particularly under a traffic volume of 1500 veh/h. As demand increases, the effects of lane-changing parameters become less.

Under low demand conditions, all parameter adjustments have less effects on acceleration. However, with higher demand levels (1800 veh/h and 2100 veh/h), the acceleration is affected more by car-following parameters than lane-changing parameters with the average deviation shown in the table. Conversely, queue delay shows a great difference with different parameter adjustments compared to the default value under low demand. As traffic volume increases, queue delays tend to maintain a similar level as the default value, which is limited to the lane capacity.

In conclusion, these results highlight the relationships among demand, parameter settings and operational impact within the Wiedemann 99 car-following model and lane-changing model. The majority of parameters in the Wiedemann 99 model demonstrate notable effects on operations, particularly under conditions of low demand. Notably, CC0 and CC2 show significant influences on operational outcomes, with adjustments to these parameters leading to great changes in safety distances and following behaviours. However, CC9 shows a relatively minimal impact across all demand conditions, indicating its limited influence on operational dynamics. Similarly, lane-changing parameters show more effects under conditions of low demand.

4.3 Conflict performance

For conflict performance assessment, the scenarios were created based on the following three factors: demand level, MPRs of AVs and category of AVs. The vehicle input for the simulation varied with four different scenarios: 1500 veh/h, 1650 veh/h, 1800 veh/h and 1950 veh/h. For each scenario, the MPRs of AV were adjusted from 0% to 100% in 10% increments, with the remaining percentage of vehicles being HV. The categories of AVs include cautious AVs and aggressive AVs. For the conflict thresholds, the maximum time-to-collision is 1.5 seconds, maximum post-encroachment time is 5 seconds.

Figures 9-13 compare cautious and aggressive vehicle behaviour using SSAM measuring metrics with aggregated average data, like TTC, PET and other safety-related surrogates under varying demand levels. To examine the effects of driving behaviour and traffic demand level on those conflict metrics, a two-way ANOVA

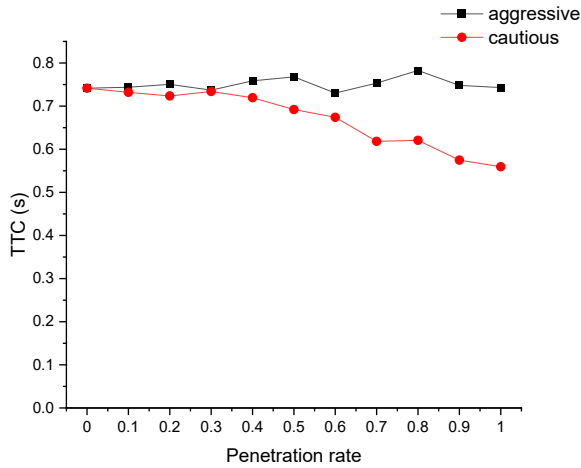
was conducted. The analysis was performed using a significant level of $p = 0.05$, meaning that any p-value below 0.05 was considered statistically significant. Additionally, DF stands for Degrees of Freedom, and F value is a ratio that compares the variance within groups.

Figure 14 shows the number of conflicts during the simulation, including lane-changing conflicts, near-end conflicts and total conflicts number. Figures 15-18 illustrate the spatial distribution of conflict points along the merging area, providing the insight into where conflicts are most likely to occur under various traffic conditions.

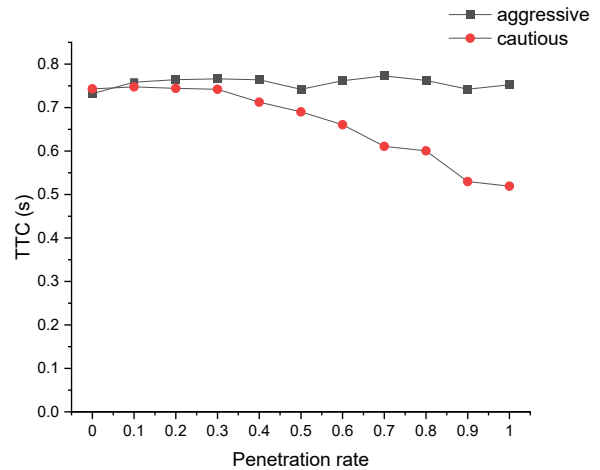
From Figure 9 we can find that under low demand levels, both cautious AVs and aggressive AVs start lower TTC value (around 0.75 s) at 0% penetration rate and gradually decrease; while under high demand level, both logics start the TTC value around 0.8 s and decline steeper than under low demand. The TTC values of Aggressive AVs remain consistently higher than those of cautious AVs and decline slightly more gradually than cautious AVs. The trend for cautious AVs steepens after 60% penetration and ends at the lowest TTC at full penetration.

Table 13 shows that driving behaviour has a high F-value (52.97) and very low p-value, indicating a strong and statistically significant effect on TTC. Traffic demand level shows a very low F-value (0.268) and a high p-value (0.8482), meaning it does not significantly affect TTC. The differences in TTC across low, medium and high traffic levels are not statistically meaningful. The interaction between driving behaviour and demand level is also not significant, suggesting that the effect of driving logic on TTC does not depend on traffic demand level.

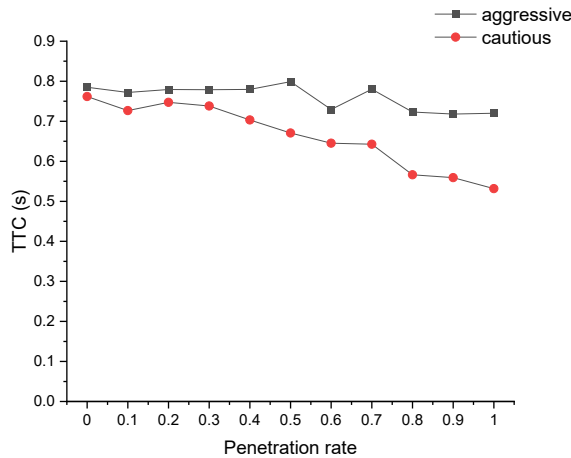
Aggressive AVs offer better TTC performance than cautious ones across all penetration rates at all demand levels. This is due to more assertive gap acceptance leading to more stable flows and fewer abrupt slowdowns. Cautious AVs exhibit worsening TTC with increased penetration, especially after 60%, indicating potential platooning or compounding hesitancy.



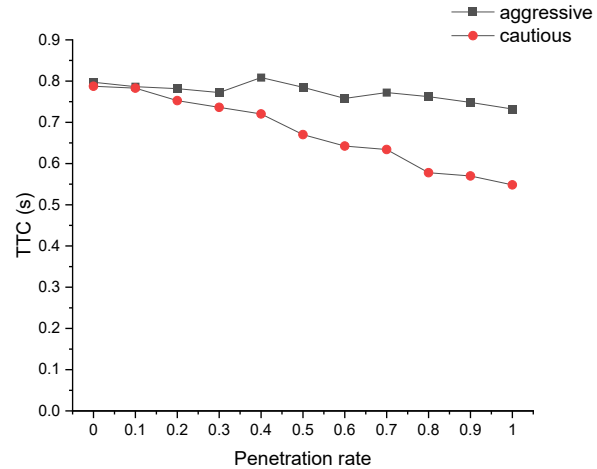
(a) demand in 1500 veh/h



(b) demand in 1650 veh/h



(c) demand in 1800 veh/h



(d) demand in 1950 veh/h

Figure 9 Time-to-collision under varying demand levels

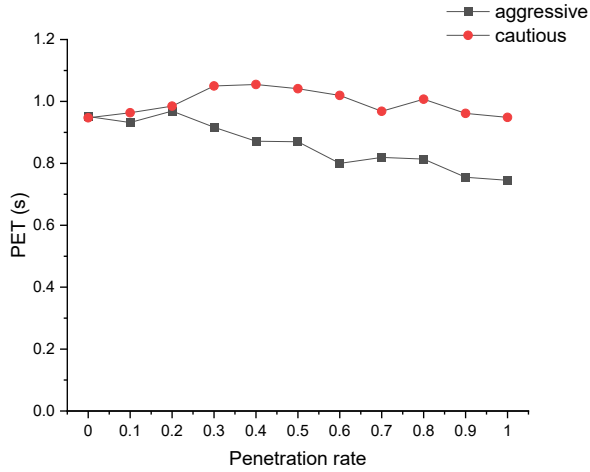
Table 13 Two-way ANOVA results examining the effects of driving behaviour and traffic demand level on Time to Collision (TTC)

	DF	Sum of Squares	Mean Square	F Value	P Value
Demand level	3	0.00281	9.37992E-4	0.26812	0.8482
Driving behaviour	1	0.1853	0.1853	52.96738	<0.0001
Interaction	3	0.00134	4.4646E-4	0.12762	0.94346

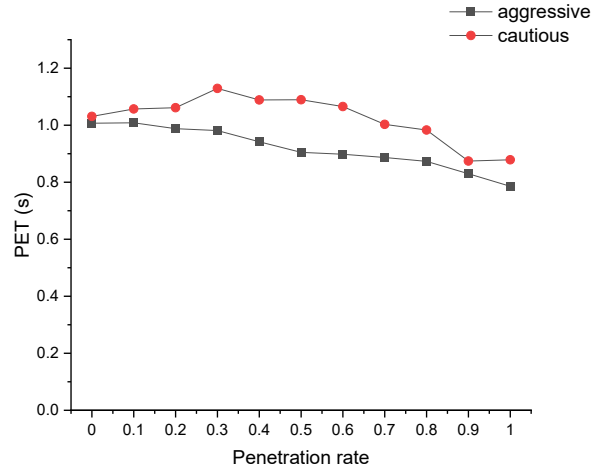
Figure 10 illustrates the post-encroachment time for cautious and aggressive driving logics. At low demand levels, mixed traffic with cautious AV have larger gaps between vehicles in conflict zones as the PET values are higher than aggressive logic, which indicates safer vehicle interactions. Under low demand levels, PET remains relatively stable with a slight increase at 50% penetration. Under high demand levels, the PET values show a slight increase, but the values drop as the penetration rate rises. For aggressive AVs, the PET values drop slightly at all penetration rates and are lower than cautious ones under all demand levels. Additionally, at a high demand level, the PET values for aggressive and cautious AVs approach one another, suggesting reduced behavioural distinction.

The ANOVA results in Table 14 show that both driving behaviour and demand level are significantly influenced PET. However, the effect of driving behaviour on PET does not significantly depend on traffic demand level.

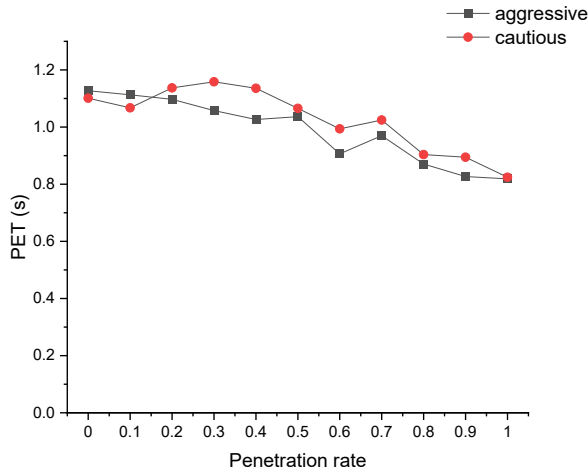
The PET results suggest that cautious AVs provide better safety margins than aggressive AVs. However, as traffic demand and AV penetration increase, the safety advantage of cautious behaviours diminishes. The convergence of PET values at high demand levels indicates that the impact of driving logic becomes less distinct under congested conditions.



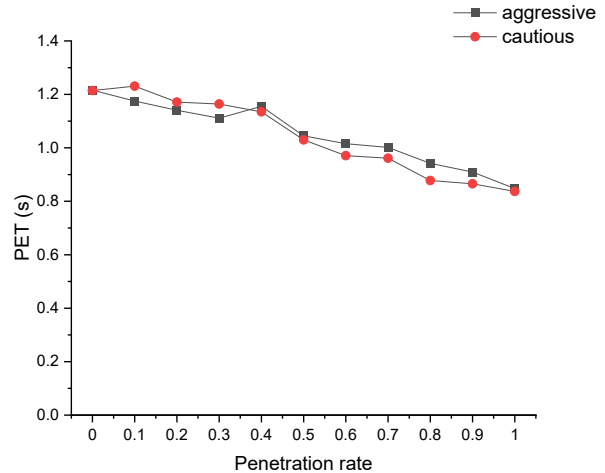
(a) demand in 1500 veh/h



(b) demand in 1650 veh/h



(c) demand in 1800 veh/h



(d) demand in 1950 veh/h

Figure 10 Post encroachment time under varying demand levels

Table 14 Two-way ANOVA results examining the effects of driving behaviour and traffic demand level on Post encroachment time (PET)

	DF	Sum of Squares	Mean Square	F Value	P Value
Demand level	3	0.17128	0.05709	5.59763	0.00155
Driving behaviour	1	0.10322	0.10322	10.12064	0.00209
Interaction	3	0.07022	0.02341	2.29503	0.0841

Figure 11 illustrates the deceleration rate of cautions and aggressive AV under varying penetration rates and different demand levels. As the AV penetration rate increases, the DR of cautious AVs become less negative, while aggressive ones show an increase in its negative trend. Under higher demand level, both logics show a diminishing negative trend. However, cautious AV has less negative DR values than aggressive ones, indicating smoother braking. This reflects conservative behaviour, with larger gaps reducing the need for abrupt deceleration. For aggressive logic, DR values are more negative than cautious ones, indicating stronger braking

actions.

The results in Table 15 show that both driving behaviour and traffic demand level independently influence deceleration rate, but they do not interact each other.

The results of the deceleration rate suggest that cautious AVs support more stable and gradual braking due to conservative gap management, especially as penetration increases. Aggressive AVs, on the other hand, continue to show stronger brakes, which may indicate more reactive driving.

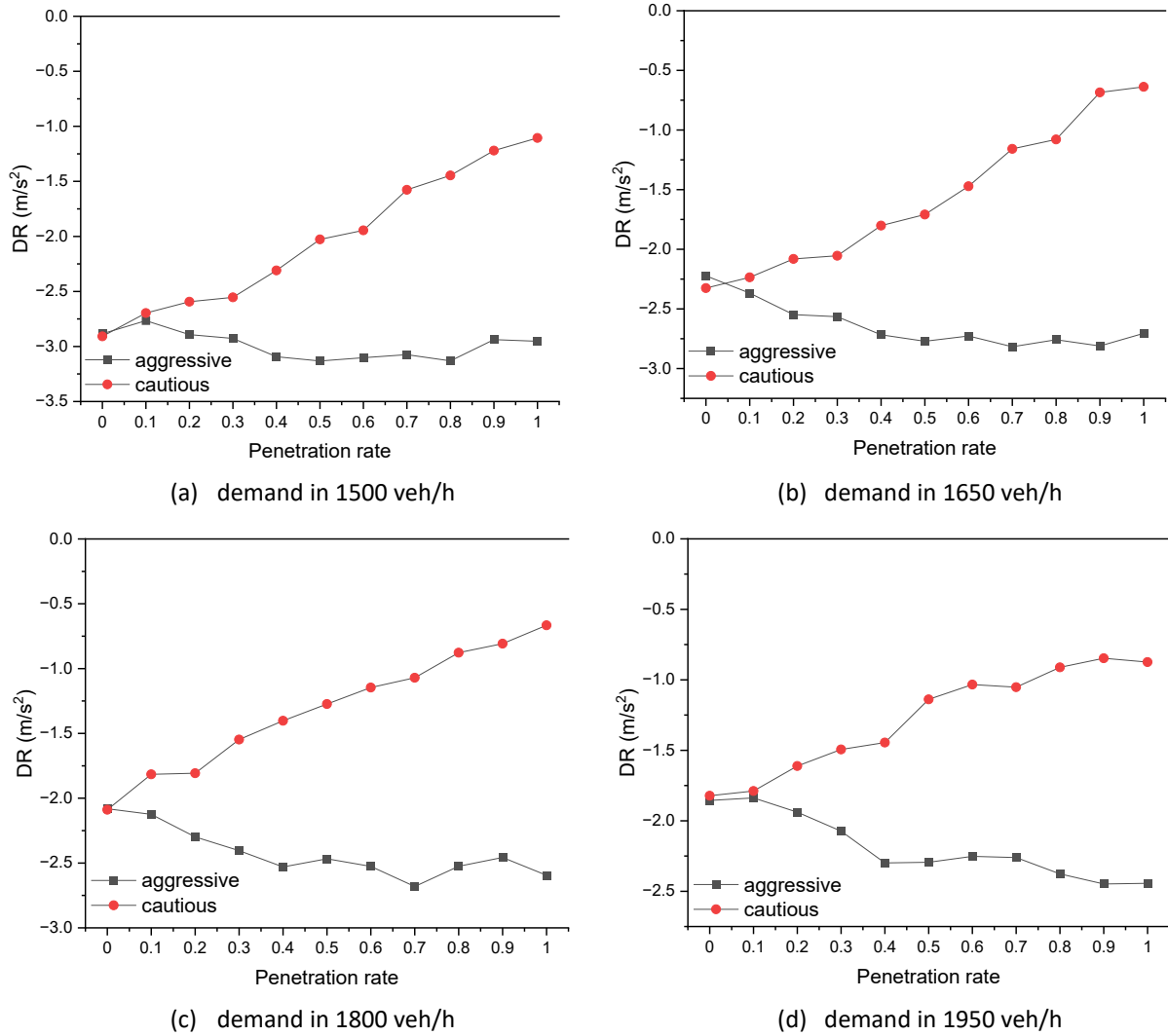


Figure 11 Deceleration rate under varying demand levels

Table 15 Two-way ANOVA results examining the effects of driving behaviour and traffic demand level on Deceleration rate (DR)

	DF	Sum of Squares	Mean Square	F Value	P Value
Demand level	3	7.68375	2.56125	16.45213	<0.0001
Driving behaviour	1	22.52897	22.52897	144.71425	<0.0001
Interaction	3	0.13858	0.04619	0.29672	0.82766

Figure 12 illustrates the maximum speed for cautious and aggressive vehicles under varying penetration rates under four demand levels. As demand level increases, maximum speeds decrease for both driving logics. For cautious AV, maximum speeds drop with a higher penetration rate, suggesting cautious vehicles face more interactions and adapt by driving slower. For aggressive AV, the MaxS is consistently higher than the cautious one, highlighting faster and more decisive manoeuvres.

Table 16 shows that driving behaviour has a very high F-value (193.11) and an extremely low p-value (<0.0001), indicating a strong and statistically significant effect on the dependent variable. Traffic demand level also shows a high F-value (22.99) with a very low p-value (<0.001), suggesting that it significantly influences the outcome. In contrast, the interaction between driving behaviour and demand level has a very low F-value (0.16) and a high p-value (0.921), indicating that the combine effect of these two factors is not statistically significant.

The results of maximum speeds highlight the trade-off between safety and performance. Cautious AVs prioritize conservative speed adjustments in dense environments, whereas aggressive AVs maintain higher operational speeds, potentially enhancing throughput but with less conservative behaviour.

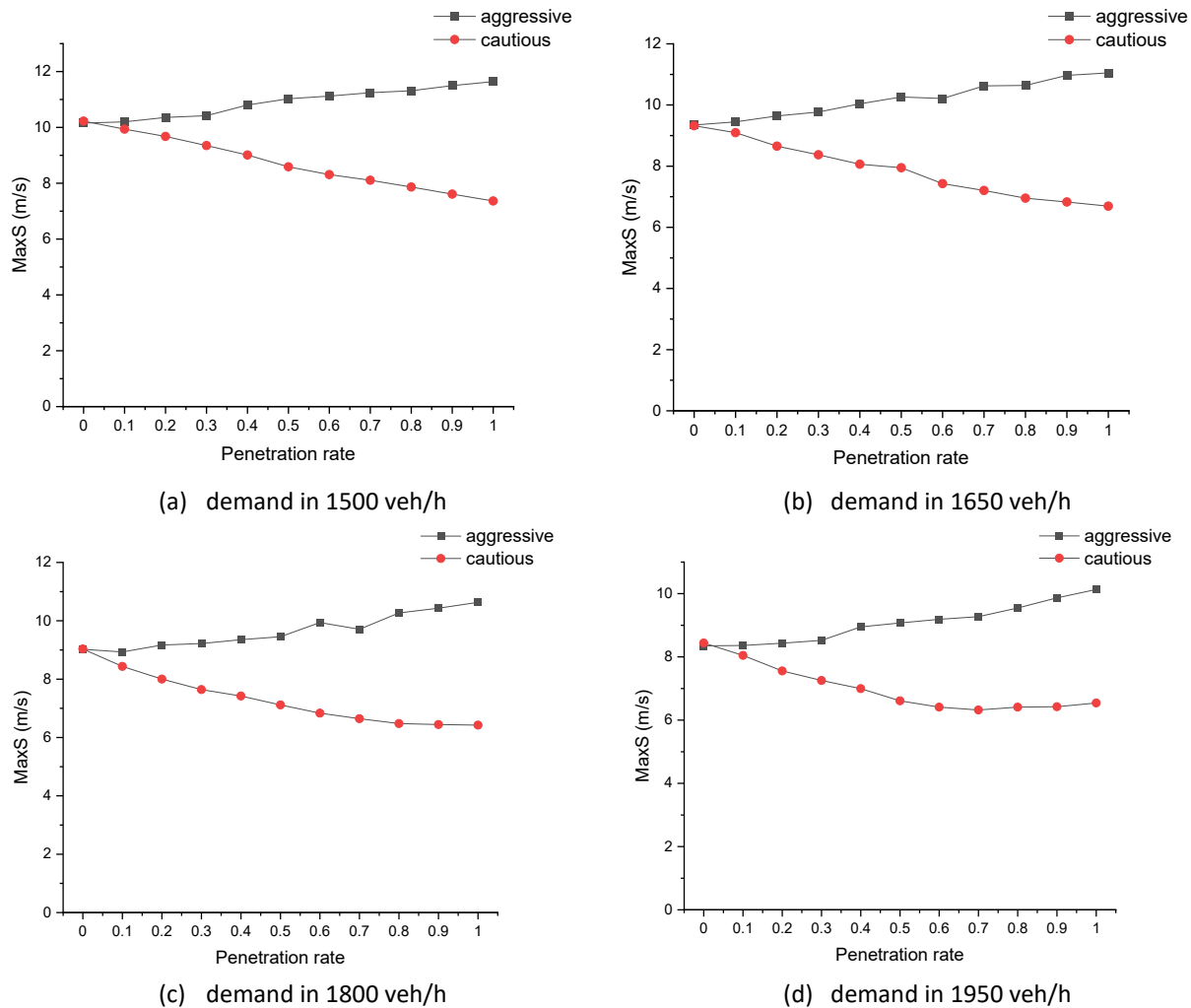


Figure 12 Maximum speed under varying demand levels

Table 16 Two-way ANOVA results examining the effects of driving behaviour and traffic demand level on Maximum

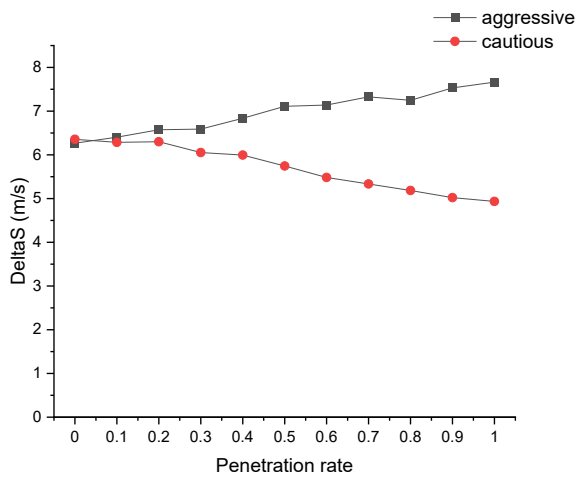
speed (MaxS)

	DF	Sum of Squares	Mean Square	F Value	P Value
Demand level	3	38.60055	12.86685	22.99513	<0.0001
Driving behaviour	1	108.05668	108.05668	193.1147	<0.0001
Interaction	3	0.27344	0.09115	0.16289	0.92103

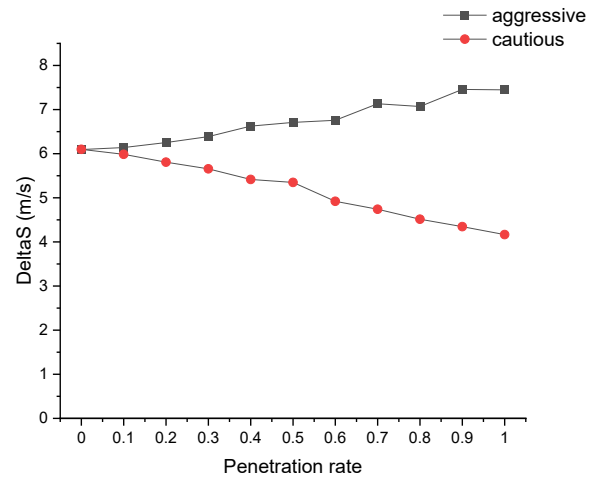
Figure 13 shows the difference in vehicle speeds for cautious and aggressive vehicles under varying penetration rates under four demand levels. Across all demand levels, the speed difference for both driving logics shows little variation. However, cautious AVs show decreasing variation in speed with higher penetration rates, suggesting more uniform and predictable behaviour. In contrast, the overall variation in speed increases for aggressing AVs, reflecting more dynamic and varied driving responses.

Table 17 shows that driving behaviour has a very high F-value (177.44) and a very low p-value (<0.001), indicating a strong and statistically significant effect on vehicle speed variation. This suggests that autonomous vehicles with different behavioural profiles (aggressive, cautious) exhibit significantly different average speeds. Travel demand level also shows a high F-value (12.11) and a low p-value (<0.001), meaning it significantly affects vehicle speed. However, the interaction between driving behaviour and demand level has a low F-value (1.37) and a high p-value (0.257), indicating that the combined effect of those two factors is not significant.

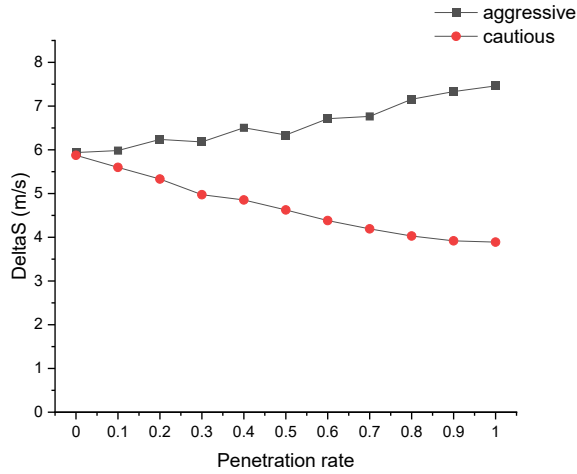
The trends suggest that cautious AVs promote more uniform traffic flow at higher market penetration, contributing to predictable vehicle behaviour. In contrast, the increased variability among aggressive AVs may lead to more fluctuating speed patterns, potentially affecting flow stability under higher AV penetration rates.



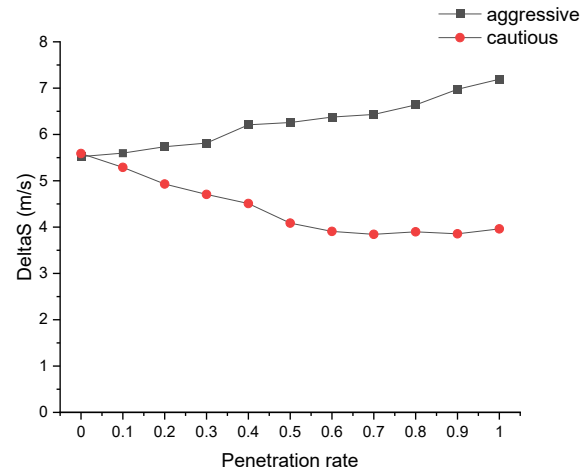
(a) demand in 1500 veh/h



(b) demand in 1650 veh/h



(c) demand in 1800 veh/h



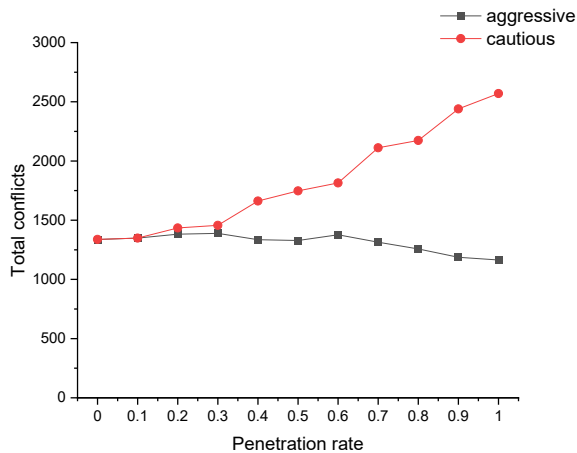
(d) demand in 1950 veh/h

Figure 13 Difference in vehicle speeds under varying demand levels

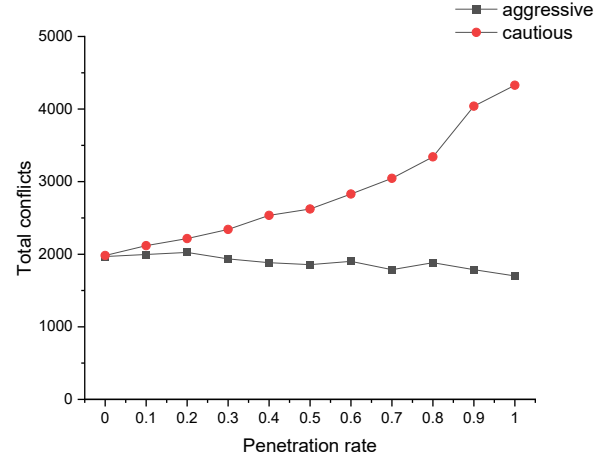
Table 17 Two-way ANOVA results examining the effects of driving behaviour and traffic demand level on Difference in vehicle speeds (DeltaS)

	DF	Sum of Squares	Mean Square	F Value	P Value
Demand level	3	12.12408	4.04136	12.11387	<0.0001
Driving behaviour	1	59.19775	59.19775	177.44359	<0.0001
Interaction	3	1.37421	0.45807	1.37305	0.25702

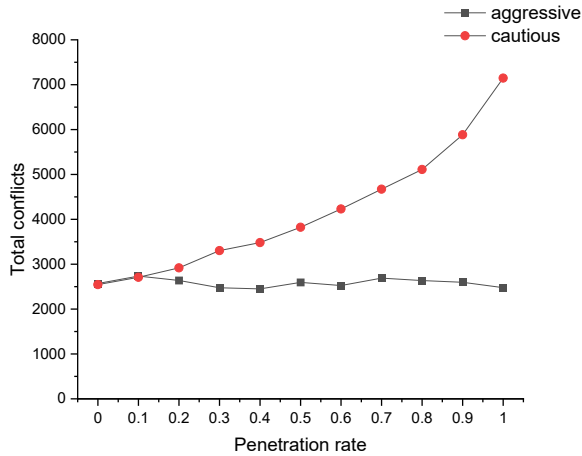
Figure 14 shows the total conflicts of cautious AV and aggressive AV under varying penetration rates. Cautious AV has higher total conflicts compared to aggressive AV at all penetration rate under all demand levels, which due to conservative driving behaviour, creates bottlenecks and frequent interactions. For aggressive AV, conflicts increase moderately under higher demand levels but remain relatively stable at varying penetration rates.



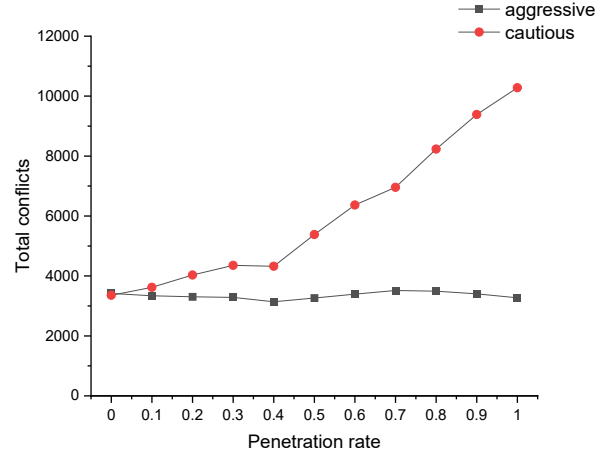
(a) demand in 1500 veh/h



(b) demand in 1650 veh/h



(c) demand in 1800 veh/h



(d) demand in 1950 veh/h

Figure 14 Total conflicts under varying demand levels

Figures 15-18 use conflict points and location data, showing the distribution of conflicts compared with cautious and aggressive vehicles under 0%, 50% and 100%, with kernel density estimates. The X-axis shows the position on the road, Y-axis shows the conflict density, and the curve shape shows how delay is distributed. A high density of conflicts is observed around the position at 510, suggesting a hotspot likely due to merging or lane changing. Under the same penetration rate, aggressive AVs show a sharper peak in conflict density at hotspot, indicating riskier interactions. Cautious AVs produce a more distributed conflict profile, suggesting smoother and safer interactions over space.

Figure 15 shows both cautious and aggressive driving logics exhibit similar conflict density distributions under low traffic demand, characterized by sharp peaks, indicating localized concentrations of conflicts. As demand increases to 1650 veh/h shown in Figure 16, the conflict distribution for cautious AVs becomes more spread out with a higher penetration rate, suggesting a smoother and less concentrated pattern of interactions. In contrast, aggressive AVs tend to maintain a relatively sharper and more consistent conflict profile.

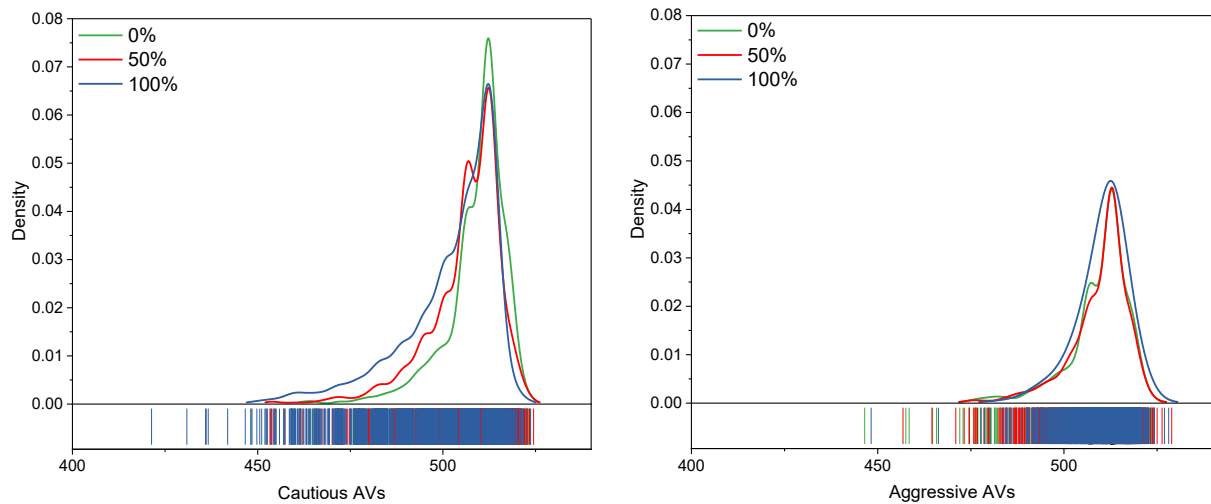


Figure 15 Conflict points distribution in demand 1500 veh/h

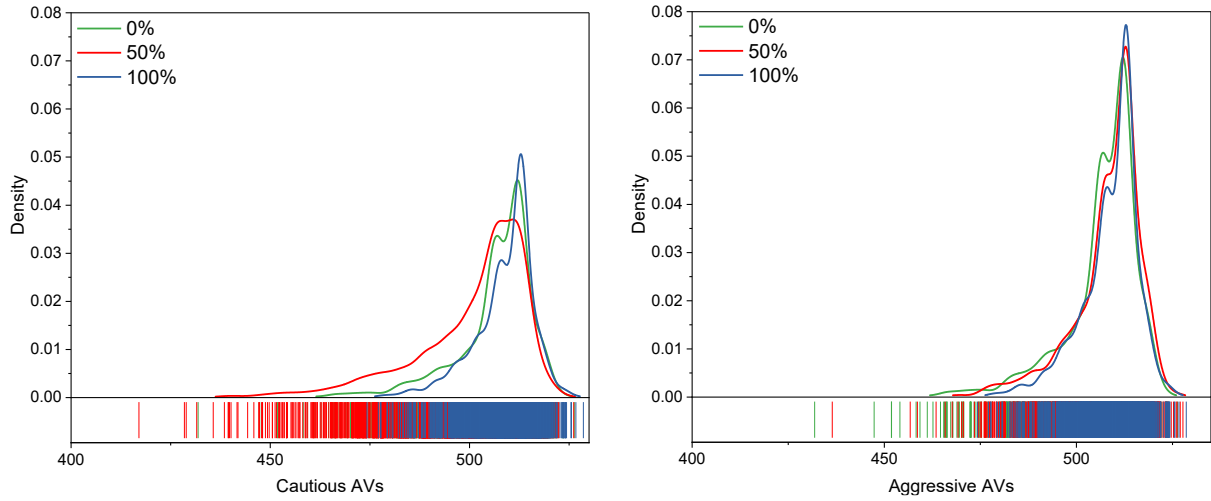


Figure 16 Conflict points distribution in demand 1650 veh/h

At higher demand levels (1800 veh/h and 1950 veh/h) shown in Figure 17 and Figure 18, the conflict densities tend to become wider distributed at lower AV penetration rates for both driving logics. However, as AV penetration increases, a divergence appears: cautious AVs continue to show increasingly distributed conflict profiles, while aggressive AVs revert to sharper, more localized peaks, indicating increased conflict concentration in the hotspot.

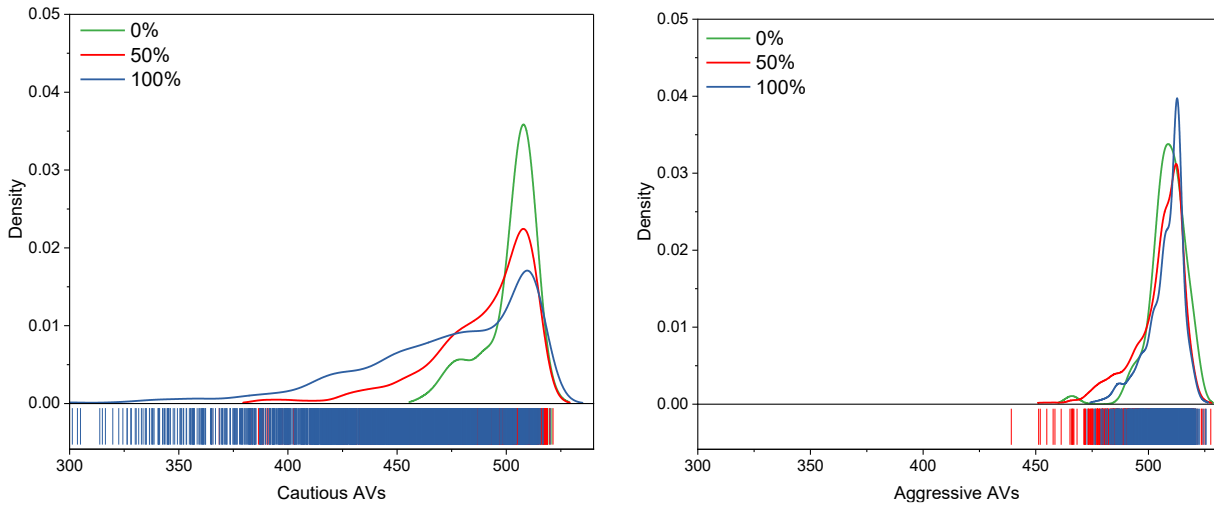


Figure 17 Conflict points distribution in demand 1800 veh/h

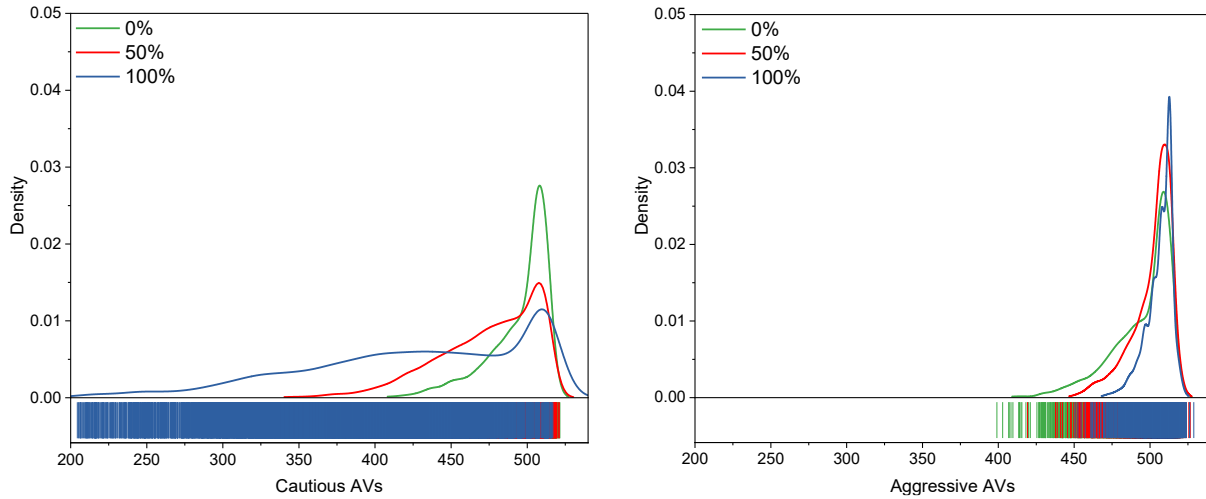


Figure 18 Conflict points distribution in demand 1950 veh/h

The conflict density distribution plots illustrate a minimal difference in conflict behaviour between cautious and aggressive AVs when the traffic flow is light and interactions are limited. As traffic demand increases, notable differences emerge. The conflict density distribution for cautious AVs begins to spread out, particularly at higher AV penetration rates. This broader distribution indicates a more dispersed pattern of conflict locations or timing, due to the conservative behaviour of cautious AVs in managing space and reacting to surrounding vehicles. Under higher traffic demand, at a low AV penetration rate, both driving logics show more spread-out conflict distributions, which means that when most vehicles are human-driven, conflicts happen in many different locations, due to inconsistent driving behaviour in heavy traffic. With more cautious AVs, conflict distribution becomes even more spread out, which suggests that cautious AVs maintain more space and react earlier. This behaviour may improve safety by reducing intense conflict. For aggressive AVs, the conflict density becomes more concentrated, forming sharper peaks. This indicates that aggressive AVs tend to create localized hotspots of conflict, especially near the bottleneck. Their behaviour, such as fast merging and less yielding may help maintain flow but also increase the risk of intense interactions in certain areas.

4.4 Parameters influencing conflict impact

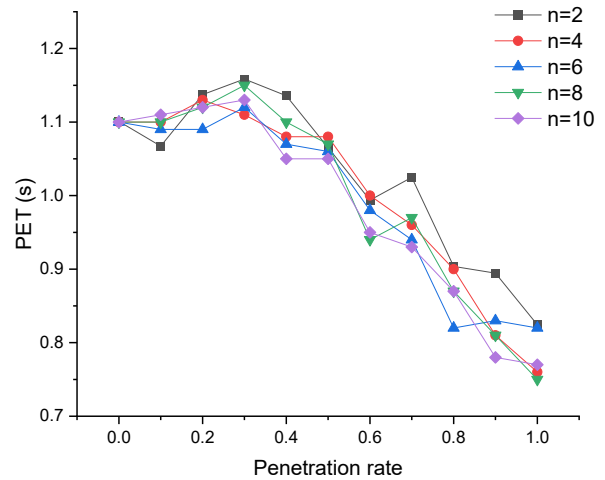
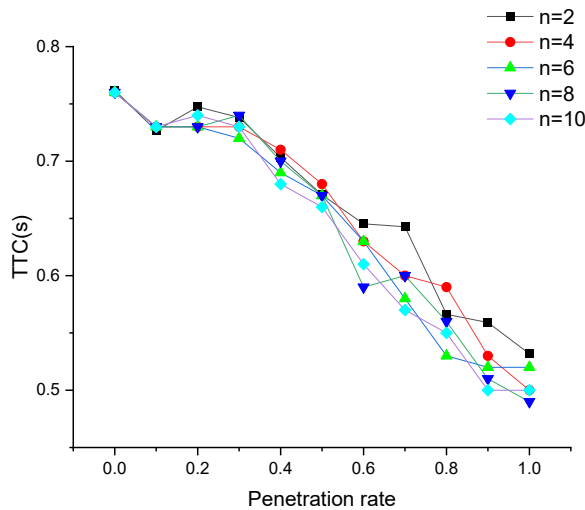
To evaluate how individual lane-changing parameters influence traffic safety, we conducted a parameter study. By varying one parameter at a time across different driving behaviours, such as the number of interaction objects, number of interaction vehicles and maximum deceleration, the safety impacts are then quantified using established metrics like TTC, PET and DR.

The number of interaction objects refers to the number of preceding vehicles or the number of other network objects, such as reduced speed areas, conflict areas and priority rules along the path in order to react to them. The number of vehicles measures the number of preceding vehicles that the vehicle perceives along its route or path to react to them. Maximum deceleration refers to the highest rate at which a vehicle can safely reduce its speed.

Table 18 Testing parameter values

Parameter	Default value of cautious AVs	Default value of Aggressive AVs	Testing values for each parameter				
Number of interaction objects	2	10	2	4	6	8	10
Number of interaction vehicles	1	9	1	3	5	7	9
Maximum deceleration (m/s ²)	-3.5	-4	-2	-3	-4	-5	-6

Figure 19 and Figure 20 show how adjustments to the number of interaction objects of cautious AVs and aggressive AVs affect the safety outcomes. The number of interaction objects influences cautious and aggressive AVs differently. Cautious AVs maintain stable safety performance regardless of object number. This is because cautious AVs are programmed to maintain larger time gaps, earlier braking and more defensive manoeuvres, allowing them to respond safely. In contrast, aggressive AVs become riskier in fewer interaction objects, as they are more likely to make assertive manoeuvres, such as sharp lane changes or close-gap merging. This can lead to higher conflict intensity, as reflected in surrogate safety metrics like shorter PET and higher DR. Aggressive AVs rely on quick, opportunistic decisions, so when fewer objects are perceived, they may not anticipate downstream conflicts effectively.



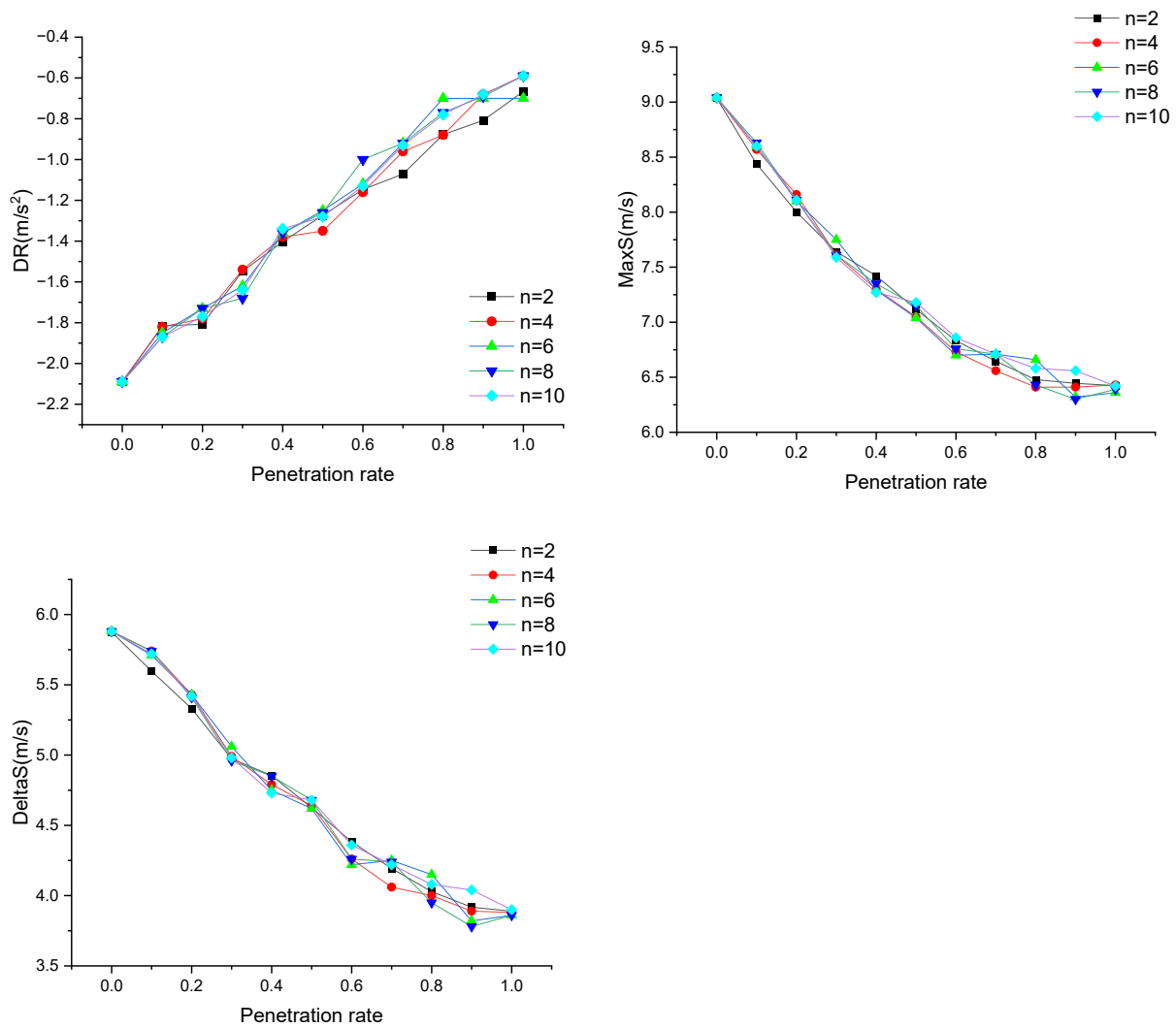
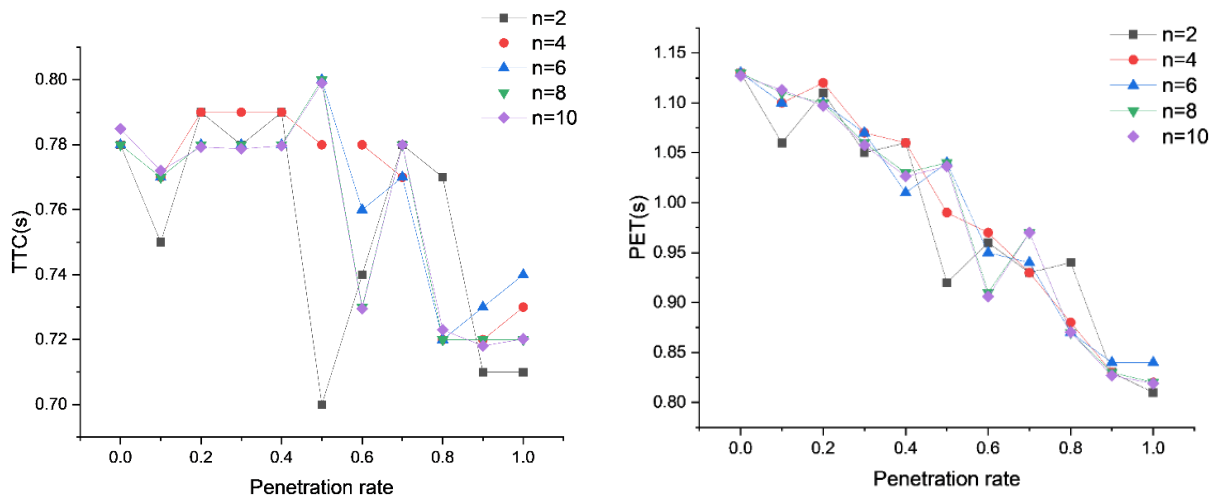


Figure 19 Safety metrics for varying number of interaction objects of cautious AVs



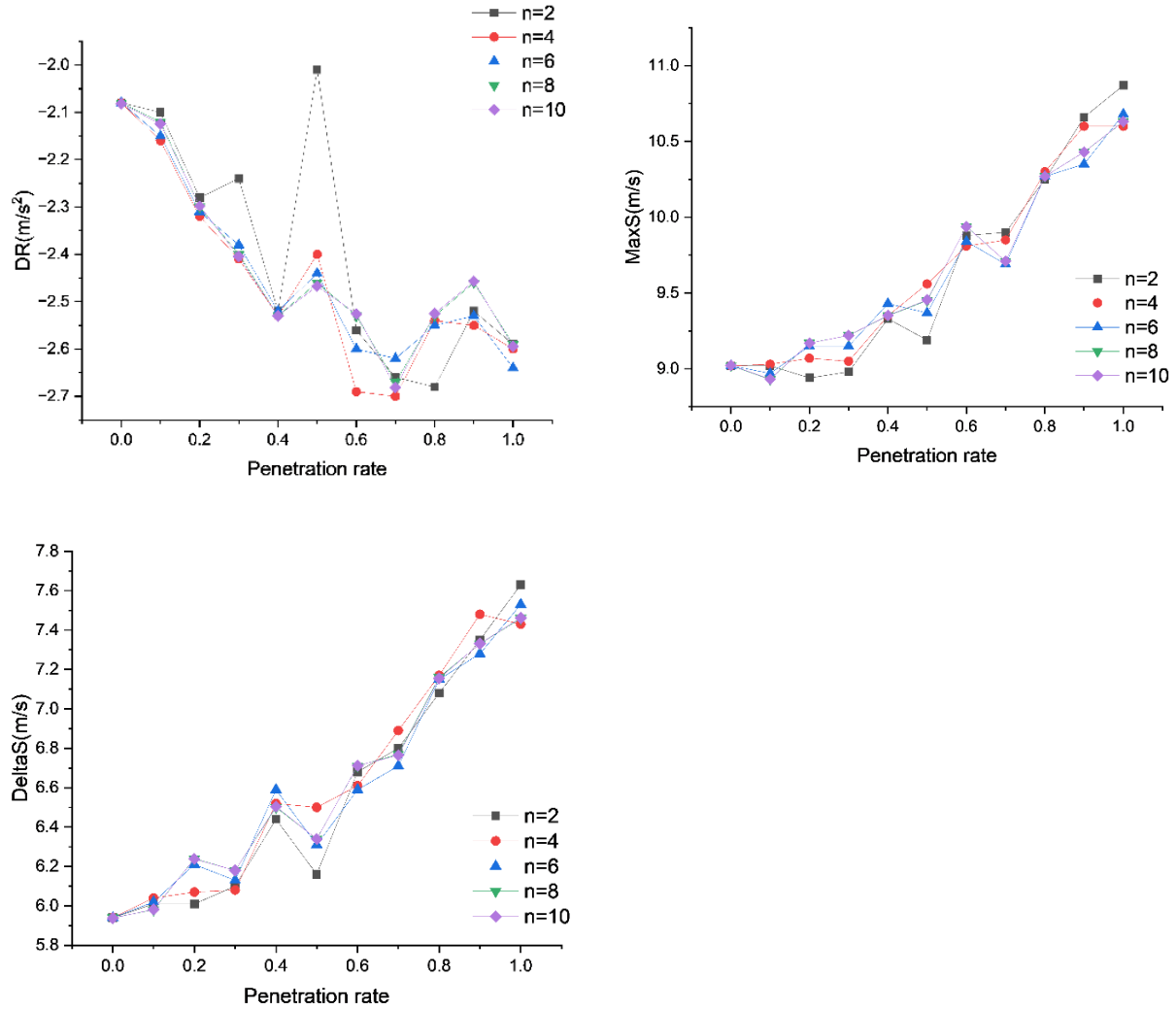


Figure 20 Safety metrics for varying number of interaction objects of aggressive AVs

Figure 21 and Figure 22 show how changes in the number of interaction vehicles affect safety outcomes for both cautious AVs and aggressive AVs. The results indicate that both logics tend to perform better when the number of interaction vehicles is lower. Cautious AVs show stable severity of conflict likelihood across varying levels of AV penetration. Aggressive AVs, on the other hand, also benefit from having fewer interaction vehicles, but their performance is more sensitive to changes in interaction vehicles.

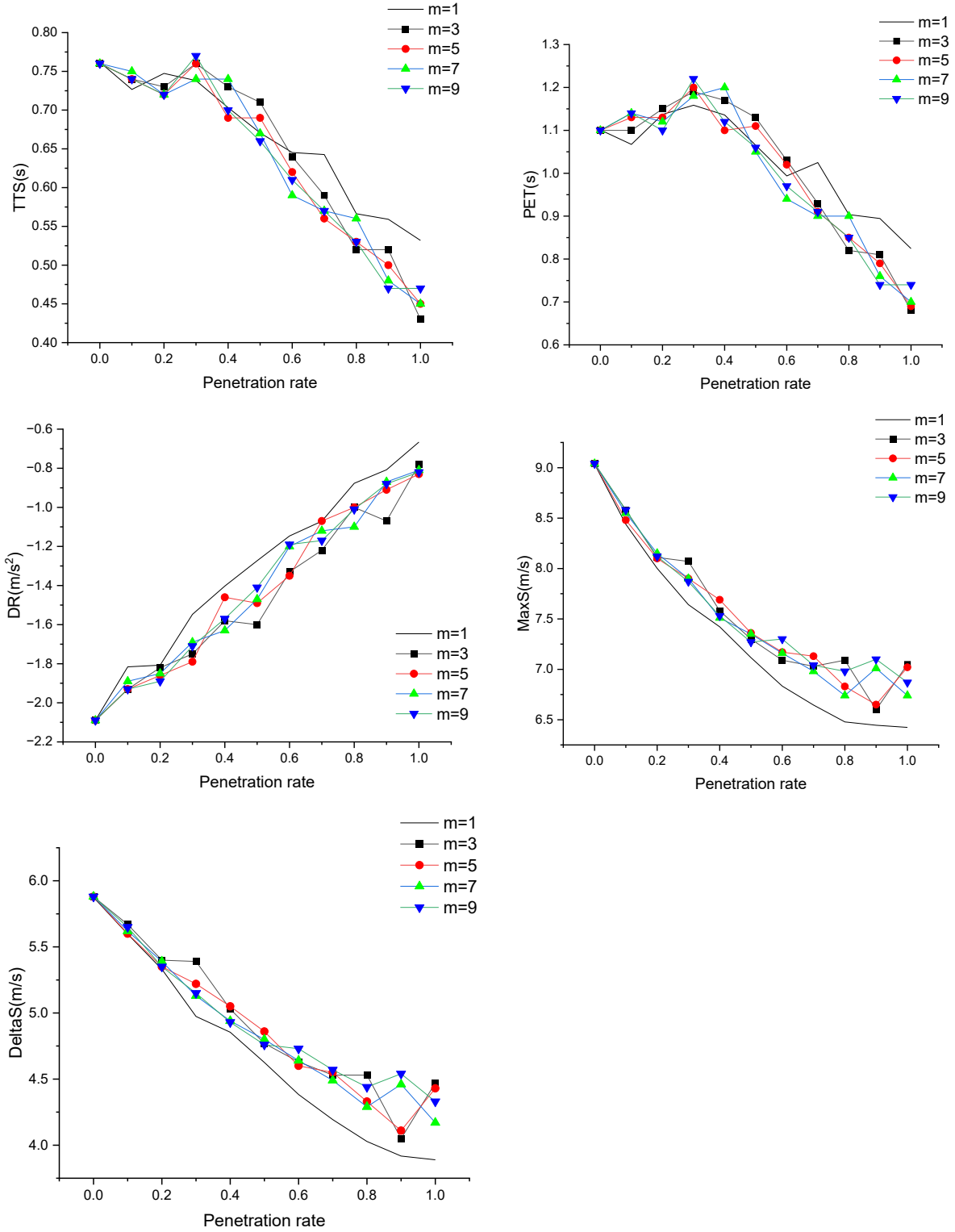


Figure 21 Safety metrics for varying number of interaction vehicles of cautious AVs

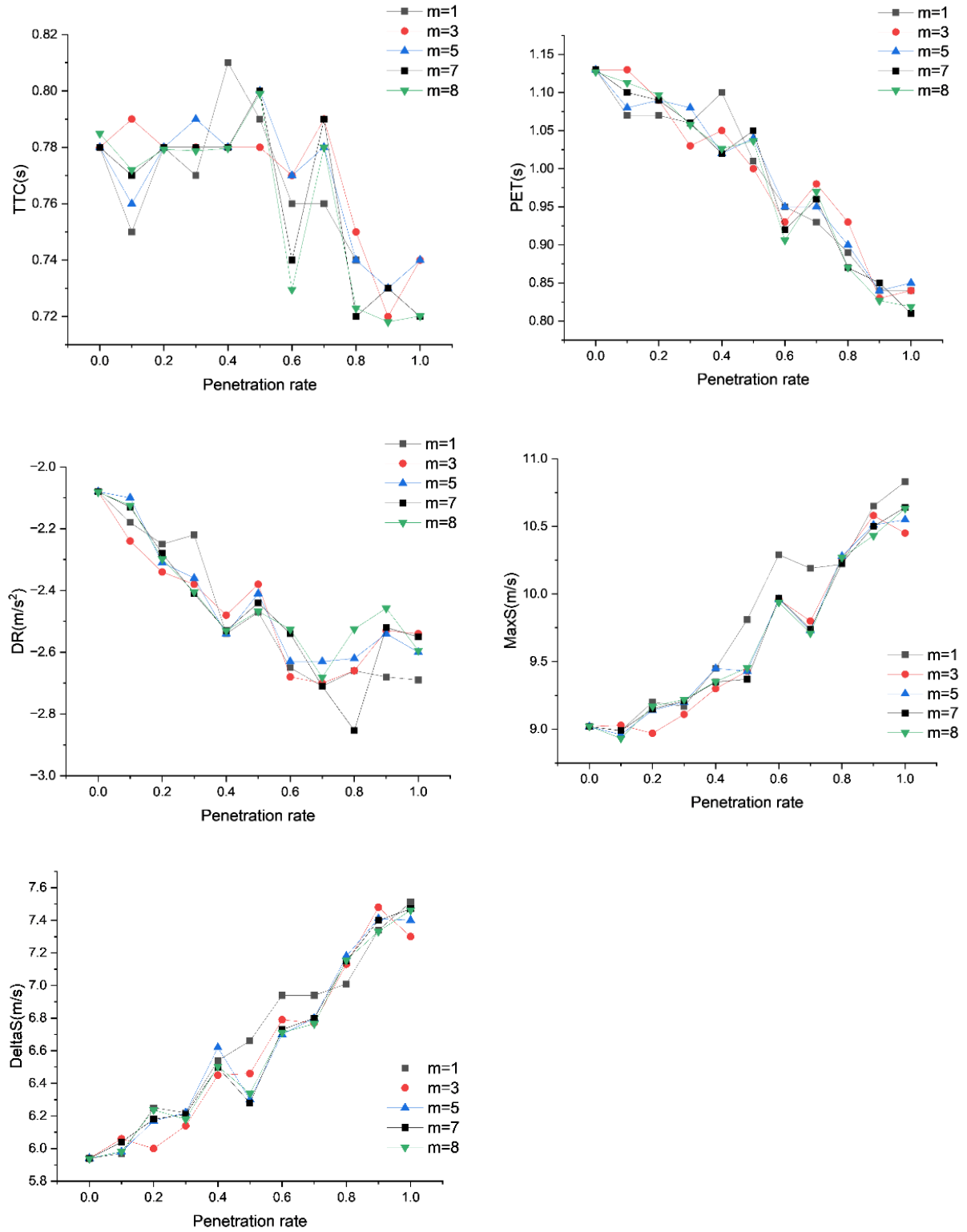


Figure 22 Safety metrics for varying number of interaction vehicles of aggressive AVs

Figure 23 and Figure 24 show the varying maximum deceleration influence the safety. Varying the maximum deceleration setting showed minimal impact on the performance for both driving logics. This lack of significant difference can be attributed that under normal traffic conditions, even near bottlenecks, vehicles rarely operate at their maximum deceleration limits.

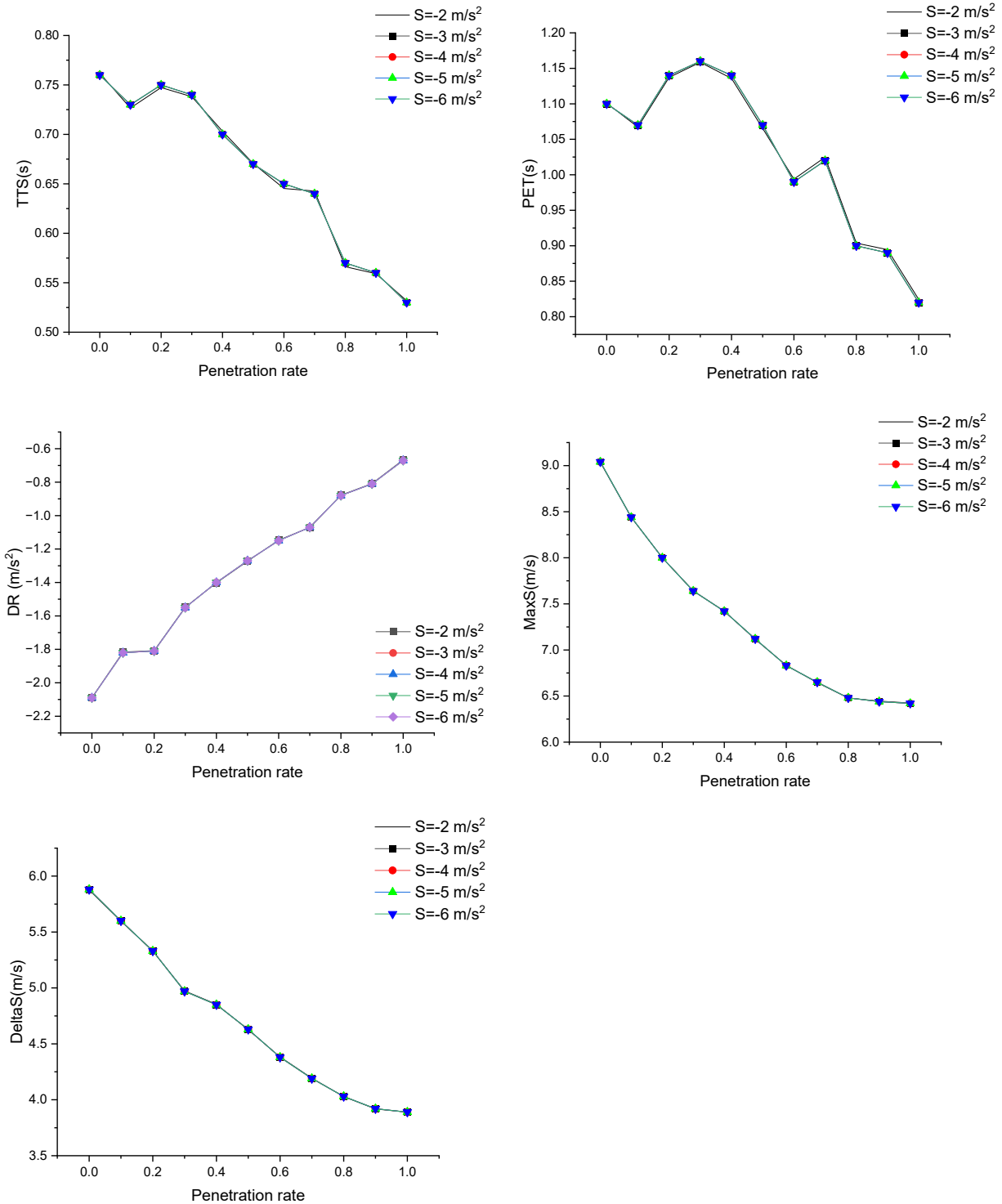


Figure 23 Safety metrics for varying maximum deceleration of cautious AVs

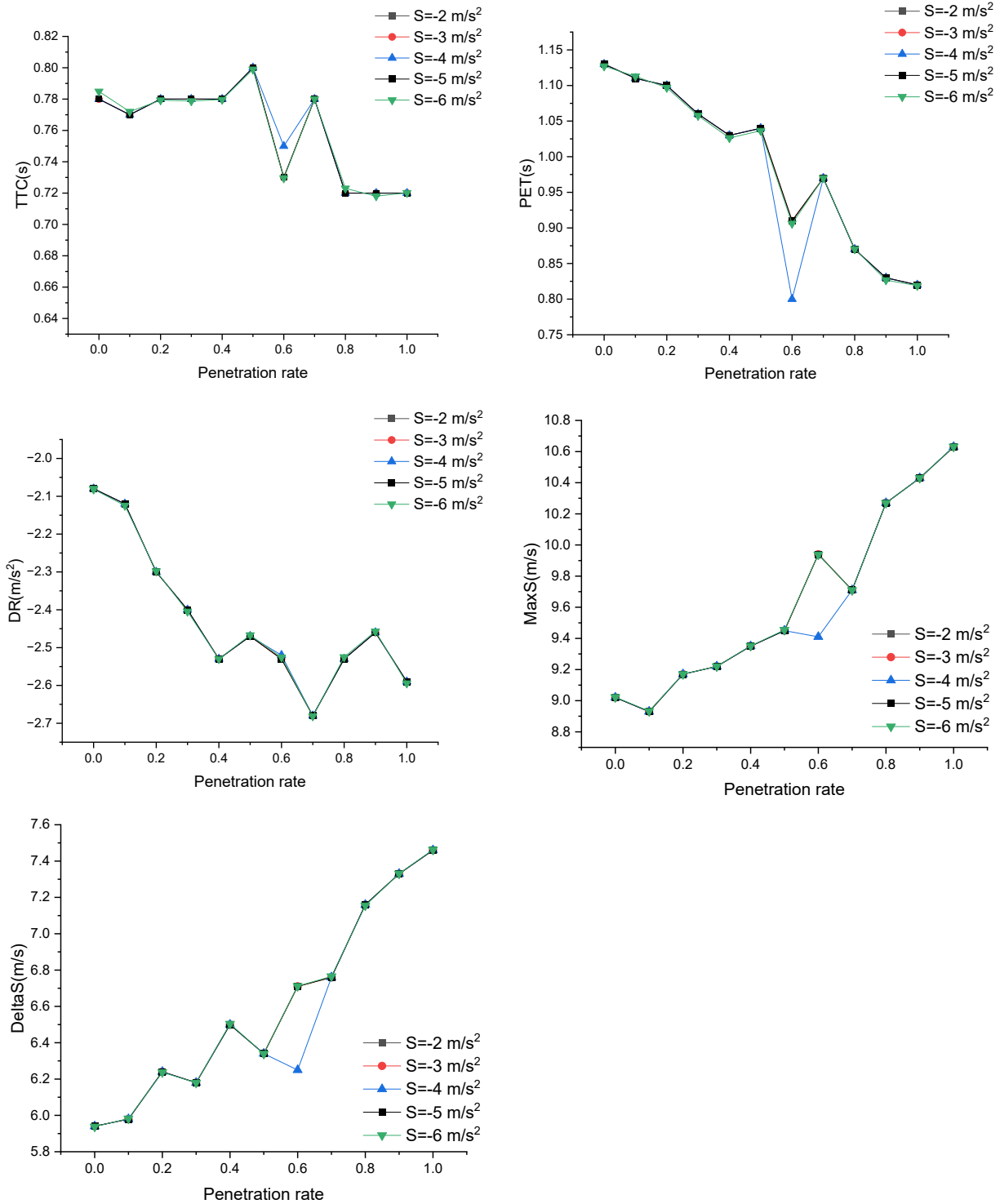


Figure 24 Safety metrics for varying maximum deceleration of aggressive AVs

In conclusion, the number of interaction objects affects the two driving logics in different ways. Cautious AVs remain stable and are less sensitive to environmental complexity because their driving decisions remain predictable safe under both simple and complex interaction scenarios. Aggressive AVs show a greater sensitivity

to the number of interaction objects and require more situational awareness to maintain safe performance. This implies that improving perception systems and cooperative information sharing is important for aggressive AVs in complex or constrained environments.

Moreover, vehicles with more interaction vehicles will result in higher potential severity of collision. A higher number of interaction vehicles leads to more frequent adjustments in speed, headway or changing lanes, which can increase the likelihood of traffic conflicts. A lower number of perceived vehicles decreased the total conflict count but resulted in more severe conflicts due to late reactions. More interaction vehicles can increase the frequency of reactions and potential conflicts. These findings suggest that reducing interaction complexity, either by fewer surrounding vehicles or by the improved coordination, can lower conflict risk and increase stability. In particular, the sensitivity of aggressive AVs to interaction complexity highlights the need for careful calibration of AV behaviour models in mixed traffic.

Varying the maximum deceleration setting showed minimal impact on the performance of both cautious and aggressive AVs. Even for aggressive AVs, which have shorter headways and quicker responses, the maximum deceleration threshold is not engaged unless a critical conflict happens. Most interactions are managed through moderate braking and lane-changing behaviour before applying the maximum deceleration. As a result, the differences in this parameter do not influence merging conflict outcomes, particularly when AVs are operating within a structured, rule-based driving environment.

Chapter 5 Conclusions

5.1 Summary

This study investigated the performance of autonomous vehicles (AVs) with different driving logics in a mixed traffic environment. The analysis focused on varying AVs market penetration rates and traffic demand levels. These scenarios are placed on lane-drop bottlenecks, where mandatory lane changes frequently lead to congestion and safety risks. As AVs become increasingly integrated into road networks, understanding their behaviour in complex merging scenarios is critical for ensuring safe and efficient traffic flow, especially in mixed traffic.

Using VISSIM microsimulation and surrogate safety analysis, the study modelled three AV driving styles—cautious, normal and aggressive. Efficiency was evaluated through stop delay and vehicle delay, while safety was assessed using surrogate indicators such as time-to-collision (TTC), post-encroachment time (PET), deceleration rate (DR), and conflict counts. The results highlight important trade-offs between traffic efficiency and safety outcomes, as well as the influence of behavioural model parameters on system dynamics.

This study emphasizes the importance of adaptive AV behaviour design, where AVs can adjust their driving logic based on real-time traffic composition, penetration rate, and environment complexity. Such adaptability will be essential for achieving both safe and efficient traffic flow as autonomous vehicles become an integral part of future transportation systems.

5.2 Findings

The simulation results highlight that each AV driving logic presents distinct benefits and limitations.

Cautious AVs adopt conservative behaviours, such as smoother acceleration, longer headways and gradual braking, which help maintain stable and uniform traffic flow, though often at the cost of increased delays. Aggressive AVs, on the other hand, follow vehicles more closely, change lanes more assertively, and decelerate rapidly, aiming to minimize traffic delays but with higher potential risks. Normal AVs offer a balanced strategy, maintaining reasonable headway and responding dynamically to traffic conditions.

In terms of efficiency, the results show that cooperation is beneficial for all driving logics and helps reduce delays. However, the impact of AV behaviour varies with penetration level: cautious AVs lead to increased delays as their penetration grows, while aggressive AVs show decreasing delays with higher penetration rates. Normal AVs maintain stable performance across all penetration levels.

From a safety perspective, simulation metrics such as time-to-collision, post-encroachment time demonstrate key differences between cautious and aggressive AVs. Aggressive AVs exhibit better TTC values and fewer recorded conflicts due to quicker responses, but their higher speeds and fluctuating driving patterns increase the severity and risk of potential collisions, particularly under high density conditions. Cautious AVs, although show lower TTC values at higher penetration due to platooning effects, show advantages in merging margins, stable deceleration profiles and lower speed variability, reinforcing their role in maintaining a uniform traffic stream.

This study contributes an understanding of how AV behaviour settings interact with traffic conditions and network complexity. It highlights that no single AV behaviour is optimal across all scenarios. Cautious AVs are best suited for early-stage deployment, ensuring stability and predictability in mixed traffic. Normal AVs provide

the most versatile and balanced strategy, especially in transitional periods with moderate AV penetration. Aggressive AVs are most effective in high penetration, fully automated networks, where their assertiveness is supported by uniform behaviour and coordination.

5.3 Future work

Despite these insights, the study has some limitations. The simulation framework does not account for real-world variability such as communication failures, sensor errors, or human unpredictability. Future research could incorporate connected vehicle technologies, real-time decision-making algorithms, or multiple lane freeway scenarios to further evaluate the performance of different AV logics under realistic traffic conditions. Additionally, although this study utilizes the surrogate safety assessment models to evaluate conflicts, the analysis primarily relied on individual safety indicators in an isolated manner. While these metrics provide valuable insights, analysing them independently may not fully capture the composite safety performance of different AV driving logics. Future work should focus on applying a weighted scoring system or a multi-criteria evaluation framework to gain a comprehensive safety index.

In conclusion, this study emphasizes the importance of adaptive AV behaviour design, where AVs can adjust their driving logic based on real-time traffic composition, penetration rate, and environment complexity. Such adaptability will be essential for achieving both safe and efficient traffic flow as autonomous vehicles become an integral part of future transportation systems.

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Appendix A

This appendix presents the results of the two-way ANOVA for the effects of driving behaviour and traffic demand on conflict performance metrics discussed in Section 4.3. Factor A presents the different demand level, categorized into 1500 veh/h, 1650 veh/h, 1800 veh/h and 1950 veh/h; Factor B presents the different driving behaviour, categorized into cautious and aggressive. The following dependent variables were analyzed separately: time-to-collision (TTC), post-encroachment-time (PET), deceleration rate (DR), maximum speed (MaxS) and difference of vehicle speed (DeltaS).

TTC

Table A1 Two-way ANOVA results of demand level and TTC value

	N	Mean	SD	SEM	Variance
1500	22	0.71118	0.06234	0.01329	0.00389
1650	22	0.70996	0.07665	0.01634	0.00587
1800	22	0.7117	0.07806	0.01664	0.00609
1950	22	0.72393	0.07976	0.017	0.00636

Table A2 Two-way ANOVA results of driving behaviour and TTC value

	N	Mean	SD	SEM	Variance
aggressive	44	0.76008	0.02214	0.00334	4.90356E-4
cautious	44	0.66831	0.0782	0.01179	0.00611

Table A3 TTC value calculation

	N	Mean	SD	SEM	Variance
	88	0.71419	0.07345	0.00783	0.00539

Table A4 Two-way ANOVA results of interaction between driving behaviour and demand level

		N	Mean	SD	SEM	Variance
1500	aggressive	11	0.75059	0.01478	0.00446	2.18442E-4
	cautious	11	0.67177	0.06727	0.02028	0.00453
1650	aggressive	11	0.75622	0.01253	0.00378	1.57097E-4
	cautious	11	0.66371	0.08644	0.02606	0.00747
1800	aggressive	11	0.7604	0.03072	0.00926	9.43481E-4
	cautious	11	0.663	0.08145	0.02456	0.00663
1950	aggressive	11	0.77311	0.02207	0.00665	4.87163E-4
	cautious	11	0.67474	0.08689	0.0262	0.00755

Table A5 Two-way ANOVA results of driving behaviour and demand level

	DF	Sum of Squares	Mean Square	F Value	P Value
Demand level	3	0.00281	9.37992E-4	0.26812	0.8482
Driving behaviour	1	0.1853	0.1853	52.96738	<0.0001
Interaction	3	0.00134	4.4646E-4	0.12762	0.94346
Model	7	0.18946	0.02707	7.73637	<0.0001
Error	80	0.27988	0.0035		

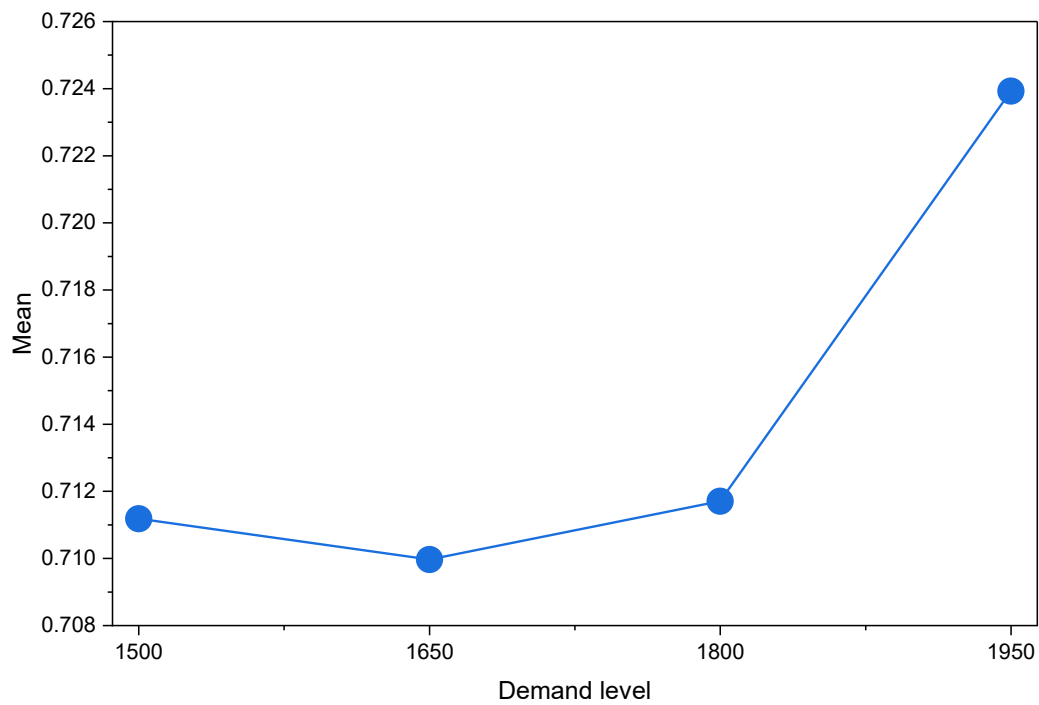
Corrected Total	87	0.46933
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At the 0.05 level, the population means of Demand level are not significantly different.

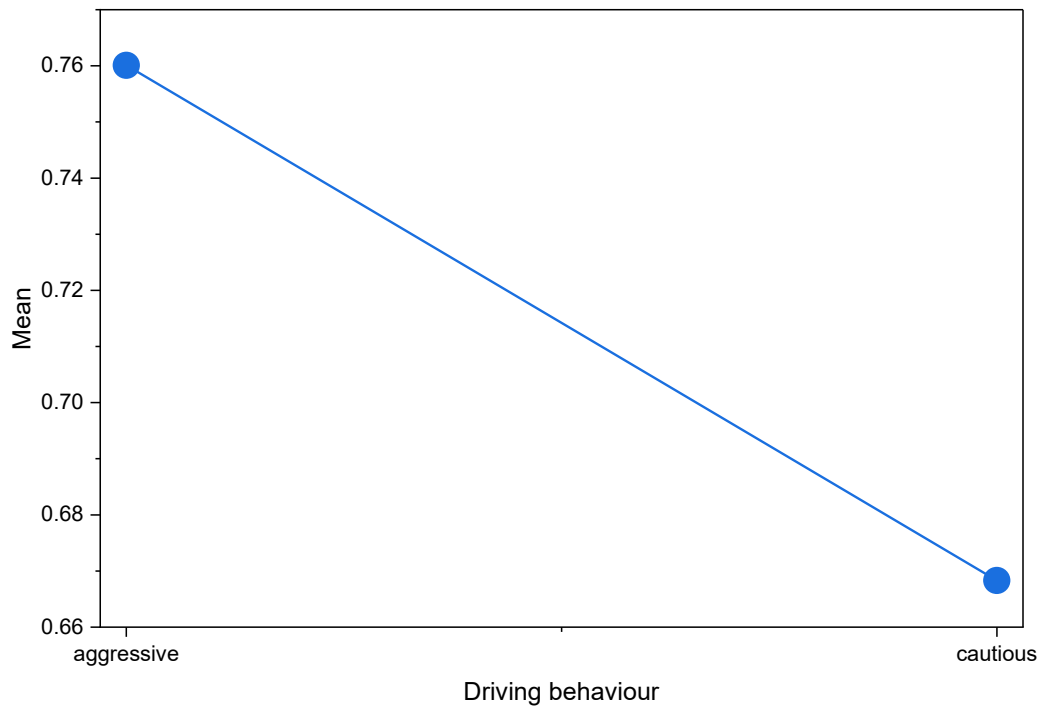
At the 0.05 level, the population means of Driving behaviour are significantly different.

At the 0.05 level, the interaction between Demand level and Driving behaviour is not significant.

(a) Factor A



(b) Factor B



(c) Interaction

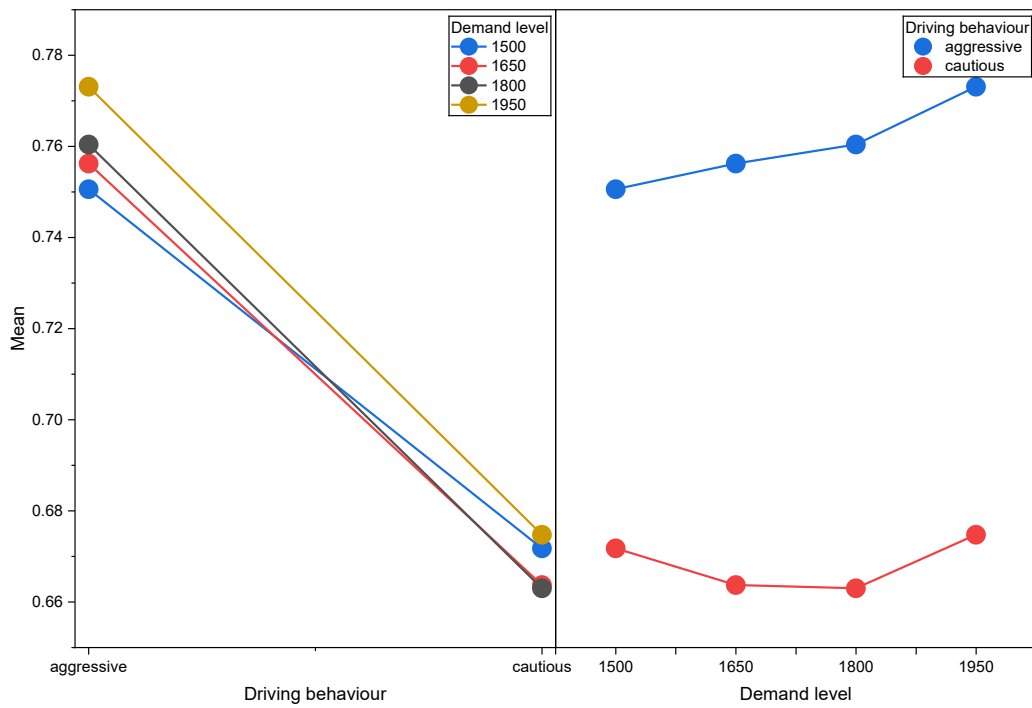


Figure A1 Two-way ANOVA results of driving behaviour and demand level for TTC value

PET

Table A6 Two-way ANOVA results of demand level and PET value

	N	Mean	SD	SEM	Variance
1500	22	0.9268	0.09256	0.01973	0.00857
1650	22	0.97115	0.09374	0.01998	0.00879
1800	22	1.00708	0.11236	0.02395	0.01262
1950	22	1.04624	0.1309	0.02791	0.01714

Table A7 Two-way ANOVA results of driving behaviour and PET value

	N	Mean	SD	SEM	Variance
aggressive	44	0.95357	0.11976	0.01805	0.01434
cautious	44	1.02207	0.10125	0.01526	0.01025

Table A8 Two-way ANOVA results of interaction between driving behaviour and demand level

		N	Mean	SD	SEM	Variance
1500	aggressive	11	0.85849	0.07768	0.02342	0.00603
	cautious	11	0.99512	0.04111	0.0124	0.00169
1650	aggressive	11	0.91858	0.07376	0.02224	0.00544
	cautious	11	1.02372	0.08325	0.0251	0.00693
1800	aggressive	11	0.98632	0.1144	0.03449	0.01309
	cautious	11	1.02785	0.11169	0.03367	0.01247
1950	aggressive	11	1.0509	0.11921	0.03594	0.01421
	cautious	11	1.04158	0.1474	0.04444	0.02173

Table A9 Two-way ANOVA results of driving behaviour and demand level

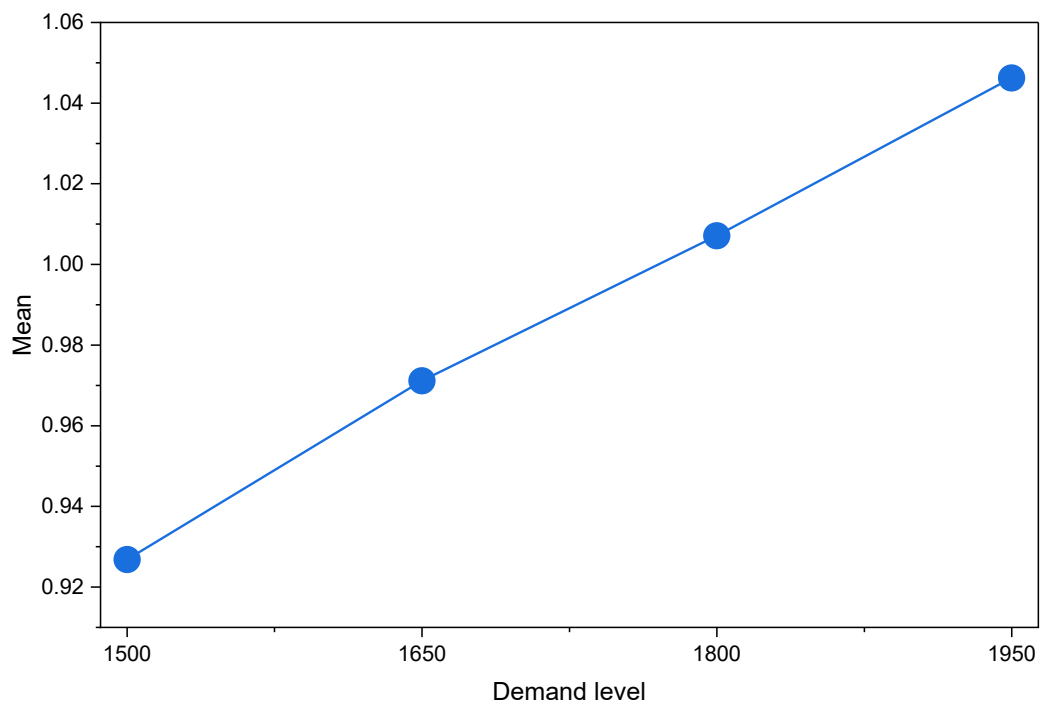
	DF	Sum of Squares	Mean Square	F Value	P Value
Demand level	3	0.17128	0.05709	5.59763	0.00155
Driving behaviour	1	0.10322	0.10322	10.12064	0.00209
Interaction	3	0.07022	0.02341	2.29503	0.0841
Model	7	0.34473	0.04925	4.82837	1.42309E-4
Error	80	0.81595	0.0102		
Corrected Total	87	1.16068			

At the 0.05 level, the population means of Demand level are significantly different.

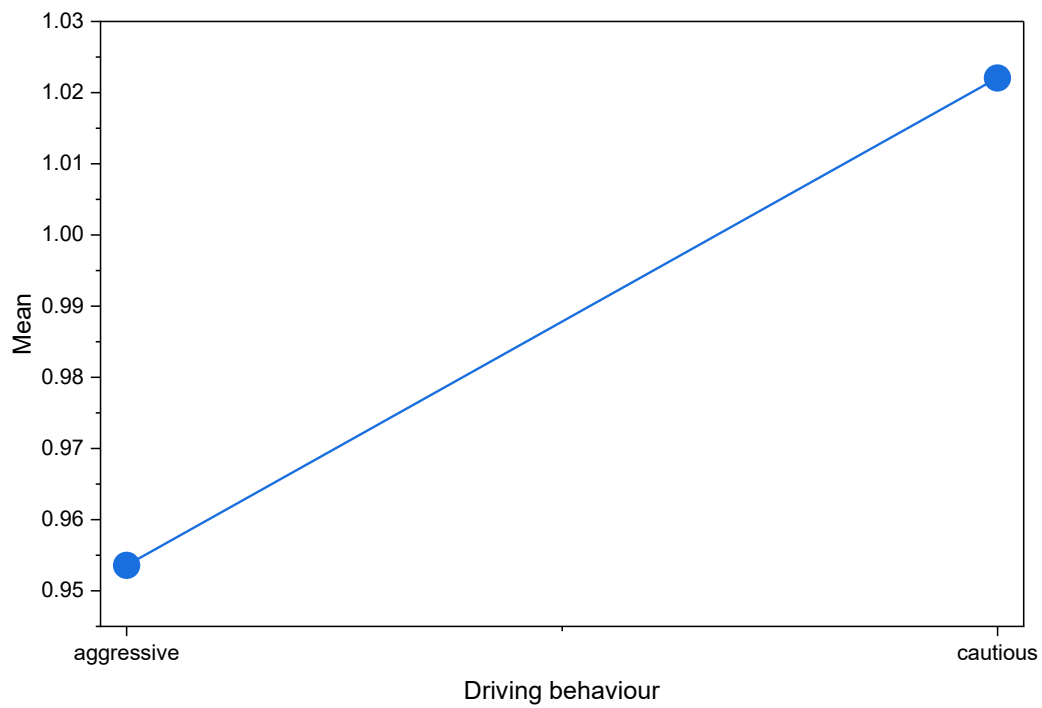
At the 0.05 level, the population means of Driving behaviour are significantly different.

At the 0.05 level, the interaction between Demand level and Driving behaviour is not significant.

(a) Factor A



(b) Factor B



(c) Interaction

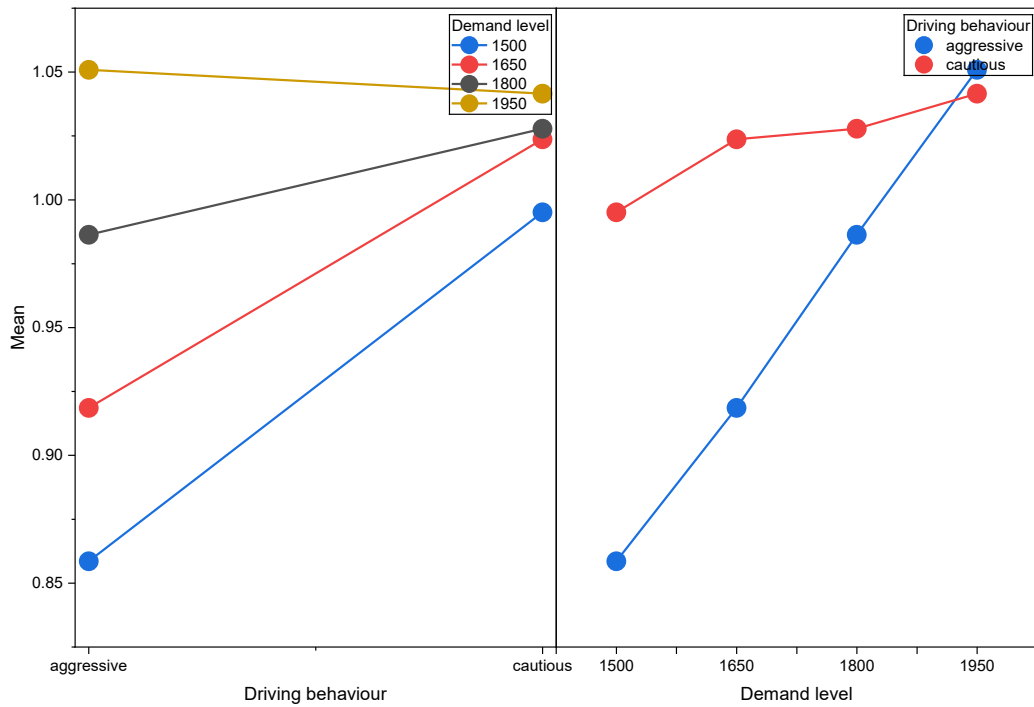


Figure A2 Two-way ANOVA results of driving behaviour and demand level for PET value

DR

Table A10 Two-way ANOVA results of demand level and DR value

	N	Mean	SD	SEM	Variance
1500	22	-2.51239	0.6589	0.14048	0.43415
1650	22	-2.10213	0.7011	0.14948	0.49155
1800	22	-1.8724	0.66243	0.14123	0.43882
1950	22	-1.73175	0.55493	0.11831	0.30795

Table A11 Two-way ANOVA results of driving behaviour and DR value

	N	Mean	SD	SEM	Variance
aggressive	44	-2.56064	0.34758	0.0524	0.12081
cautious	44	-1.54869	0.59223	0.08928	0.35074

Table A12 Two-way ANOVA results of interaction between driving behaviour and demand level

		N	Mean	SD	SEM	Variance
1500	aggressive	11	-2.99012	0.12229	0.03687	0.01495
	cautious	11	-2.03467	0.62824	0.18942	0.39468
1650	aggressive	11	-2.63713	0.19275	0.05812	0.03715
	cautious	11	-1.56713	0.60448	0.18226	0.36539
1800	aggressive	11	-2.42625	0.18791	0.05666	0.03531
	cautious	11	-1.31856	0.45975	0.13862	0.21137
1950	aggressive	11	-2.18908	0.22582	0.06809	0.05099
	cautious	11	-1.54869	0.59223	0.08928	0.35074

cautious	11	-1.27442	0.36821	0.11102	0.13558
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Table 13 Two-way ANOVA results of driving behaviour and demand level

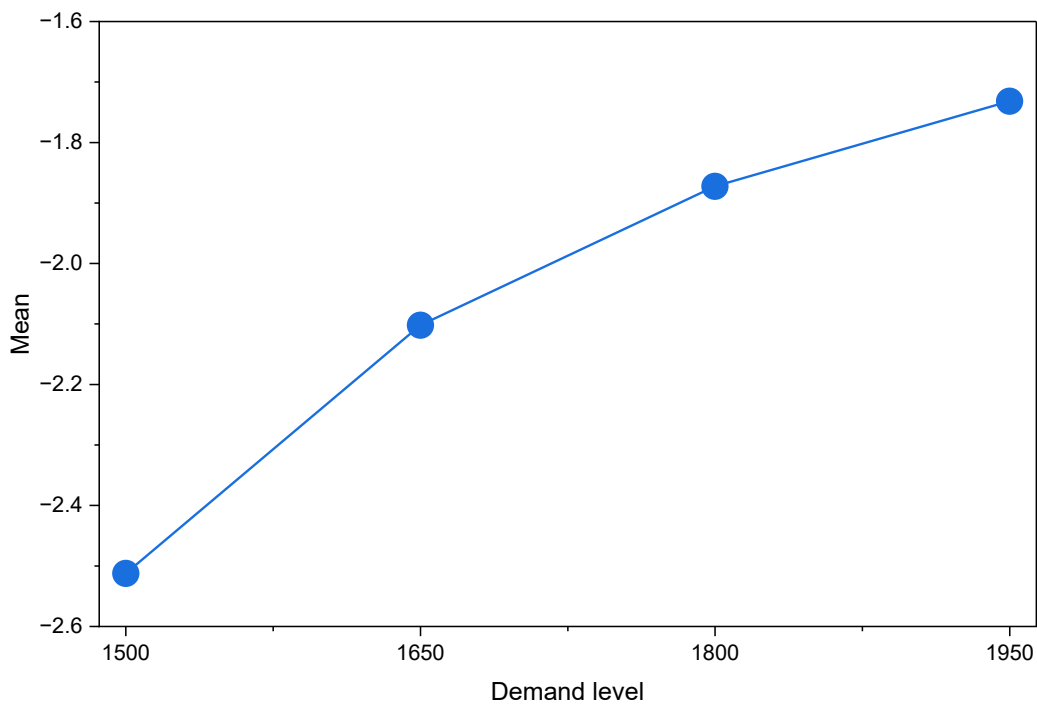
	DF	Sum of Squares	Mean Square	F Value	P Value
Demand level	3	7.68375	2.56125	16.45213	<0.0001
Driving behaviour	1	22.52897	22.52897	144.71425	<0.0001
Interaction	3	0.13858	0.04619	0.29672	0.82766
Model	7	30.3513	4.3359	27.85154	<0.0001
Error	80	12.45432	0.15568		
Corrected Total	87	42.80562			

At the 0.05 level, the population means of Demand level are significantly different.

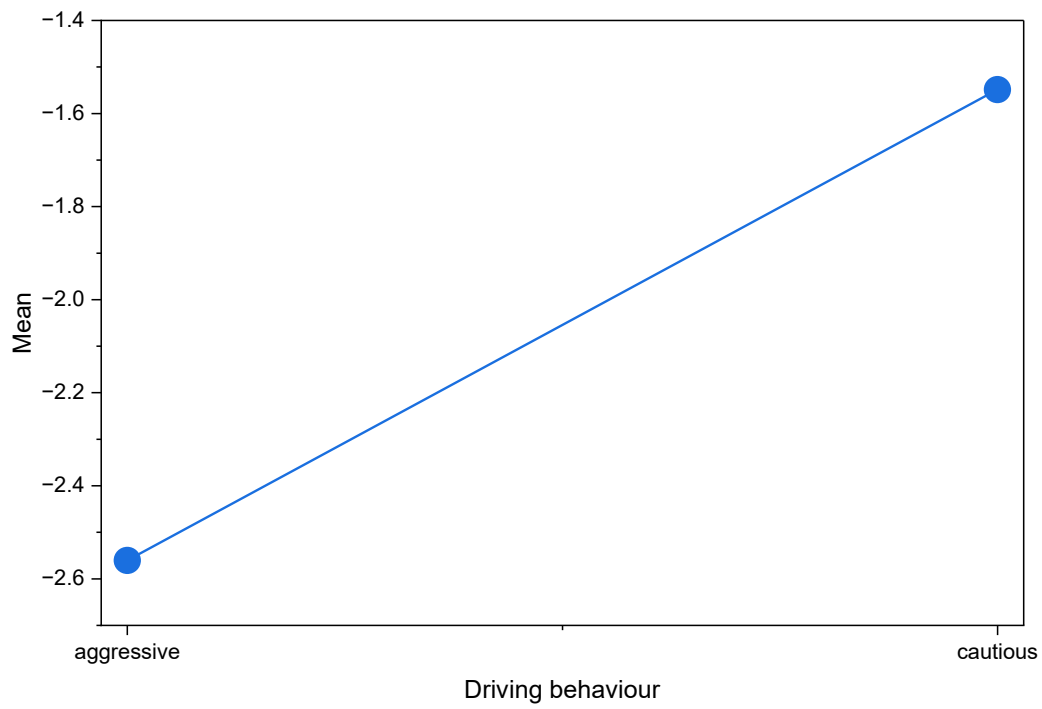
At the 0.05 level, the population means of Driving behaviour are significantly different.

At the 0.05 level, the interaction between Demand level and Driving behaviour is not significant.

(a) Factor A



(b) Factor B



(c) Interaction

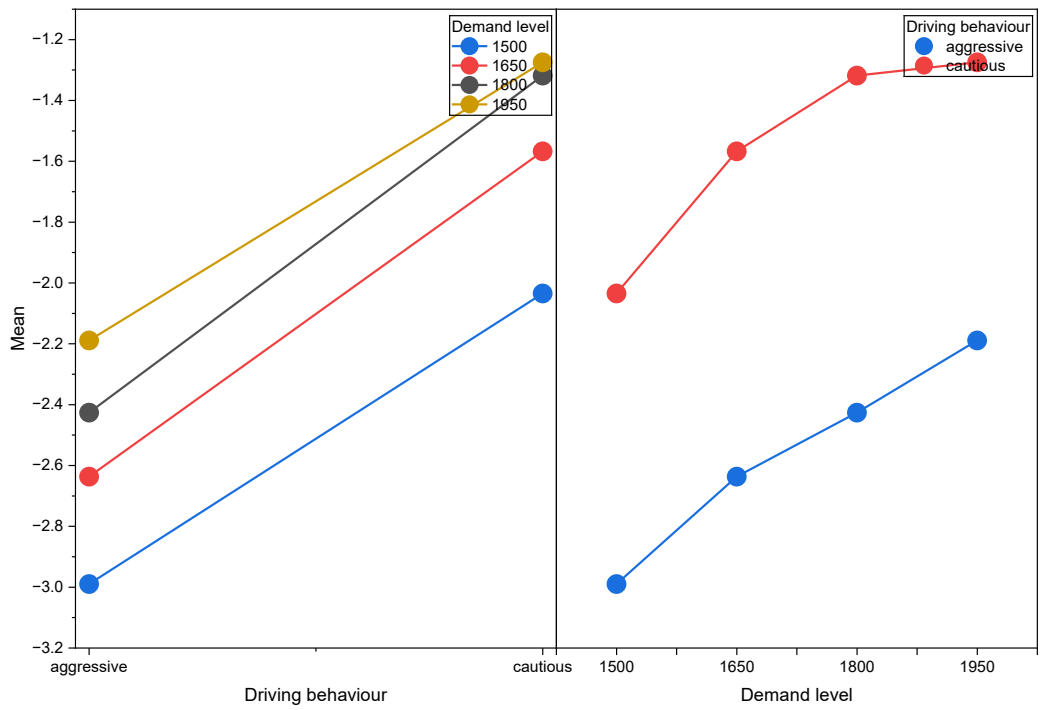


Figure A3 Two-way ANOVA results of driving behaviour and demand level for DR value

MaxS

Table A14 Two-way ANOVA results of demand level and MaxS value

	N	Mean	SD	SEM	Variance
1500	22	9.80933	1.34423	0.28659	1.80696
1650	22	9.02589	1.40384	0.2993	1.97077
1800	22	8.48241	1.40047	0.29858	1.96131
1950	22	8.03219	1.24545	0.26553	1.55114

Table A15 Two-way ANOVA results of driving behaviour and MaxS value

	N	Mean	SD	SEM	Variance
aggressive	44	9.94557	0.88318	0.13314	0.78001
cautious	44	7.72934	1.07938	0.16272	1.16505

Table A16 MaxS value calculation

N	Mean	SD	SEM	Variance
88	8.83745	1.48438	0.15824	2.20338

Table A17 Two-way ANOVA results of interaction between driving behaviour and demand level

		N	Mean	SD	SEM	Variance
1500	aggressive	11	10.88824	0.53284	0.16066	0.28392
	cautious	11	8.73043	0.97459	0.29385	0.94983
1650	aggressive	11	10.18211	0.59179	0.17843	0.35021
	cautious	11	7.86967	0.92051	0.27755	0.84735
1800	aggressive	11	9.64846	0.59119	0.17825	0.3495
	cautious	11	7.31635	0.88201	0.26594	0.77794
1950	aggressive	11	9.06346	0.61511	0.18546	0.37837
	cautious	11	7.00091	0.73435	0.22141	0.53927

Table A18 Two-way ANOVA results of driving behaviour and demand level

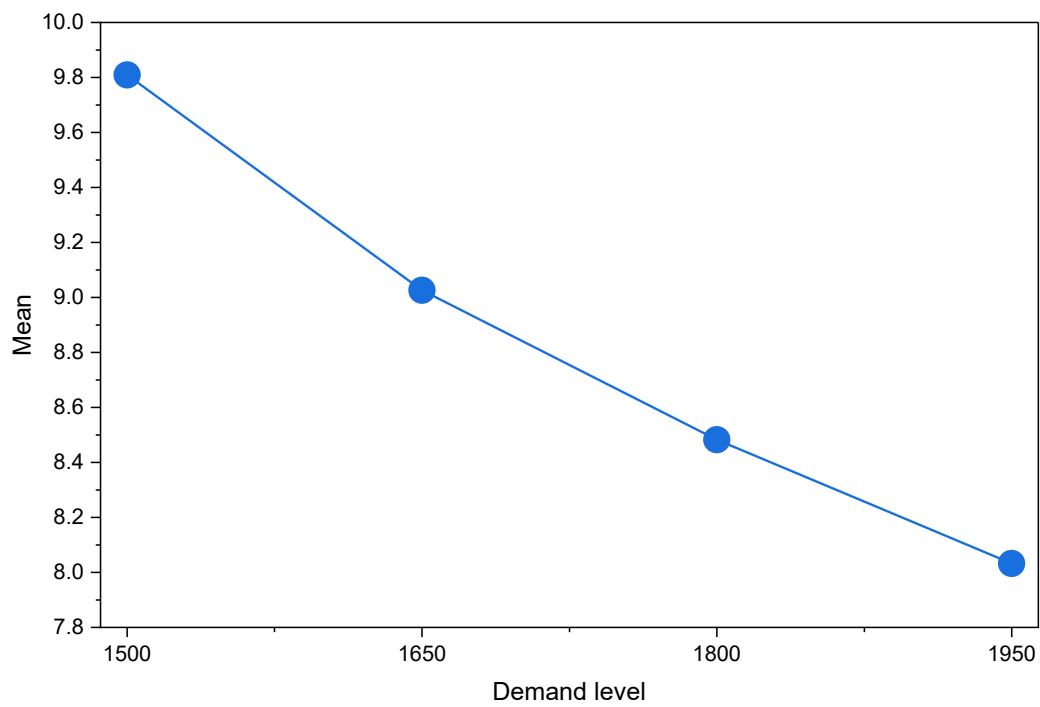
	DF	Sum of Squares	Mean Square	F Value	P Value
Demand level	3	38.60055	12.86685	22.99513	<0.0001
Driving behaviour	1	108.05668	108.05668	193.1147	<0.0001
Interaction	3	0.27344	0.09115	0.16289	0.92103
Model	7	146.93067	20.9901	37.51268	<0.0001
Error	80	44.76373	0.55955		
Corrected Total	87	191.6944			

At the 0.05 level, the population means of Demand level are significantly different.

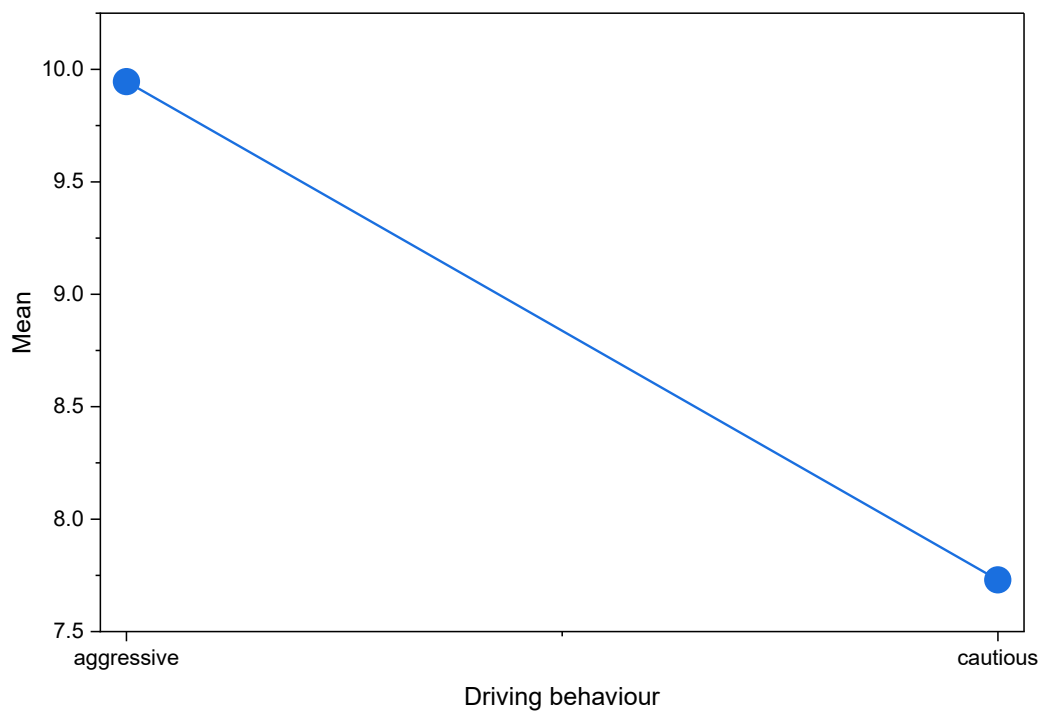
At the 0.05 level, the population means of Driving behaviour are significantly different.

At the 0.05 level, the interaction between Demand level and Driving behaviour is not significant.

(a) Factor A



(b) Factor B



(c) Interaction

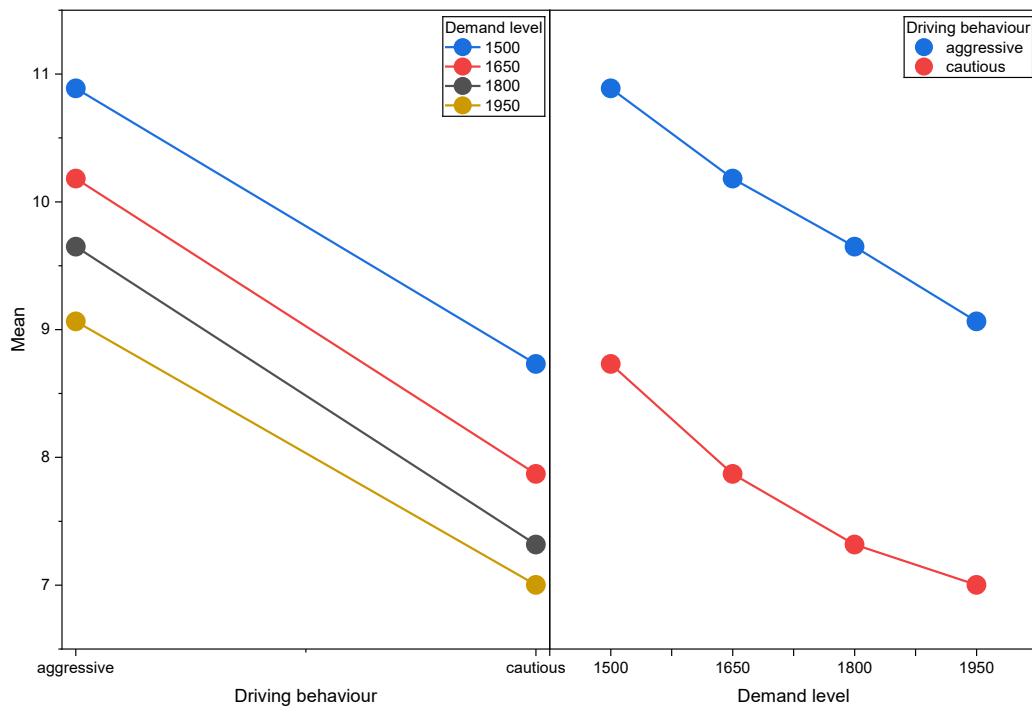


Figure A4 Two-way ANOVA results of driving behaviour and demand level for MaxS value

DeltaS

Table A19 Two-way ANOVA results of demand level and DeltaS value

	N	Mean	SD	SEM	Variance
1500	22	6.33533	0.81461	0.17367	0.66359
1650	22	5.95788	0.98308	0.20959	0.96645
1800	22	5.64886	1.14487	0.24409	1.31072
1950	22	5.33294	1.10206	0.23496	1.21454

Table A20 Two-way ANOVA results of driving behaviour and DeltaS value

	N	Mean	SD	SEM	Variance
aggressive	44	6.63893	0.55972	0.08438	0.31329
cautious	44	4.99857	0.78823	0.11883	0.62131

Table A21 DeltaS value calculation

N	Mean	SD	SEM	Variance
88	5.81875	1.06881	0.11394	1.14236

Table A22 Two-way ANOVA results of interaction between driving behaviour and demand level

		N	Mean	SD	SEM	Variance
1500	aggressive	11	6.97163	0.46753	0.14097	0.21859
	cautious	11	5.69904	0.53313	0.16074	0.28423
1650	aggressive	11	6.7336	0.49327	0.14873	0.24332
	cautious	11	5.18215	0.67997	0.20502	0.46237

1800	aggressive	11	6.60055	0.53214	0.16045	0.28317
	cautious	11	4.69716	0.69047	0.20818	0.47674
1950	aggressive	11	6.24995	0.54989	0.1658	0.30238
	cautious	11	4.41592	0.63097	0.19024	0.39812

Table A23 Two-way ANOVA results of driving behaviour and demand level

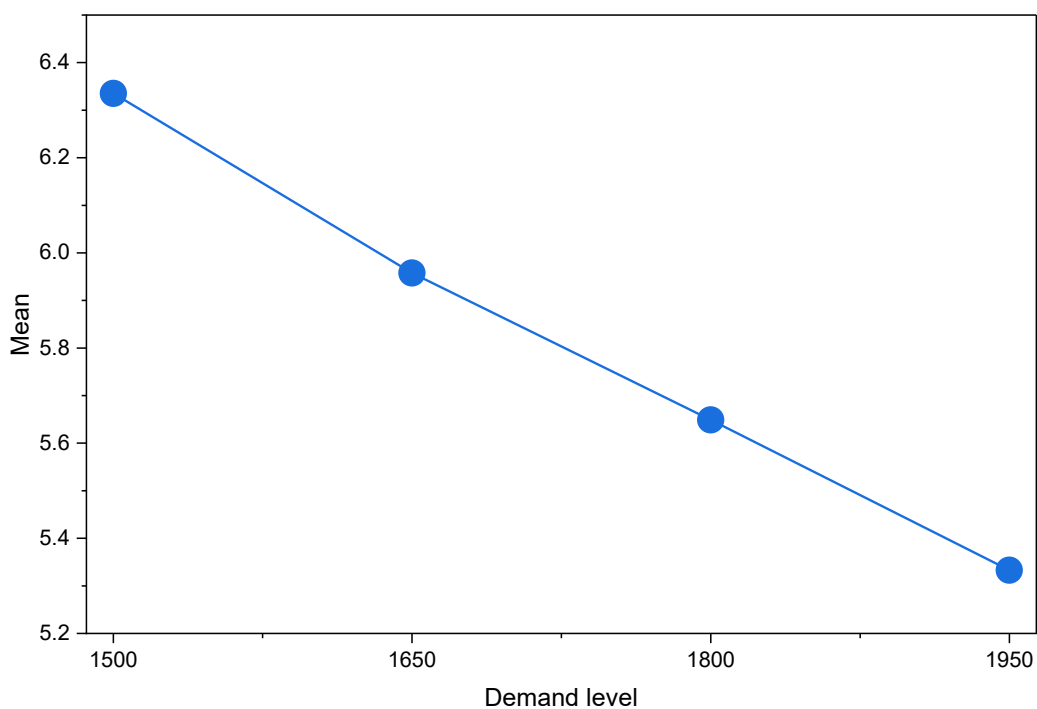
	DF	Sum of Squares	Mean Square	F Value	P Value
Demand level	3	12.12408	4.04136	12.11387	<0.0001
Driving behaviour	1	59.19775	59.19775	177.44359	<0.0001
Interaction	3	1.37421	0.45807	1.37305	0.25702
Model	7	72.69605	10.38515	31.12919	<0.0001
Error	80	26.68916	0.33361		
Corrected Total	87	99.38521			

At the 0.05 level, the population means of Demand level are significantly different.

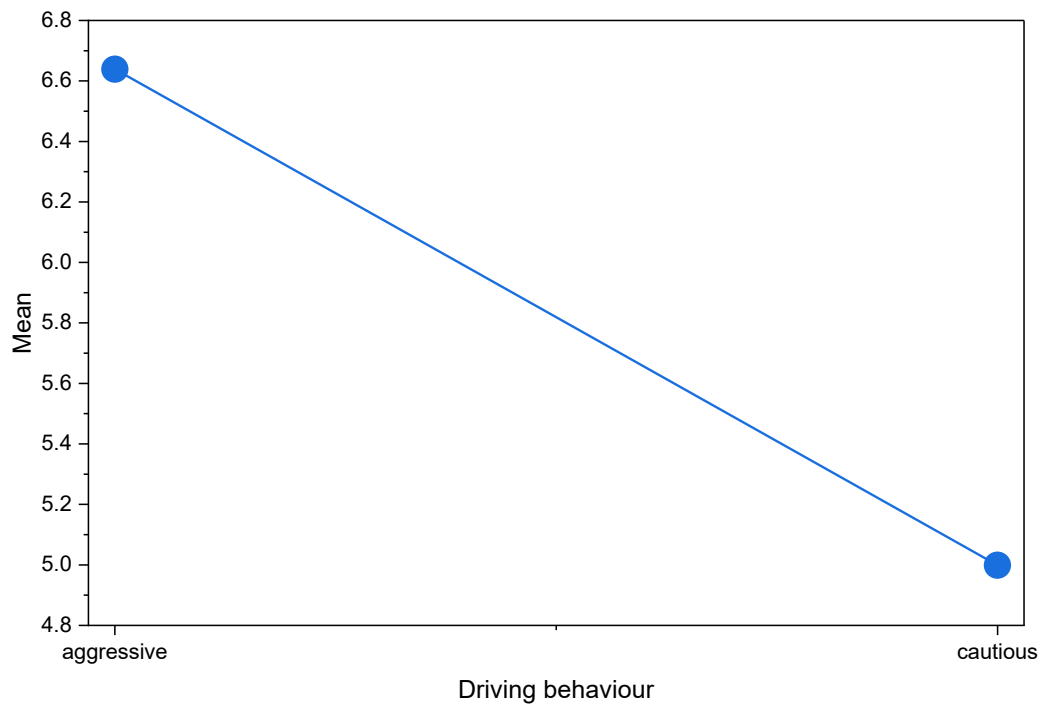
At the 0.05 level, the population means of Driving behaviour are significantly different.

At the 0.05 level, the interaction between Demand level and Driving behaviour is not significant.

(a) Factor A



(b) Factor B



(c) Interaction

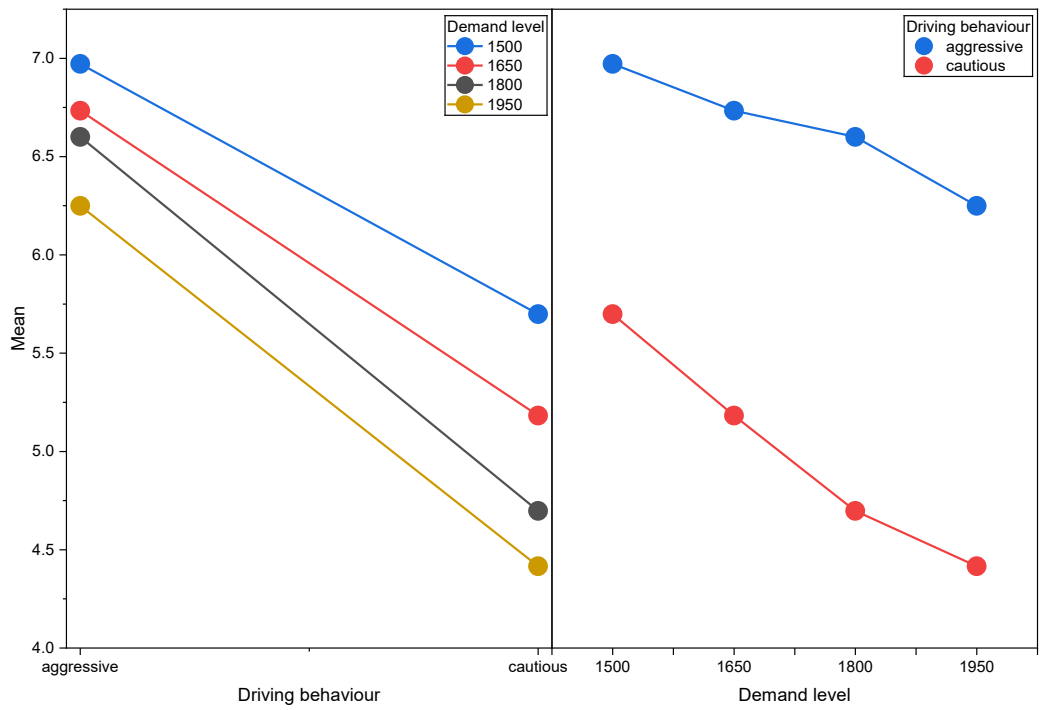


Figure A5 Two-way ANOVA results of driving behaviour and demand level for DeltaS value