CHALMERS
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Advanced driver assistance systems (ADAS) usage and resulting safety effects

Master's thesis in Mobility Engineering MSc

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CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2025
www.chalmers.se

Master's thesis 2025

Data Analysis to Investigate Advanced Driver Assistance Systems (ADAS) Usage and Resulting Safety Effects

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Master's Thesis 2025
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Cover: XC90 equipped with Volvo's adaptive cruise controller with queue assist.

Typeset in LaTeX
Printed by Chalmers Reproservice
Gothenburg, Sweden 2025

Assessing the Patterns and Safety Benefits of Advanced Driver Assistance Systems (ADAS)
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Abstract

The development of active safety systems such as Adaptive Cruise Control (ACC), Lane Keeping Aid (LKA), and Volvo's Pilot Assist (PA) has the potential to improve road safety. These systems assist drivers in performing driving tasks through the use of cameras, radar, and Light Detection and Ranging (LIDAR). However, to what extent are these systems actually used in real-world driving? When and where are they activated, and how do their usage differ among different drivers? What measurable safety effects can be achieved by using these systems in various driving scenarios?

This thesis investigates usage patterns of Advanced Driver Assistance Systems (ADAS), with a particular focus on time gap settings of PA and ACC, types of system deactivations, and lane deviation in comparison to manual driving. In addition, the thesis explores general ADAS usage and the contexts in which these systems are engaged. Typical driving scenarios, such as car following, car approaching, and cut-in scenarios are defined and analyzed to understand how ADAS operates within each scenario.

The result showed that the usage of ADAS, both ACC and PA, are used to a greater extent on high speed roads such as highways and expressways compared to rural roads. Additionally, drivers who engage ACC and PA during car following and car approaching scenarios tend to maintain greater safety margins in terms of time gap and Time to Collision (TTC) compared to those driving manually. The analysis further revealed that drivers who set larger time gaps when using ACC or PA also tend to maintain greater time gaps during manual driving. Drivers with PA activated also showed to maintain the lowest mean lane deviations, while manual driving resulted in the highest mean lane deviations on highways, expressways, and rural roads.

Keywords: Active Safety, ADAS, ACC, LCA, PA, fleet data, Volvo Cars

Acknowledgements

We would like to express our sincere gratitude to everyone who has supported us throughout the process of writing this thesis. A special thank you goes to our supervisors at Volvo Cars Corporation, Thomas Streubel and Pär Gustavsson, for their inspiration, motivation, and sharing of knowledge within the fields of Active Safety and Driver Behavior. Their insights and guidance were instrumental in shaping the direction of our work and guiding the thesis to its successful conclusion.

We would also like to extend our heartfelt thanks to our examiner, Jonas Bärgman, and our academic supervisor, Pierluigi Olleja, for their continuous support, and valuable feedback throughout the course of this thesis. A special thanks also goes to all coworkers at the Volvo Cars Safety Center for generously sharing their expertise and insights on the database, which greatly supported our work.

Your contributions have been essential to the success of this thesis, and we are truly grateful.

Felix Renberg, Gabriel Wendel, Gothenburg, May 2025

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance System
CC	Cruise Control
FRC	Functional Road Class
LCA	Lane Centering Assist
LDW	Lane Departure Warning
LIDAR	Light Detection and Ranging
LKA	Lane Keeping Aid
NDD	Naturalistic Driving Data
NDS	Navigation Data Standard
PA	Pilot Assist
THW	Time Head Way
TTC	Time To Collision

Nomenclature

Below is the nomenclature of variables that have been used throughout this thesis.

Variables

d	Distance
n	Number of observations
μ	Mean of data set
U	Mann-Whitney U Test statistic
v_e	Ego vehicle speed
v_t	Target vehicle speed
x_e	Ego vehicle position
x_t	Target vehicle position
χ^2	Chi-squared test statistic

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Introduction

Advancements in vehicle automation have led to the development of Advanced Driver Assistance Systems (ADAS) with SAE Level 2 Driving Automation capabilities (SAE International, 2021). Level 1 Driving Automation refers to ADAS with either longitudinal or lateral support while level 2 is the combination of both. Longitudinal support includes systems such as Adaptive Cruise Control (ACC), while lateral support includes systems such as Lane Centering Assist (LCA). ACC maintains a set speed while automatically adjusting the vehicle's speed to keep a safe distance from the car ahead using radar and camera sensors (Kummetha et al., 2020). LCA supports the driver in keeping the vehicle centered in the lane with assisted steering (Sternlund et al., 2017).

SAE Level 2 is defined as partial driving automation, where the driver remains actively engaged in the driving task and must continuously supervise the system while it provides support with steering, braking, and acceleration (SAE International, 2021). Volvo's level 2 system is called Pilot Assist (PA) which combines ACC and LCA. Other brands have similar systems, e.g. Mercedes Drive Pilot and GM Super Cruise. PA and ACC are user-activated ADAS meaning that the driver is able to manually activate/deactivate the system. Activation is done via buttons on the steering wheel and can be deactivated either by using the same steering wheel buttons or pressing the brake pedal.

ACC and PA have the potential to improve road safety by assisting drivers in maintaining safe following distances and staying centered in the lane. However, accurately assessing their safety effect requires a comprehensive approach that includes different types of analysis. One essential component of such an assessment is understanding how these systems are actually used in real world conditions.

Without detailed knowledge of system usage, particularly for user-activated ADAS, comparisons between vehicles with and without these systems may not provide a complete or reliable picture of their safety impact (Gershon et al., 2021). Therefore, a more accurate evaluation involves analyzing the actual usage and engagement of these functions during driving (Mehler et al., 2023). Furthermore, public crash databases typically lack detailed information on ADAS status during crashes or the extent of its use (Lennox et al., 2024).

Studies have highlighted the importance of driving context and it's influences on driver behavior and on the use of ADAS (Zhai et al., 2018). Driving context primarily includes factors such as road type and weather conditions, which can affect how and when drivers use ADAS. For instance, a study from Kidd and Reagan (2019) showed that level 1 and/or level 2 Driving Automation are mainly used on high speed roads such as interstates and during free-flowing traffic, while it was used to a lesser extent on curvy country roads. Previous research has also shown that driving context has an impact on driving behavior (Ahlström et al., 2018; Zhai et al., 2018). For this reason, the thesis includes scenario-based analyses to examine how ADAS are utilized across different traffic scenarios. Safety benefits can then be evaluated using safety metrics such as Time to Collision (TTC) and time gap, which can provide quantifiable measures of criticality.

Naturalistic driving data (NDD) makes it possible to capture real-world driving behavior and ADAS use across varying conditions. Unlike controlled experiments, NDD contains authentic interactions with ADAS in everyday settings. Studies like the 100-Car Study (Neale et al., 2002) and the MIT Autonomous Vehicle Technology study (Fridman et al., 2019) have shown how road type, traffic, and other contextual factors influence driver decisions and system usage. This thesis investigates the extent and contexts in which ACC and PA are used by drivers, based on an analysis of data collected from Volvo Car Corporation employees driving company cars. The fleet data represents NDD, capturing everyday driving on public roads without experimental control. Thus, it provides an authentic view of driver behavior and interaction with the systems. The data was collected using an external wireless communication and data acquisition unit installed in each vehicle. These units provide continuous and detailed recordings of vehicle signals (Johanson, 2025).

1.1 Background

In a previous study by Sternlund et al. (2017), the safety benefits of vehicle technologies have been assessed by comparing crash involvement rates between vehicles equipped with the technologies and those without them. The study employed an induced exposure method to compare crashes that were sensitive and non-sensitive to Lane Departure Warning (LDW) and Lane Keeping Aid (LKA) systems in Volvo passenger cars, both with and without these systems. This was done using data from the Swedish Traffic Accident Data Acquisition (STRADA) database (Sternlund et al., 2017). The LDW/LKA systems were estimated to reduce head-on and single-vehicle injury crashes on Swedish roads (70–120 km/h, dry or wet surfaces) by 53%, with a lower limit of 11% (95% Confidence Interval (CI)). Across all speed limits and road conditions, the reduction was 30%, with a lower limit of 6% (95% CI) (Sternlund et al., 2017). A study by Masello et al. (2022) using road safety reports from the United Kingdom found that full deployment of the six most common ADAS could reduce road accident frequency in the UK by 23.8% equating to an annual decrease of 18,925 accidents. Furthermore, studies have shown that using ACC increases longitudinal margins, such as time headway (THW), and reduces the frequency of close-following events (Malta et al., 2012). Moreover, ACC is also linked to fewer harsh braking events compared to manual driving (Kummetha et al., 2020; Malta et al., 2012).

There is limited research done on driver behavior, exposure to safety critical events, and crash involvement in assisted driving compared to manual driving (Masello et al., 2022; Lennox et al., 2024). SAE Level 2 driving automation features, such as Adaptive Cruise Control (ACC) and Lane Keeping Assist (LKA), are relatively recent developments, introduced in the 1990s and early 2000s respectively. Evaluating their effectiveness in reducing crash risk remains challenging, as publicly available crash databases often lack sufficient information about ADAS status at the time of a crash or the extent of its usage (Lennox et al., 2024).

Gershon et al. (2021) emphasizes the need for studies to explore the safety benefits of ADAS through investigations of NDD over extended time periods. Mehler et al. (2023) suggest that NDD collection comparing ADAS performance when active versus inactive offers a valuable alternative or complement to traditional methods. This approach can provide consumers with insights into overall safety benefits of the technology.

1.2 Aim and Research Questions

The aim of this master thesis is to investigate the contexts and patterns of ADAS usage as well as evaluate the safety effects of ADAS, using data from Volvo passenger cars equipped with ACC and PA. To achieve this, the following research questions are defined:

- How and in what contexts are ADAS used?
    - What are the general usage patterns with respect to road type, posted speed limit, and traffic conditions?
    - What are the typical patterns of system deactivation, including deactivation via brake pedal or button press?
- How do low distance settings during ADAS usage compare to time gap values during manual driving?
- How does lane positioning differ between PA-, ACC-, and manual driving?
- What safety effects can be observed from the use of ADAS systems such as PA and ACC, based on key safety metrics like TTC and time gap?
    - How do safety metrics such as TTC and time gap vary across different driving scenarios, including car approaching, car following, and cut-in scenarios?

1.3 Limitations

Key limitations have been identified that influence the scope and outcome of the thesis. These limitations regard the dataset, under which condition the data was collected, and the characteristics of the involved participants. Below is a list that summarize these limitations:

- **Demographic data is not included in analyses:** Demographic data is only available for the vehicle owner, but since the car can be driven by other people (e.g., family or friends), this data may not accurately reflect the actual driver. For this reason, the analyses were conducted on a vehicle level.

- **The main drivers are all Volvo employees:** This means they may be more familiar with the available ADAS functions, which could influence how and to what extent they use them.

- **The Volvo cars in the dataset are mainly driven in and around Gothenburg, Sweden:** This means that the data only reflects driving environments and road conditions found in Gothenburg and its surrounding areas. Thus the generalizability of the findings is reduced.

- **Lack of GPS and location data:** The fleet data provided did not include any position information, making it difficult to determine the exact driving context (e.g., rural road, expressway, highway).

- **Unbalanced amount of data across drivers:** Some drivers may be over-represented in the dataset, contributing a disproportionately large share of the data. These individuals may exclusively use either PA or ACC and consistently select a specific distance setting, which could skew the results.

2

Theory

This section introduces the technologies and concepts relevant to the thesis. It describes the ADAS considered in the analysis, focusing on ACC and PA. The operation and functionality of each system are explained to provide a technical foundation for understanding their use and potential safety impacts. The section then presents a set of safety metrics, such as time gap, THW, and TTC, which are used to evaluate driving behavior and system performance. As well as statistical methods used to analyze results.

2.1 ADAS Systems

Vehicles equipped with Advanced Driver Assistance Systems (ADAS) are becoming increasingly common in modern transportation. SAE Level 2 automated vehicles, also known as partial automation systems, control both longitudinal and lateral motion by managing acceleration, deceleration, and steering under the driver's supervision. This level of automation is typically achieved through the combined use of ACC and LCA (SAE International, 2021). The following sections provide an overview of ACC, PA, and LKA systems.

2.1.1 Adaptive Cruise Control (ACC)

Adaptive Cruise Control (ACC) is an extension to standard cruise control (CC) that enables the vehicle's CC to adapt the vehicle speed to the traffic environment. It works by detecting vehicles ahead that travels with a lower speed that are within the path. If a slower vehicle is detected ahead, often defined as target vehicle, the ACC system will reduce the vehicle speed and thus adapt the clearance, or time gap, between the ACC vehicle and the target vehicle. If the target vehicle is no longer within the ACC vehicle's path, the system will accelerate the vehicle back to the cruise control speed which is set by the driver. Thus the ACC vehicle is able to autonomously slow down and speed up in traffic without intervention from the driver. ACC speed is controlled via engine throttle control and limited brake operation (US Software System Safety Working Group, 2005).

To activate ACC in Volvo cars the driver needs to push the ACC button on the steering wheel which puts it in active mode. Pushing the button again will set the system to standby mode. The desired speed is then set by pushing + and - buttons (Volvo Car Corporation, 2022).

When the ACC is active, the system controls the vehicle to either maintain a predefined speed or maintain a safe time gap to the target vehicle, depending on which speed is lower. In order to activate ACC in Volvo cars the vehicle must be moving at speeds of 15 km/h or higher. The lowest speed setting for Volvo's PA and ACC systems is 30 km/h. However, the system is capable of following a forward vehicle down to 0 km/h. (Volvo Car Corporation, 2024).

To sense the target vehicle Volvo's ACC system use a combination of camera and radar sensors. The ACC system compares the user-specified time gap to the target vehicle with the time gap determined by radar signals. If the calculated time gap is shorter than the user-specified time gap, the system responds by reducing the vehicle's speed or applying the brakes. If the calculated time gap is longer, the system increases the vehicle's speed until it matches that of the target vehicle or reaches the user-specified speed.

2.1.2 Lane Keeping Aid (LKA)

Lane departure systems, such as Lane Keeping Aid (LKA), is commonly used in modern vehicles to enhance safety and comfort. Lane departure typically occurs on long straight roads such as highways which are characterized by monotonous driving conditions. These departures could happen as a result of drowsiness or a lack of attention. The departures could lead to serious crashes both with other vehicles and also stationary obstacles (López et al., 2017).

LKA systems actively supports the driver of a vehicle to stay within a marked lane. When the system detects that the vehicle is on path of crossing a line and if the driver did not activate the turn signal, it applies a corrective steering input to guide the vehicle back into the lane. If steering alone is insufficient or unsafe, the system may also activate the brakes. Additionally, it can alert the driver with steering wheel vibrations if necessary (Bishop, 2005). Some LKA systems provide assistance for centering the vehicle within the lane. Lane detection is typically achieved by using cameras, but has also been done by using Light Detection and Ranging (LIDAR) (López et al., 2017).

2.1.3 Pilot Assist (PA)

PA is a level 2 ADAS developed by Volvo that combines ACC and LCA, designed to assist drivers by maintaining a set speed, keeping a safe distance from the vehicle ahead, and providing steering assistance to help keep the car centered within its lane. This system is primarily intended for use on well marked highways and similar major roads, improving driving comfort and reducing driver fatigue during long trips. Using a forward-facing camera and radar sensors, the system monitors the distance to the vehicle ahead and detects lane markings on the road surface. Based on this information, it automatically adjusts the vehicle's speed to maintain a user selected time interval to the target vehicle and provides gentle steering inputs to help keep the car centered within its lane (Volvo Car Corporation, 2024).

The system requires clearly visible marked lines on the road to work correctly. If that is not the case, the system will deactivate LCA while still keeping ACC activated. The driver retains full control of the vehicle when the system is active and can override the PA at any time. The system still requires the driver to have their hands on the steering wheel, to help apply steering inputs especially in curves, even when the system is active. The system will issue warnings if it detects that the driver do not have their hands on the steering wheel. If the driver does not take action by holding the steering wheel, the system will deactivate (Volvo Car Corporation, 2024).

2.2 Safety Metrics

To be able to quantify what safe driving is, safety metrics are often used. Safety metrics are measurements to evaluate the criticality of driving situation (Yan et al., 2024). In the following section, some of the most commonly used longitudinal safety metrics are described.

2.2.1 Time Head Way (THW)

Time Headway (THW), is the time gap in seconds between two vehicles measured from the same common part of both vehicles, e.g. front bumper to front bumper (SAE International, 2015). Figure 2.1 illustrates the THW safety metric between the ego- and the target vehicle.

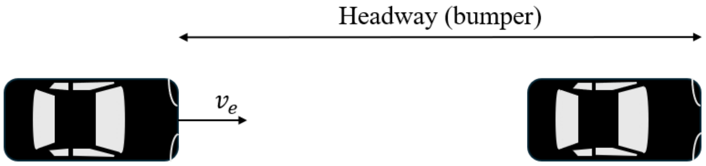

Figure 2.1: THW is the time it takes for the ego vehicle to travel the headway distance. Here the headway distance is defined as front bumper to front bumper when traveling at a speed of v_e.

2.2.2 Distance- and Time Gap

Distance gap is defined as the longitudinal distance along the traveled way, measured in meters, between ego vehicle's leading surface (front bumper) and the target vehicle's trailing surface (rear bumper or trailer hitch if a trailer is connected to the vehicle). The distance is usually used to asses the clearance between two vehicles to ensure safe following distances (SAE International, 2015).

Time gap is the time required for the ego vehicle to cover the current distance to the target vehicle. Thus, this method assumes that the speed of the ego vehicle remains constant, and is used to evaluate the temporal spacing between the vehicles (SAE International, 2015). Figure 2.2 illustrates how time gap is calculated.

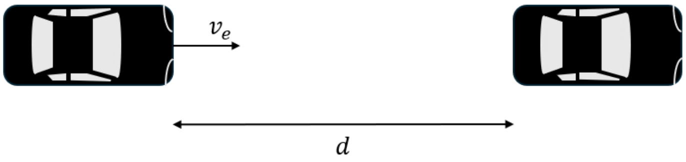

Figure 2.2: Distance, d, is the distance gap between the ego vehicle and the target vehicle. The time gap is the time it takes for the ego vehicle with velocity, v_e, to collide with the target vehicle.

2.2.3 Time To Collision (TTC)

Time To Collision (TTC) is a safety metric that defines the time it takes for a collision to happen if two cars continue with their current speed. TTC is defined as the distance between the target vehicle and the ego vehicle, divided by the difference in their velocities, see Equation 2.1, where x_t is the position of the target vehicle, x_e is the position of the ego vehicle, v_t is the speeds of the target vehicle, and v_e is the speed of the ego vehicle. Figure 2.3 illustrates how TTC is calculated.

$$TTC = \frac{x_t - x_e}{v_e - v_t} = \frac{d}{v_e - v_t} \tag{2.1}$$

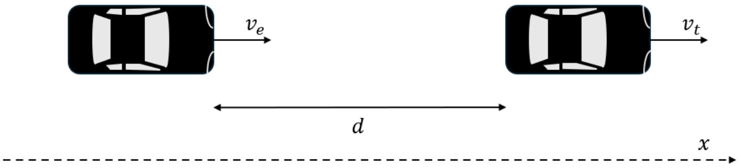

Figure 2.3: TTC calculated as the difference in position between the two vehicles (distance d), divided by the difference in velocity, $v_e - v_t$.

2.3 Statistical Analysis

The result of the analyses were interpreted using statistical methods. These methods are presented in the following section.

2.3.1 Mann-Whitney U Test

The Mann-Whitney U test is a nonparametric test used to compare independent samples to determine whether they come from the same distribution and is used when data are not normally distributed. To perform the Mann-Whitney test the null hypothesis that two samples come from the same population against an alternative hypothesis that two samples are from different populations are formulated. The data from both samples are then combined into a single dataset and ranked from lowest to highest. Equation 2.2 defines the U statistic for both groups, where ranks are assigned from 1 to n, T represents the sum of the ranks for the respective group, and n_1 and n_2 are the sample sizes of the two groups.

$$\begin{aligned} U_1 &= n_1 n_2 + \frac{n_1(n_1+1)}{2} + T_1 \\ U_2 &= n_1 n_2 + \frac{n_2(n_2+1)}{2} + T_2 \end{aligned} \tag{2.2}$$

The U statistics from each group is then compared to the critical value which is determined based on the sample size and significance level. In this thesis, the significance level is defined as $\alpha = 0.05$, and a Bonferroni correction was applied to adjust the critical level according to the number of comparisons. If U is less or equal to the critical value the null hypothesis is rejected, indicating a significant difference between the distributions (Zhang, 2020).

2.3.2 Chi-Squared Test

Chi-squared test is a statistical method used to determine whether there is a significant difference between expected and observed frequencies in categorical data. Its used to evaluate if distribution of data for different categories occurs by chance or if there is a pattern. The two most common types of the test are:

- Chi-squared goodness-of-fit test, which checks whether the observed distribution fits a specific expected distribution.
- Chi-squared test of independence, which determines if there is a relationship between two categorical variables.

In this thesis, the Chi-squared goodness-of-fit test is used and the test is defined according to Equation 2.3.

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \tag{2.3}$$

Where χ^2 is the chi-squared test statistic, O_i is the observed frequency in category i, E_i is the expected frequency in category i, and n is the total number of categories

The result of the test is a test statistic (χ^2) and a p-value. The p-value is calculated using the chi-squared distribution with degrees of freedom defined as $\mathrm{df} = n - 1$. If the p-value is less than a chosen significance level (in this thesis defined as 0.017), the null hypothesis is rejected, indicating a statistically significant difference (Ozdemir, 2024).

3

Methods

3.1 Literature Review

A literature review was conducted to investigate previous research done on the basics of ADAS, how and to what extent those systems are used, and their potential safety impacts. Further, safety metrics were investigated to better understand which are relevant for a safety benefit analysis of the ADAS in question and what values are considered safe and critical in certain driving contexts. These threshold values was later used to assess the safety impact identified during the scenario based analyses, helping to determine whether certain events can be classified as critical.

3.2 Data Preparation and Selection

This section outlines the process used to identify relevant signals and select appropriate data for the analyses. Key steps included identifying signals of interest, defining criteria for selecting data files, and applying filtering methods to remove incomplete or low-quality data.

3.2.1 Signal and Data Selection

An extensive investigation of the available signals from the vehicle data was conducted to identify which signals was needed to answer the research questions. For example, signals to identify ADAS activation/deactivation needed to be found, as well as signals that could be used to identify road types and different traffic scenarios.

After listing all relevant signals, each signal was analyzed to determine the amount of available data in the fleet dataset and to examine the characteristics of the signal values, such as how frequently the signal was updated, and its format. The dataset consisted of files representing individual car trips from different days.

A script was developed to automate this process by looping through a number of data files and checking how many of these files contained data for the signals of interest. This approach allowed for a preliminary assessment of the availability of the signals and helped ensure that there was sufficient data. Based on these results, the reliability of each signal was evaluated.

The list of files to be processed was constructed by randomly selecting dates from each month of the year 2024, from which files would be collected. The decision to use data exclusively from 2024 was based on it being the most recent full year of available data. Using data from an entire year also ensured that seasonal variations in driving behavior were captured, as weather is an aspect that has been shown to affect ADAS usage (Orlovska et al., 2020; Lyu et al., 2018). A flowchart illustrating the algorithm is shown in Figure A.1 in Appendix A.

This approach provided a manageable amount of data that could be processed within a reasonable amount of time. The pre-processing resulted in approximately 80000 files with trips from 881 different cars.

3.3 Preprocessing and Filtering

Before beginning the analyses, it is essential to screen and filter the data. As mentioned earlier useful signals must be identified and checked to ensure they have sufficient data and are not overly noisy. The following section describes the steps taken in the data screening and filtering phase.

Since signal values change at different rates depending on when a particular signal's state changes (e.g., a change in the posted speed limit occurs less frequently than changes in vehicle speed), the signals must be interpolated to a common time array. This interpolation was performed by creating a script that aligns all signals to a common time window. To reduce computational demands and processing time, only relevant signals that were used in the analyses were interpolated. If a user-defined signal was missing, the corresponding file was excluded from further use.

The quality of the data were also verified. For each signal selected for analysis, the format if the signal (integer, float, etc.) was checked, along with whether the values fell within the defined range for that signal. Additionally, the driving duration in each file was examined to ensure that each car had been driven for a sufficient period. A minimum of five minutes of driving time was required for each file. This threshold was set to exclude short trips while avoiding excessive filtering of the available data. If the signals in a file did not meet the requirements, the file was excluded from further use.

Some files contained more than one trip. A trip in this context refers to a single drive cycle that begins when the engine starts and ends when the engine is turned off. However, in some cases the car was parked while data was still being recorded. To address this, a script was developed to identify whether a file contains multiple trips and to split the data accordingly. The trip splitting is based on a usage mode signal that indicates the operational state of the car, specifically whether it is actively driving. The algorithm monitors this signal, and when it detects a change that suggests the car has stopped driving, it marks the end of a trip. The data is then divided into multiple trips, each of which is analyzed separately. The script also checks the gear selection to ensure it is not in park, neutral, or reverse, so that only data from active driving is included.

Since the fleet data contains a large volume of information, it is not efficient to store all the processed data into a single file. To ensure efficient processing, aggregated data was stored every 500 simulated files using checkpointing in Parquet format, which is highly space-efficient for large amounts of data. Checkpointing is especially useful to mitigate the impact of any unexpected errors during simulation, as it ensures that all the processed data up until that point is saved and can be recovered. Once all data files had been processed, the analyses could then be performed by looping through the generated Parquet files. The following section will explain these different analyses and how they were conducted.

3.4 General ADAS Usage

To gain a general understanding of how and when ADAS systems are used, a general usage analysis was conducted. This analysis evaluates ADAS usage based on the type of road the car is driving on and the posted speed limit, thus providing a general contextual overview of ADAS usage.

3.4.1 Road Type

Data was categorized according to different road types. The road types of interest were defined as expressway, highway, and rural road as these are the roads were ADAS is mainly intended to be used (Volvo Car Corporation, 2024). The different road types was identified using the Advanced Driver Assistance Interface Specifications (ADASIS) v2 protocol. The protocol is a standardized interface that enables the exchange of electronic horizon data between map providers and in-vehicle systems. It allows ADAS to assess and make use of map data from navigation databases (NDS) (Bracht et al., 2016).

The protocol enables the creation of a electronic horizon, which is a virtual representation of the road ahead, providing information such as posted speed limits and other traffic signs. The road type can be determined by analyzing the Functional Road Class (FRC) and the Type of Way signals. FRC indicates the relative importance of the road. Valid FRC values range from 1 to 6, with lower values representing higher priority roads such as highways and expressways. A value of 0 indicates an unknown importance, while a value of 7 means not applicable (N/A). Type of Way attribute describes the physical characteristics of the road (Bracht et al., 2016). Table 3.1 below lists the Type of Way attributes and their corresponding values.

Table 3.1: Type of Way attributes and their corresponding descriptions (Bracht et al., 2016).

Value	Description
0	Unknown
1	Freeway or controlled access road not including slip road or ramp.
2	Multiple carriageway
3	Single carriageway
4	Roundabout circle
5	Traffic square
6	Reserved
7	Reserved
8	Parallel road
9	Slip road or ramp on a freeway
10	Slip road or ramp not on a freeway
11	Service road or frontage road
12	Car park entrance or exit

As previously mentioned, road types of special interest include expressways, highways, and rural roads. Using FRC and Type of Way signals, the data was categorized based on driving on these road types. When analyzing the two signals, some noise was observed that caused occasional short-term fluctuations. To reduce this noise, the data was first divided into continuous segments based on changes in the speed limit signal. For each segment, the mode (most frequently occurring value) was calculated for both the FRC and the Type of Way signal. These mode values were then assigned to all data points within the corresponding segment. This approach helped reduce noise in the data and was based on the observation that speed limit signals are generally more reliable than the FRC and Type of Way signals. Equation 3.1 explains how the FRC and Type of Way signals were used to filter and classify the roads in the dataset.

$$\begin{aligned}
\text{Expressway} \iff & \Big(\text{Road Class} \in \{1,2,3,4\} \\
& \land \ \text{Speed Limit} \in \{70,80,90\} \land \text{Type of Way} \in \{1,2\}\Big) \\
& \lor \Big(\text{Road Class} \in \{1,2,3\} \land \text{Speed Limit} \in \{70,80,90\}\Big) \\
\text{Rural Road} \iff & \Big(\text{Road Class} \geq 4 \land \text{Speed Limit} \in \{70,80,90\}\Big) \\
& \lor \Big(\text{Road Class} = 0 \land \text{Speed Limit} \in \{70,80,90\}\Big) \\
\text{Highway} \iff & \ \text{Speed limit} \in \{100,110,120\}
\end{aligned} \tag{3.1}$$

If a road does not fulfill any of the conditions defined by Equation 3.1, it is classified as unknown. This was done to filter out roads that are difficult to identify and to ensure the analysis focuses only on road types where ACC and PA are intended to be used.

The ADAS usage was measured in terms of both time and distance. Time was calculated based on the sampling frequency of 40 Hz by counting the number of samples, and distance was determined by computing the difference in km in the odometer readings.

3.5 Usage Patterns

To gain a deeper understanding of how the systems are used, this section investigates the usage patterns. This includes analyzing which distance settings are most commonly selected, how drivers deactivate the systems, and how the drivers tend to override the systems.

3.5.1 Distance Setting

When using ACC or PA, drivers can choose between five distance settings. The aim of this analysis was to examine which settings were used the most. A car was required to have used ACC or PA for at least 10 % of the duration in at least one of its trips to be included in the analysis. For example, if ACC was active for 5 % of a trip and PA for 6 %, the combined usage would be 11 % which would meet the requirement. This was done because ACC and PA provide the same longitudinal assistance, which is the focus of this analysis. Importantly, this condition only had to be met for one trip. If the system was used less than 10 % on other trips, the car was still included.

In cases where a driver switched between distance settings during a trip, the most frequently used setting was assigned to that car for categorization purposes. For determining the most frequently used setting, only the periods when the car had a lead vehicle were considered. This was done to ensure that the distance setting was actually in use and relevant, as the system's behavior is only affected by the setting when there is a vehicle ahead.

To investigate whether drivers who prefer different distance settings also maintain different following distances during manual driving, the vehicles were grouped into three categories:

- Group 1: Lower than default (1 and 2)
- Group 2: Default setting (3)
- Group 3: Higher than default (4 and 5)

This grouping allowed for comparison of the average time gaps during manual driving across different user preferences. As previously mentioned, only cars that used either

PA or ACC during the trip were included to ensure the distance setting was actually in use and not adjusted without engaging the system. Drivers who used multiple distance settings during a trip were categorized based on their most frequently used setting.

To ensure the same amount of data was used from each car, a condition was set requiring that a car must have at least 500000 samples of manual driving. This threshold was determined by analyzing the number of samples available per car. For all cars that met this requirement, 500000 random time gaps were selected from their manual driving data. This approach was used to ensure a diverse representation of driving behavior and to avoid including data from only a few repeated events.

A Chi-squared goodness-of-fit test, see Section 2.3.2 was then done to see if the results was significant different or not. The total number of samples varied between the groups, so the group with the lower count was scaled to match the higher one in each comparison. This normalization ensured that differences in sample size did not bias the statistical analysis. The Chi-squared goodness-of-fit test was performed three times to compare all group combinations: Group 1 vs. Group 2, Group 1 vs. Group 3, and Group 2 vs. Group 3. Since multiple comparisons were made, a Bonferroni correction was applied to control for the increased risk of Type I error. This meant the original significance level of $\alpha = 0.05$ was divided by 3, resulting in a corrected threshold of $\alpha < 0.017$. A result below this threshold was considered statistically significant, indicating that the distribution of following distances during manual driving differed between the compared groups.

3.5.2 ADAS Deactivation

Deactivation of ACC and PA was analyzed to better understand how these systems are used in practice. The purpose of the analysis was to investigate how drivers typically deactivate the systems, whether it is more common to use the brake pedal or the deactivation button on the steering wheel. The analysis was carried out by monitoring whether ACC or PA was active, in combination with signals indicating possible causes of deactivation. These signals included brake pedal deactivation, steering wheel button presses, and hands-off-wheel warnings. In the case of PA, if the driver does not keep their hands on the steering wheel for a certain period, a series of warnings are triggered. If the driver does not respond to these warnings, the system will be deactivated. Additionally, PA deactivates if it can no longer detect lane markings, however, ACC remains active.

To identify the causes of system deactivation, instances where the system transitioned from active mode (ACC or PA) to manual driving were identified. Some cases were found where PA briefly deactivated for a fraction of a second before immediately reactivating, which could be due to steering assistance temporarily becoming unavailable. These instances were excluded from the analysis, as they do not represent intentional or meaningful deactivations.

The primary focus of the analysis was to compare the frequency of deactivations initiated by braking compared to those caused by button presses, both of which are actions taken directly by the driver. The hands-off wheel deactivations were very few and were therefore excluded from the analysis. Deactivations not initiated by the driver were excluded as the focus is on the driver usage aspect of the system.

Since the number of deactivations varies between cars, the percentage of brake versus button deactivations was calculated individually for each car. This approach ensured that each vehicle contributed equally to the overall distribution, regardless of how many deactivations they had. To ensure reliable data, only cars with at least ten deactivations for both ACC and PA were used. This criterion helped filter out vehicles with minimal usage, which could otherwise introduce noise or skew the results due to low sample sizes. For each car, the percentages of deactivation types (brake or button press) were stored separately for ACC and PA. Finally, the mean percentage of the percentages of deactivation was calculated, resulting in a normalized distribution of how the systems were typically deactivated by drivers.

A hypothesis was that brake deactivations would be more common at lower time gaps compared to button deactivations. For this analysis, the system was required to be active for at least 10 s prior to deactivation to exclude instances where it was engaged while the vehicle was already close to a lead vehicle, as such cases could lower the time gap at the moment of deactivation. The analysis also excluded instances with driver overrides, which is when the gas pedal was pressed while ACC or PA was active, to avoid including deactivations as a response to the system and not their own behavior. Additionally, any events with a cut-in occurring within the last 10 s before deactivation were excluded.

A Chi-squared goodness-of-fit test was also conducted for the time gap at deactivation. Since the total number of events differed between the two groups, the brake data was scaled to match the total number of button deactivations, allowing for a fair comparison of distribution. This was done to see if there were a significant difference between the two distributions. An α level of 0.05 was used to determine statistical significance.

3.5.3 Lane Positioning

As described in Section 2.1.3, PA supports the driver by applying steering to keep the car centered in the lane. To evaluate whether the car maintains the lane position more effectively with steering support, a signal that represents the car's deviation from the center of the lane was analyzed. This signal had a positive or negative sign depending on whether the vehicle is positioned more to the left or right within the lane. To obtain a general measure of lane positioning, both the mean and standard deviation of the absolute lane deviation were calculated. The absolute values were used to prevent left and right deviations from canceling each other out, which could misleadingly suggest perfect lane centering.

Lane changes can lead to disturbances in the data and are not desired to assess the pure lane deviation between manual driving and driving with PA system. They were therefore filtered out by using the indicator signals and certain patterns that are characteristic for lane changes (a drift followed by a jump in the data once the other lane is reached).

The threshold for detecting the lane changes was determined by visual inspection of the signal plots for individual vehicles. A sudden change exceeding 0.8 m in magnitude was identified to be able to filter out the lane changes. Figure 3.1 shows an example of how lane changes were filtered out in a trip.

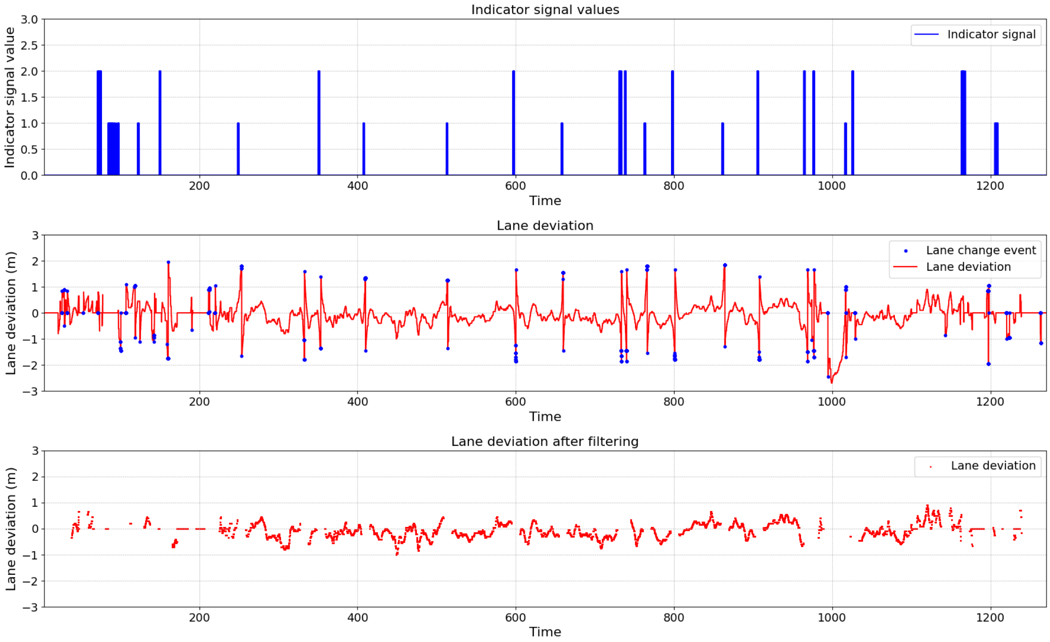

Figure 3.1: Trip for a car that shows how the lane changes is filtered out for the lane positioning.

As the signal contains both positive and negative values, the absolute value was used to calculate both the standard deviation and the mean lane deviation. This process was carried out separately for PA, ACC, and manual driving, allowing for a direct comparison between the three driving modes. Additionally, the same analysis was repeated for different road types to examine whether road characteristics influenced the results.

Lane positioning was analyzed for manual-, PA-, and ACC driving across three different road types: expressway, highway, and rural road, as well as general lane deviation which included all the three roads together. These road types were chosen because the systems are mainly designed for use on those roads.

To evaluate whether there is a significant difference in lane positioning between PA, ACC, and manual driving, a Mann-Whitney U test, see Section 2.3.1 was conducted. The test used the mean lane positioning, standard deviation, and sample size for each driving mode. Pairwise comparisons were performed between the different modes to assess whether the observed differences in lane deviation were statistically significant.

To ensure a roughly equal amount of data per car across road types, a threshold of 10 minutes of PA or ACC usage was applied. For each road type, data was only included if a car had used the system for at least 10 minutes on that specific road type. For example, if a car had 15 minutes of usage on expressways but only 5 minutes on highways, only the expressway data was included in the analysis.

3.5.4 ADAS System Override

An override of PA or ACC occurs when the driver presses the accelerator pedal and manually regains longitudinal control of the vehicle. These override events were identified using a specific signal that indicates the driver has pressed the accelerator pedal while PA or ACC was actively engaged.

Override events were classified as either PA or ACC overrides, depending on which system the driver was using at the time. The occurrence of override events was measured in two ways: frequency, defined as the number of overrides per hour, and total number of overrides. The data was grouped by car to determine which vehicles tended to override more often and for longer durations.

During the override identification process it was evident that the signal that determined if the driver overrode the system was noisy and tended to oscillate. This led to an inflated count of override events. To ensure that only genuine overrides were detected, a filter condition was applied to fill short gaps in the override signal using a rolling maximum filter with a centered window. This helped to merge closely spaced signal segments into single, continuous override events. Override events were then identified based on transitions in the filtered signal.

Before analyzing the override statistics per car, it was verified that each vehicle had at least one hour of driving time with either PA or ACC active. This step was important to avoid misleading results, as a high override frequency could occur simply due to a short duration of system usage combined with frequent overrides.

3.6 Scenario Analysis

To quantify the safety effects of ADAS usage, ADAS usage was analyzed in different traffic scenarios. This analysis enables for a comparison of driver behavior in these scenarios based on whether they were using PA, ACC, or driving manually. Additionally, safety effects can be defined using safety metrics to further evaluate the impact of ADAS usage. The following section describes how the different scenarios were identified in the data. The safety benefits of ADAS was measured by comparing safety metrics values between driving modes in different traffic scenarios.

3.6.1 Car Approaching

Car approaching scenarios were identified using range of target, range rate of target, and the ego vehicle's speed. Range rate between the ego and the target is the rate at which the distance to the target vehicle changes, which is the derivative of the range to the target.

To ensure that the scenario reflects the ego vehicle approaching a slower moving vehicle ahead, the range rate of target was required to be less than -5.04 km/h (-1.4 m/s). Accurate object detection generally does not occur until the target vehicle is within approximately 150 m, making this threshold appropriate for capturing relevant scenarios. A TTC threshold of 3.5 s was also set to ensure that the ego vehicle is close enough to the target vehicle for the situation to be considered a valid approach. This condition helps filter out cases where the target vehicle is too far ahead, even if it is being approached, and ensures that only relevant approach scenarios are included. TTC is defined according to Equation 2.1. With the signals available for this thesis this was expressed according to Equation 3.2 below.

$$\text{TTC} = \begin{cases} \dfrac{\text{Range of Target}}{|\text{Range Rate of Target}|}, & \text{if Range Rate of Target} < 0 \\ \infty, & \text{otherwise} \end{cases} \tag{3.2}$$

In addition, a duration threshold of 2 s was applied to ensure that only sustained approach scenarios were considered, filtering out brief or incidental encounters. Short, reductions in distance between vehicles can occur due to small speed fluctuations, sensor noise, or brief interactions in traffic (e.g. during lane changes). The filtering used to identify car approaching scenarios is defined in Equation 3.3. The identification of traffic scenarios, specifically car approaching, car following, traffic jam, and cut-in, as well as the mathematical expressions used, such as the one in Equation 3.3, are based on those found in the European research project L3Pilot. The project involved piloting of SAE Level 3 functions which included 1000 drivers from 100 cars across ten European countries (L3Pilot Project Consortium, 2021).

$$\begin{aligned} \text{Car Approaching Scenario} \iff & \text{Range Rate} < -1.4 \land \text{Range} < 150 \\ & \land \text{Time Gap} < 3.5 \end{aligned} \tag{3.3}$$

PA and ACC activity was checked for all scenarios. If the system was active for 100% of the samples within a scenario, the scenarios was classified as having PA or ACC engaged. For scenarios where the system was active for less than 100% of the duration, it was further checked whether the minimum time gap or minimum TTC occurred while PA or ACC was active. If so, the scenario was still considered as having PA or ACC engaged.

Overrides were also considered during the car approaching scenarios. This typically occurs when the driver wants to reduce the distance to the target vehicle or overtake it. Since the driver is in control of the vehicle during an override, these situations includes a mix of ACC/PA control and manual driving behavior. Moreover, overrides can result in reduced time gaps and TTC values, and therefore these events were not considered for the car approaching analysis. Thus, car approaching scenarios which included override from the driver were simply removed.

Override events were identified using a signal that indicated when the driver was actively overriding the ADAS. A separate analysis was conducted for these events, where the total number of overrides and the override frequency, measured as the number of overrides per hour, were calculated per car ID across different traffic scenarios. A detailed description of how overrides were identified and analyzed can be found in Section 3.5.4.

The safety metrics were analyzed by calculating the minimum and mean time gap, as well as the minimum TTC for each car approaching scenario, and plotting their distributions in histograms for manual driving, PA, and ACC driving.

The resulting distributions of safety metrics during manual driving and PA and ACC driving were compared using the Mann-Whitney U test, see Section 2.3.1. For each road type, the three driving modes were compared pairwise, resulting in three comparisons per test. Therefore, a Bonferroni correction was applied, adjusting the significance level from $\alpha = 0.05$ to $\alpha = 0.017$ to account for multiple comparisons.

3.6.2 Car Following

Car-following scenarios were identified using signals for the range rate of the target. The range rate of the target should be between 0 and -4.5 km/h (-1.25 m/s) to ensure that the target vehicle remains in front of the ego vehicle. The reason why the interval starts from 0 is because that is the maximum value of the range rate of target signal, and it does not include values where the target vehicle is moving away from the ego vehicle. To compensate for this, an additional value was defined as the difference in range of target. By calculating the difference in the range of target vehicle between consecutive samples, it was possible to identify situations where the target vehicle was moving away from the ego vehicle. A positive difference indicates an increasing gap, suggesting that the target vehicle is accelerating or the ego vehicle is decelerating. A threshold of 2 m was set for the difference of range of target to make sure that the target vehicle followed the same target vehicle and that no cut ins occur during the scenario.

Scenarios in which the target vehicle decelerated abruptly, prompting the ADAS to respond with equally aggressive braking were also identified. This reaction caused the time gap to drop just below 1 second, as illustrated in Figure B.2 in Appendix B.

A duration threshold of 20 s was set to capture car following scenarios that were considered sufficiently long to enable the analysis. Setting this threshold too low could result in misclassifying scenarios that are not truly car following scenarios. For example, a car approaching another vehicle but not engaging in sustained following behavior might be misclassified. Similarly, in stop-and-go traffic vehicles may briefly follow each other due to the stop-and-start nature, could also be wrongly labeled as car following if the duration threshold is set to a too low value.

Additionally, a time gap threshold was set to be below 3.5 s to ensure that the ego vehicle is close enough to the target vehicle, as would be the case in a following scenario. A vehicle speed threshold was set to 80 km/h (22.22 m/s) in order to find more critical car following scenarios at higher speeds. Setting a higher speed threshold focuses on more critical car following scenarios, as safety risks increase at higher speeds. At high speeds, braking distances are longer and reaction times shorter, making even small differences in following distance more dangerous and likely to result in collisions. In contrast, at lower speeds, the margin for error is larger, and drivers have more time to react. Therefore, it is more interesting to focus on higher speeds in terms of safety metrics.

Similar to car approaching overrides were also considered during the car following scenarios and car following scenarios which included override from the driver were simply removed. The car following conditions are summarized in Equation 3.4. As previously mentioned the definitions of the scenarios are based on those found in the L3Pilot project (L3Pilot Project Consortium, 2021).

$$\begin{aligned}\text{Car Following Scenario} \iff{} & \text{Range Rate} \leq 0 \land \text{Range Rate} \geq -1.25 \\ & \land \text{Vehicle Speed} > 22.22 \land \text{Time Gap} < 3.5\end{aligned} \tag{3.4}$$

After analyzing the resulting minimum time gaps using above mentioned filtering methods it was found that a substantial amount of scenarios with PA or ACC on had low time gap values, which is unreasonable since these systems are designed to keep a set distance to the target vehicle (given that the driver does not override the system). After reviewing individual event plots that included 10 s of pre-event data, it was observed that large spikes in the range of target often occurred just before the start of the following scenarios. These were interpreted as likely overtaking maneuvers, as they were typically accompanied by an increase in longitudinal acceleration before the event, followed by a decrease once the event began.

It is important to note that the data did not include an identifier for the target vehicle. In other words, there is no single signal indicating when the vehicle has identified a new target vehicle whose distance it is measuring. Instead, changes in the target vehicle can instead be identified by detecting large shifts in the measured range to the target.

Instances of cut-ins before and just as the car following scenarios starts were identified by observing significant drops in both longitudinal acceleration and range of target, see Figure B.1 in Appendix A. These events were interpreted as instances where another vehicle overtook the ego vehicle and then cut in with a small longitudinal margin (see range of target in Figure B.1), prompting the ego vehicle's ADAS to decelerate in order to maintain the set time gap, before the other vehicle accelerated away.

To address this, a condition was applied to filter out events with large spikes in range of target within the pre-event window. A condition for pre-event PA and ACC active was also defined as 3 s to ensure that the events labeled as PA or ACC active was actively using the system even before the event started.

For car following scenarios, the minimum and mean time gaps were identified for each scenario, and the distributions were plotted in histograms for manual driving, PA, and ACC driving. Similar to the car approaching scenarios, the distributions of safety metrics during car following scenarios were compared using the Mann-Whitney U test. Additionally, the distance setting used in each car following scenario was identified to understand which settings were most commonly represented during these scenarios.

3.6.3 Cut-in

A cut-in scenario occurs when another vehicle enters the ego vehicle's lane from an adjacent lane with a small distance and time gap to the ego vehicle. In the data, cut-in scenarios were identified by analyzing the difference in the range of target signal. Specifically, the detection algorithm looked for significant negative changes in the range of target between two consecutive samples. A threshold of -4 m was used to indicate a sudden appearance of an object in front of the ego vehicle, which is characteristic of a cut-in scenario.

To ensure the detected object was actually close to the ego vehicle, the range of target was also required to be below 100 m. If a vehicle changes lanes with a safe margin, it can still cause a large change in the range of target, even though it does not represent a cut-in.

Additionally, a speed threshold of 80 km/h (22.22 m/s) was applied. This was done to focus on cut-in scenarios occurring during higher speeds, where the safety implications are more significant, and to exclude less critical cut-ins, such as those that may happen during low-speed conditions like traffic jams. The cut-in conditions are summarized in Equation 3.5 below. As previously mentioned the mathematical definitions were based on those stated in the L3Pilot project (L3Pilot Project Consortium, 2021).

$$\begin{aligned}\text{Cut-in Scenario} \iff\; & \text{Range of Target Difference} \leq -4 \\ & \wedge \text{abs(Range of Target} + \text{Range of Target Diff)} < 100 \\ & \wedge\; \text{Vehicle Speed} > 22.22\end{aligned} \tag{3.5}$$

Once a sample satisfies the conditions defined in Equation 3.5, data from two seconds before and after that index are extracted and defined as a cut-in scenario.

For cut-in events, the minimum longitudinal acceleration of each scenario was identified, and the distribution was plotted using histograms to examine how the braking responses of PA and ACC differ from manual driving. Additionally, the minimum and mean time gaps, as well as the minimum TTC for each scenario, were identified and their distributions plotted for each driving mode. The time gap two seconds after the cut-in was also analyzed to assess how the ADAS adjusted the gap compared to how drivers adjusted it during manual driving. This analysis only includes situations where the driver did not intervene by braking or deactivating the system, and instead allowed PA or ACC to manage the braking. Similar to the car approaching and car following scenarios, the Mann-Whitney U test was performed on the safety metric distributions to determine whether there were significant differences between the driving modes.

3.6.4 Traffic Jam

Traffic jam situations were identified by examining the posted speed limit, vehicle speed, and the distance to the target vehicle. The posted speed limit should be 100 km/h or above to indicate that the car is driving on a highway. The vehicle speed should be 60 km/h or below to reflect that the car is driving slower than the posted speed limit, as in a traffic jam. Additionally, the distance to the target vehicle should be less than 40 m to ensure that the driver is following a car in front. A duration threshold of 180 s was also set to ensure that the vehicle remains in a real traffic jam for a sufficient amount of time. The filtering for traffic jam is summarized in Equation 3.6. The above thresholds and Equation 3.6 are based on those found in the L3Pilot project (L3Pilot Project Consortium, 2021).

$$\begin{aligned}\text{Traffic Jam Condition} \iff \; & \text{Speed Limit} \geq 100 \land \text{Vehicle Speed} \leq 16.7 \\ & \land \text{Range} < 40\end{aligned} \tag{3.6}$$

The usage of PA and ACC was calculated based on the time spent with the system active during traffic jams, as well as the percentage of cars in the dataset that engaged ADAS while driving in traffic jams.

4

Results

In the following chapter the result of the thesis are presented for three main categories of ADAS usage: general and contextual usage, usage style, and scenario-based safety benefit analysis. These results aim to provide insight into were drivers use with PA and ACC in practice, how drivers use the systems, and what there are for safety benefits by using ADAS.

4.1 General and Contextual Usage

The following section presents the results regarding the general and contextual usage of PA and ACC. The usage is grouped by posted speed limit and road type. Across the entire processed dataset, a total of 1063295 km were driven and 20490.62 hours of driving time. Of this 134380 km (≈ 12.6%) and 1589.03 hours (≈ 7.8%) were driven with PA active, while ACC was active for 162271 km (≈ 15.3%) and 1942.96 hours (≈ 9.5%).

4.1.1 Posted Speed Limits

Figure 4.1 and Figure 4.3 illustrate ADAS usage in the complete dataset grouped by posted speed limit, in terms of time and distance, respectively. Figure 4.1 shows that ACC was more commonly used across all posted speed limits except roads with 120 km/h speed limit were PA has slightly higher usage.

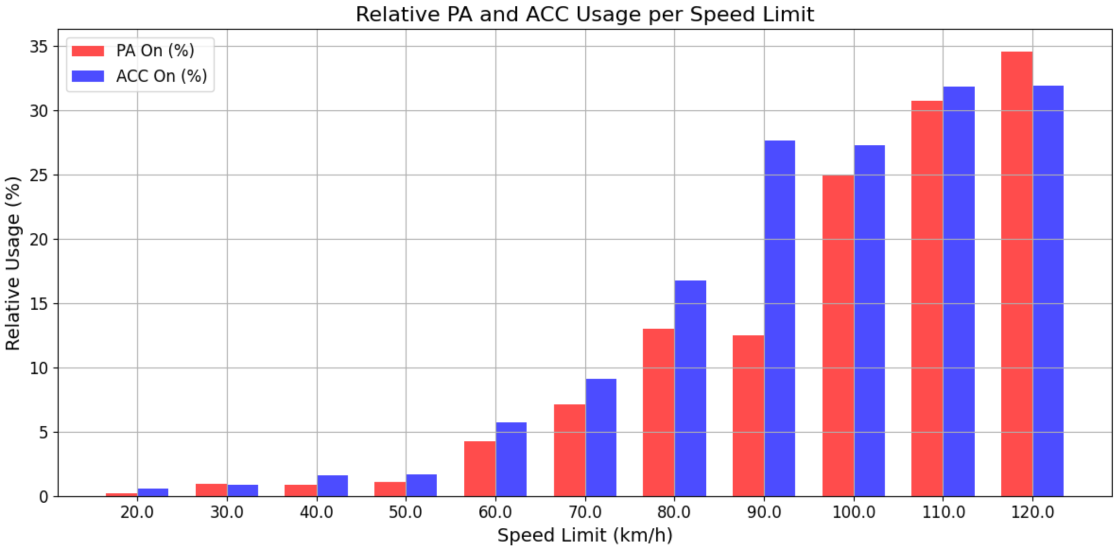

Figure 4.1: Relative usage of PA and ACC in percent, with respect to time, grouped by posted speed limit.

For comparison, the total driving time in hours, including PA, ACC, and manual driving, for each posted speed limit is presented in Figure 4.2. This shows the distribution of total driving time across different speed limits in the dataset. Most time was spent driving on lower speed roads, 50 km/h and 70 km/h, while less time was spent on high speed roads, 100 - 120 km/h. One possible reason for the differing usage of PA and ACC on 90 km/h roads could be that considerably less time was spent driving on roads with this speed limit compared to others, see Figure 4.2. With fewer driving hours available in this posted speed limit, the observed usage rates may be less representative and more sensitive to individual driver preferences.

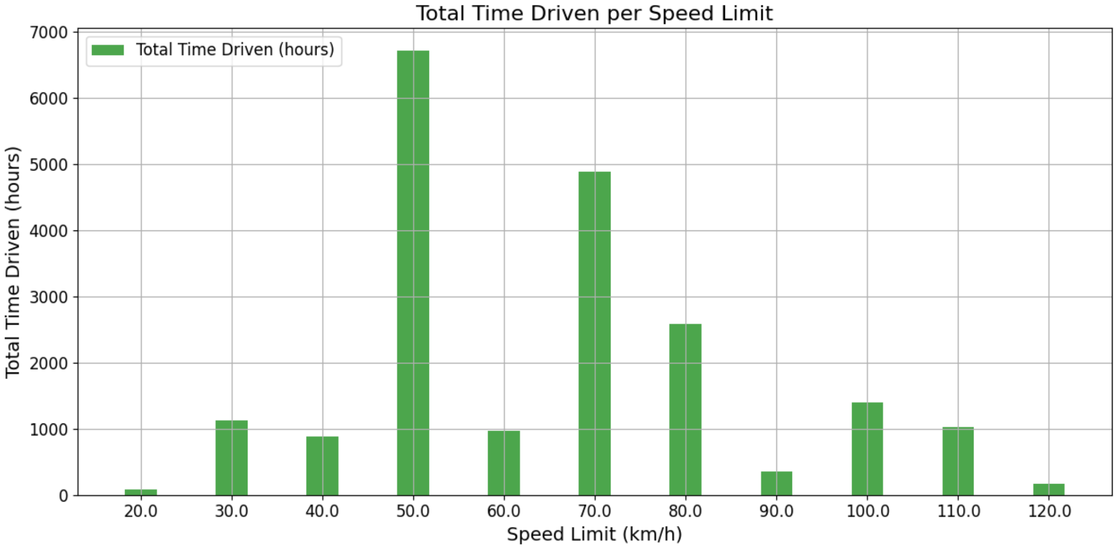

Figure 4.2: Total time driven for each posted speed limit.

Figure 4.3 shows the total relative distance driven with PA or ACC on per posted speed limit, compared to Figure 4.1 which illustrates the usage with respect to time. The results are very similar to those in Figure 4.1 and further show that ADAS are primarily used on higher-speed roads.

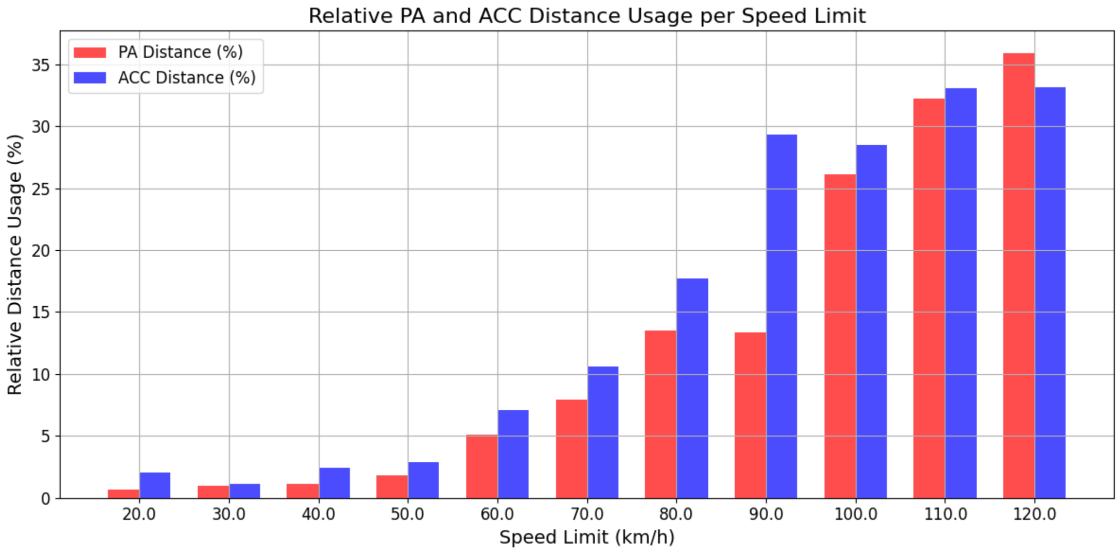

Figure 4.3: Relative usage of PA and ACC in percent, with respect to distance, grouped by posted speed limit.

Total distance driven in km per posted speed limit is shown in Figure 4.4. The figure reveals that a large portion of the distance was covered on high-speed roads (100–120 km/h), despite relatively less time being spent on these roads compared to lower-speed roads. This is expected, as higher speeds result in covering longer distances in shorter periods of time.

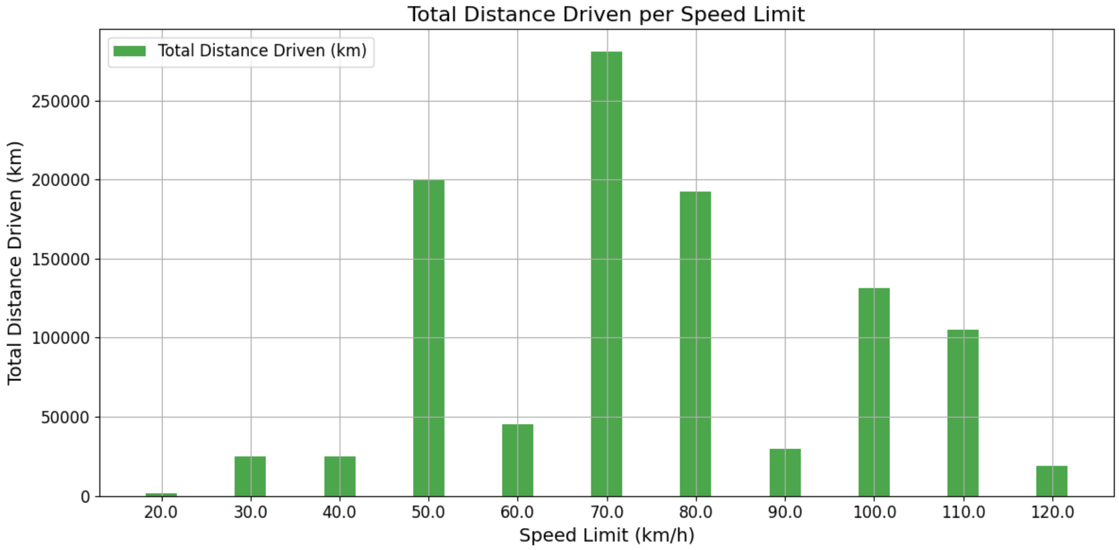

Figure 4.4: Total distance driven for each posted speed limit.

As can be seen in Figure 4.1 and Figure 4.3 PA and ACC usage was more prominent when driving on higher speed roads, especially on road speeds above 100. This is in accordance with previous research that shows ADAS usage is more common on highways and high speed roads (Kidd and Reagan, 2019; Perez et al., 2024; Orlovska et al., 2020). It also corresponds to the main intended usage according to the user manual (Volvo Car Corporation, 2024).

4.1.2 Road Type

Figure 4.5 illustrates PA and ACC usage over time grouped by road type. The method used to categorize road types is described in Section 3.4.1. As previously mentioned, the road type labeled "Unknown" refers to roads for which a specific road type could not be identified. Figure 4.5 shows that both PA and ACC are primarily used on highways, which is consistent with the patterns observed in Figure 4.1 and Figure 4.3.

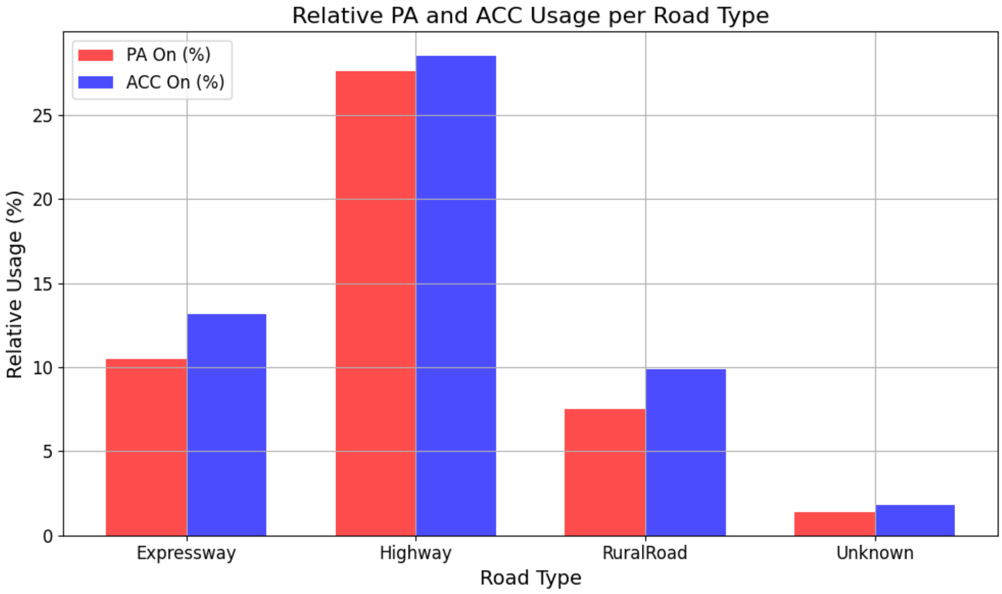

Figure 4.5: Relative usage of PA and ACC in percent, with respect to time, grouped by road type.

Figure 4.6 shows the total time spent driving on each road type. Majority of time was spend driving on unknown road types followed by expressway, rural roads, and lastly highways.

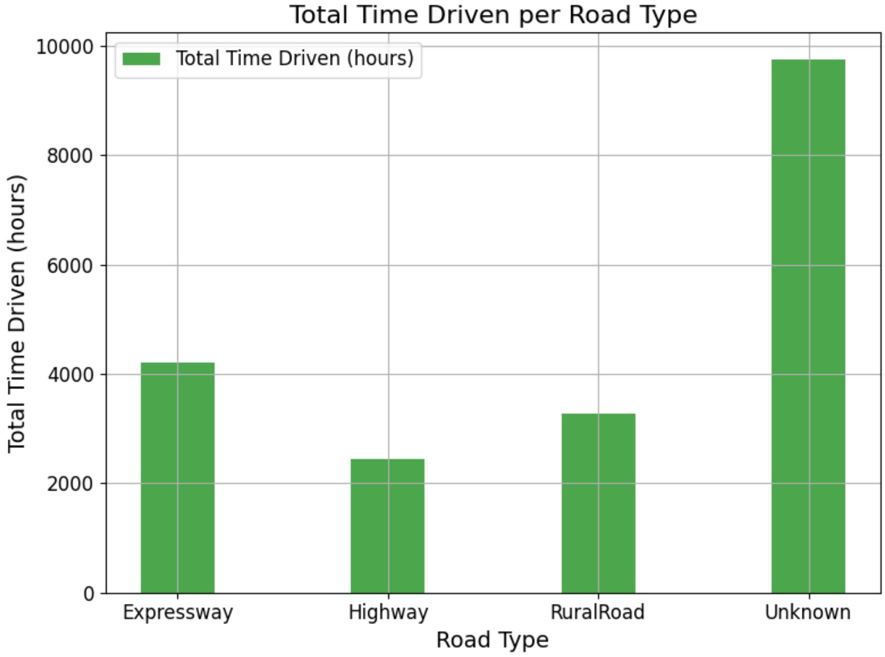

Figure 4.6: Total time driven for each road type.

Figure 4.7 illustrates PA and ACC usage per road type in terms of distance driven, which shows similar results as Figure 4.5.

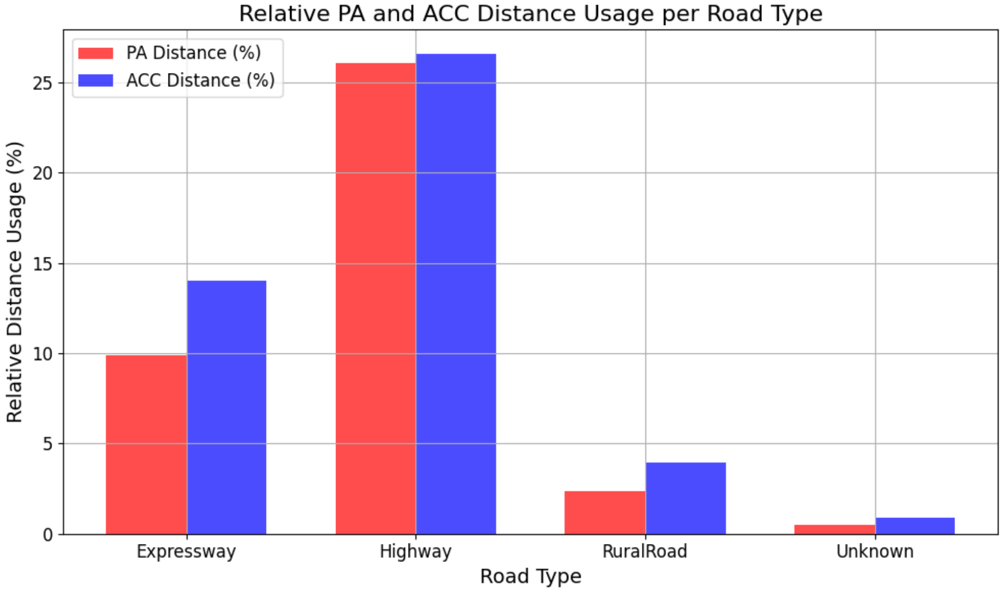

Figure 4.7: Relative usage of PA and ACC in percent, with respect to distance, grouped by posted road type.

The total distance driven on each road type followed a pattern very similar to the time spent driving on those road types, see Figure 4.6.

As can be seen in Figure 4.5, PA and ACC are mainly used on expressways and highways, i.e. high speed roads, which is in accordance with Figure 4.1 and Figure 4.3. Figure 4.6 show that a substantial portion of the data originates from driving on "Unknown" road types. This category includes roads such as those found in city and other urban environments. However, since the usage of PA and ACC is very low on these roads, as seen in Figure 4.5 and Figure 4.7, they are not as interesting for further analysis and PA and ACC are not primarily intended to be used on these types of roads (Volvo Car Corporation, 2024).

4.1.3 Traffic Jam

The traffic jam analysis showed that PA and ACC were active for 16.25 % and 14 % of the total time spent in traffic jams, respectively. Further analysis revealed that most of the drivers in the dataset never chose to activate the system at all during traffic jams, see Figure D.1 and Figure D.2 in Appendix D.

4.2 Usage Style

ACC and PA are activated with buttons on the steering wheel. While active, the driver can adjust the target speed and select from five different distance settings to the lead vehicle. The systems are deactivated either by pressing the button again or by applying the brake. In the following section, preferences in the distance settings and deactivation behavior are presented.

4.2.1 Distance Setting

When using ACC or PA there is a setting for the distance to the car in front. Figure 4.8 shows the distribution of the selected distance settings for the cars that have used ACC or PA for at least 10 % of one trip. For cars where the driver switched between multiple settings during a trip, the most frequently used setting was selected. Importantly, only times when the system was active and a lead vehicle was present were considered when determining the most-used setting. This ensures that the distance setting was actually relevant and in use. It is also worth noting that the factory default is setting 3. A lower distance setting corresponds to a shorter following distance to the vehicle ahead, while a higher setting results in a longer following distance.

As shown in Figure 4.8, it is more common to use one of the lower settings together with the default setting. 21.81 % of drivers change between different settings during trips.

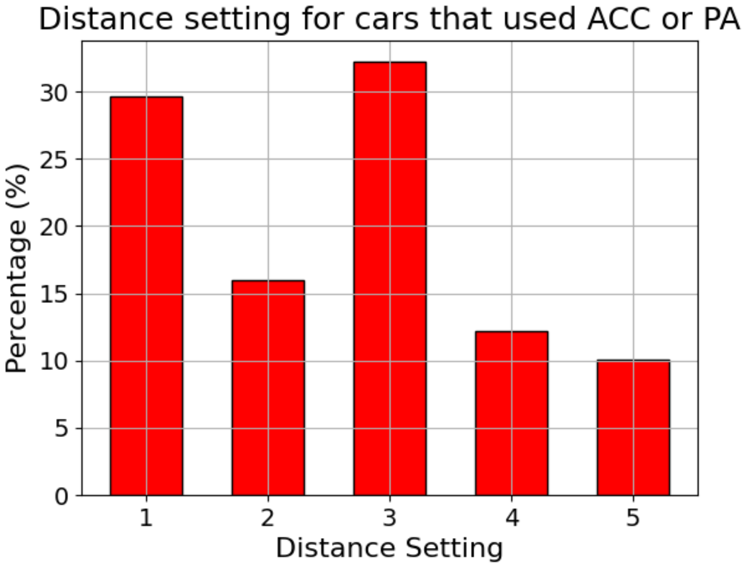

Figure 4.8: Relative amount of distance settings used for cars in which ACC or PA was activated.

Different preferences of distance settings could be an indication of difference in preferred time gap to a lead vehicle. Figure 4.9 shows the time gaps during manual driving, divided into 3 groups based on the most frequently used distance setting. All time gaps below 3 s from all trips are included. Figure 4.10 shows the histograms in Figure 4.9 as line plots for easier comparison. Note that this analysis contains data from all road types.

As seen in the Figure 4.10, drivers who prefer lower distance settings also tend to maintain shorter following distances during manual driving. Similarly, those who use higher distance settings generally maintain longer time gaps. The result of the Chi-squared goodness-of-fit test for the different group comparison are listed in Table 4.1. As mentioned in Section 3.5.1 Group 1 are distance settings lower than default, Group 2 is the default setting, and Group 3 are higher than default.

Table 4.1: Chi-squared goodness-of-fit test comparing distance settings groups.

Comparison	**p-value**	**Result**
Group 1 and 2	< 0.001	Significant difference
Group 1 and 3	< 0.001	Significant difference
Group 2 and 3	< 0.001	Significant difference

Since all p-values were below the significance level $\alpha = 0.017$, the results indicate that there is a statistically significant difference between all three groups.

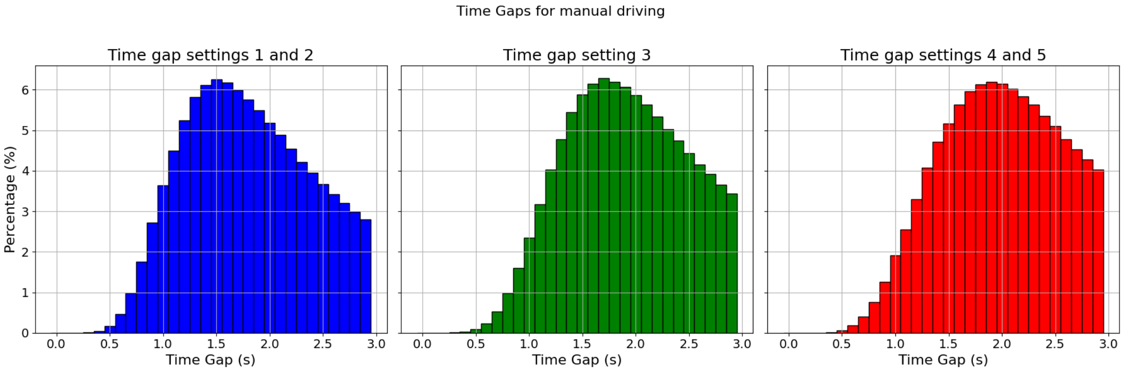

Figure 4.9: Time gaps during manual driving (ACC and PA are inactive) categorized based on each cars most frequently used distance setting.

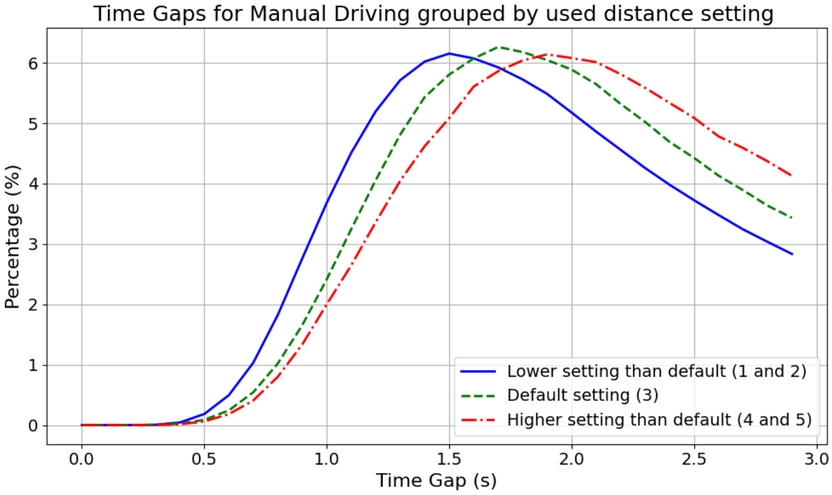

Figure 4.10: Time gaps during manual driving (ACC and PA are inactive) categorized based on each cars most frequently used distance setting.

4.2.2 Deactivation Events

As can be seen in Figure 4.11, the results show that the shares of deactivation by brake and by button press are similar. Total number of deactivations was 39769.

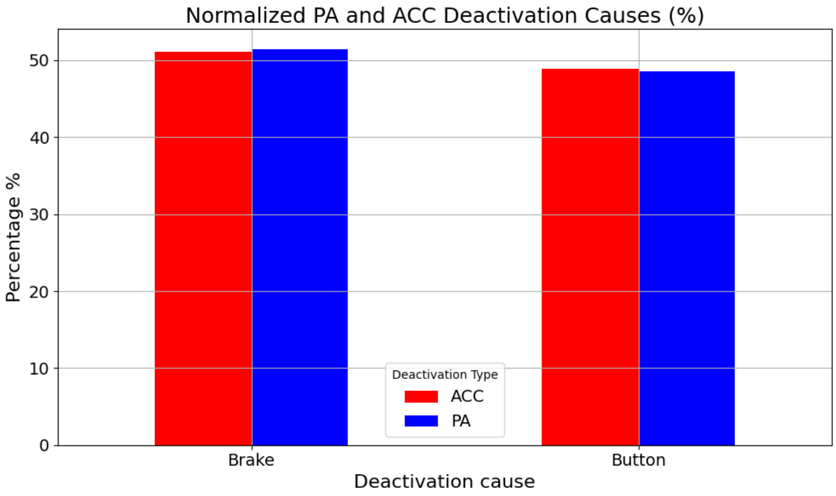

Figure 4.11: Distribution of PA and ACC deactivations by cause, brake or button press, shown as a percentage of total deactivations.

Figures 4.12 and 4.13 show the ACC and PA deactivations caused by either button press or brake input, where the time gap was below 3 s. The percentages represent the share of each deactivation type relative to the total number of deactivations. Here, deactivation events including overrides and also events with less than 10 s ACC or PA have been removed.

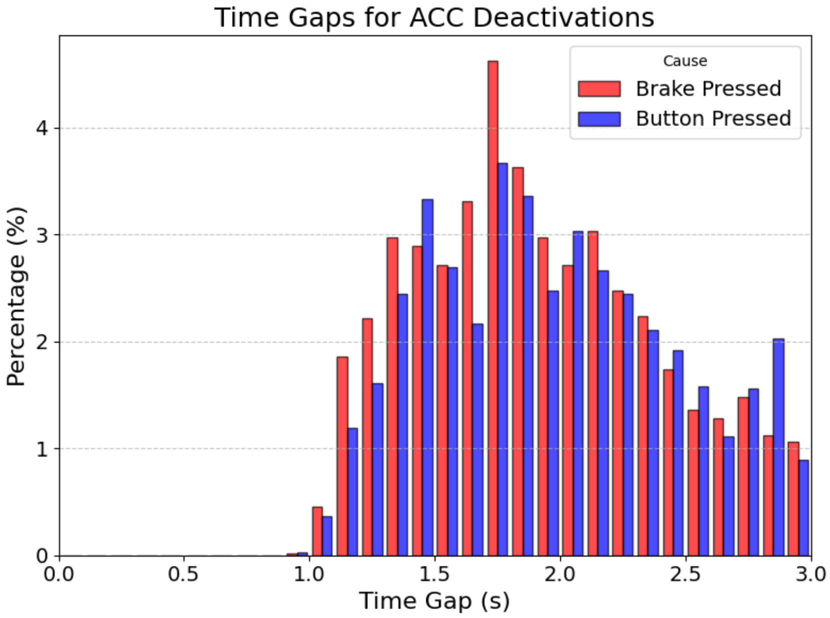

Figure 4.12: Time gap distribution for ACC deactivation.

The results in Figure 4.12 shows that ACC deactivation by braking is more frequent in lower time gaps. 46.76 % of the total brake deactivations had a time gap under 3 s and 42.07 % of the total button deactivations had a time gap under 3 s.

Figure 4.13 shows that brake deactivations of PA occur more frequently at lower time gaps compared to button deactivations. Specifically, 46.36 % of the brake deactivations occurred with a time gap below 3 s, while the corresponding percentage for button deactivations was 34.86 %. The result of the Chi-squared goodness-of-fit test for PA and ACC deactivation comparing brake and button press deactivations is shown in Table 4.2. The test shows that there is significant difference between brake and button press deactivations for both PA and ACC.

Table 4.2: Chi-squared goodness-of-fit test comparing type of deactivation, brake or button press.

Comparison	**p-value**	**Result**
ACC deactivation	< 0.0001	Significant difference
PA deactivation	0.004	Significant difference

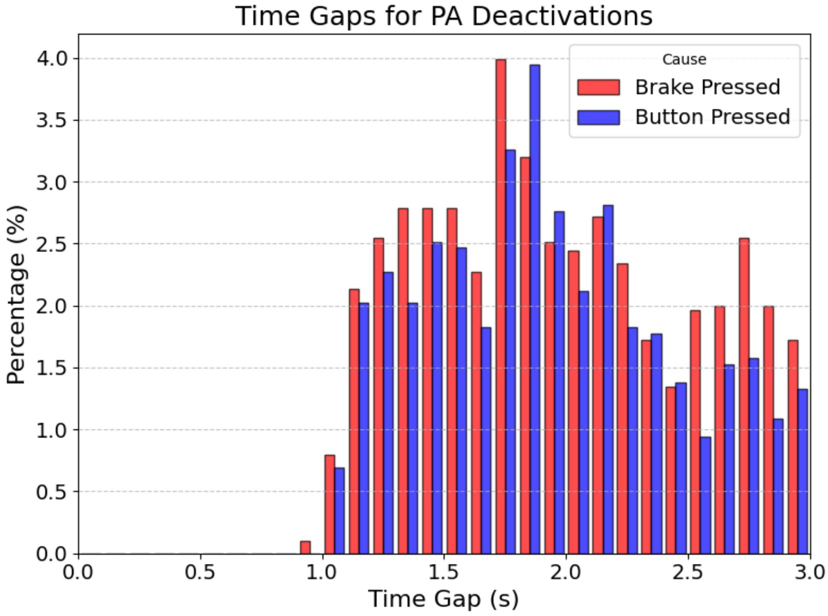

Figure 4.13: Time gaps distribution for PA deactivations.

4.2.3 Lane Deviation

Figure 4.14 illustrates the mean deviation from the middle of the lane for PA, ACC, and manual driving, across all road types. PA driving results in the lowest mean lane deviation for all road types while ACC and manual driving have similar values in mean lane deviation across all road types.

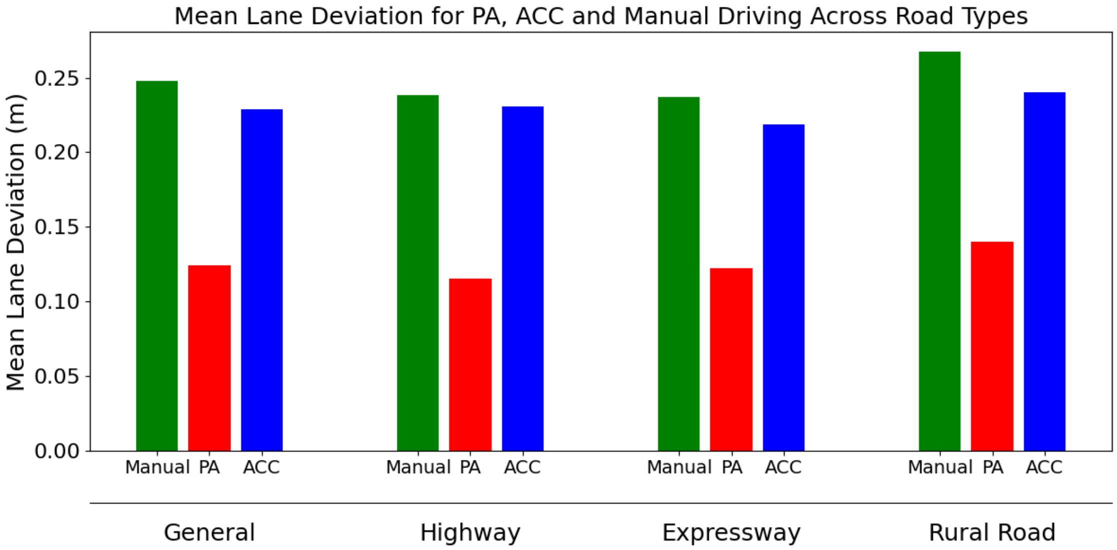

Figure 4.14: Mean deviation from the center of the lane across all driving modes and road types.

Figure 4.15 shows the standard deviation of the lane positioning across different road types. Similar to the mean lane deviation, it indicates that PA results in less lane deviation compared to both ACC and manual driving. Manual driving also here has the highest deviation.

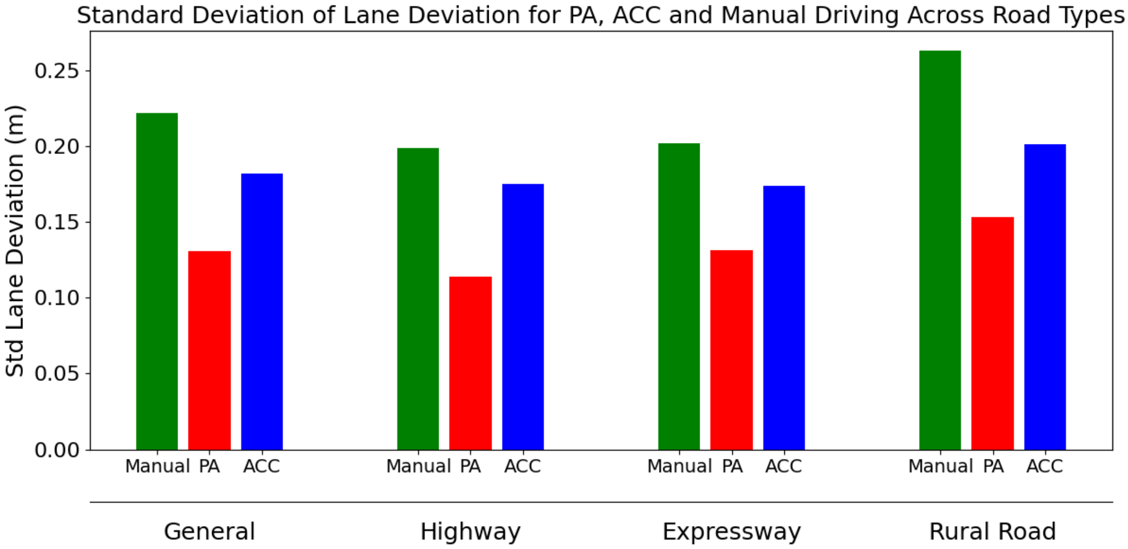

Figure 4.15: Standard deviation across all driving modes and road types for lane positioning.

Table 4.3 list the result from the Mann-Whitney U test comparing the distributions of mean lane deviations across driving modes and road types. The result shows that there is significant difference in mean lane deviation between all driving modes across all road types.

Table 4.3: Mann-Whitney U test results comparing the distributions mean lane deviation across driving modes and road types, significance level $\alpha = 0.017$.

Group	**Comparison**	**p-value**	**Result**	**Effect size(r_{rb})**
General	PA vs ACC	< 0.001	Significant difference	0.92
General	PA vs Manual	< 0.001	Significant difference	0.94
General	ACC vs Manual	< 0.001	Significant difference	0.24
Highway	PA vs ACC	< 0.001	Significant difference	0.97
Highway	PA vs Manual	< 0.001	Significant difference	0.97
Highway	ACC vs Manual	0.012	Significant difference	0.12
Expressway	PA vs ACC	< 0.001	Significant difference	0.92
Expressway	PA vs Manual	< 0.001	Significant difference	0.96
Expressway	ACC vs Manual	< 0.001	Significant difference	0.32
Rural Road	PA vs ACC	< 0.001	Significant difference	0.86
Rural Road	PA vs Manual	< 0.001	Significant difference	0.91
Rural Road	ACC vs Manual	< 0.001	Significant difference	0.27

4.2.4 ADAS System Override

The override analysis revealed that in some cars overrides occurred often, both during car approaching and car following scenarios with some cars recording override frequencies above 200 per hour, see Figure E.1 and Figure E.2 in Appendix E. Some drivers also choose to override often during traffic jams, see Figure E.3 in Appendix E. However, it became evident that only a limited amount of data met the traffic jam criteria defined in Equation 3.6. As a result, few override events were observed during traffic jams.

4.3 Scenario-based Safety Effect Analysis

The following section presents the results of the scenario-based analyses, including the minimum and mean distributions for car-approaching, car-following, and cut-in scenarios, as well as statistical analyses of the distributions. In total 564,236 car approaching scenarios, 51,072 car following scenarios, and 52,348 cut-in scenarios were identified from the data.

4.3.1 Car Approaching

Each car approaching scenario was categorized based on whether it was driven entirely (100 percent) with PA/ACC active or entirely under manual driving, determined by the proportion of time within the scenario that each driving mode was active. Figure 4.16 shows the minimum time gaps for car approaching scenarios during manual driving when PA were on, and when ACC were on.

As shown in Figure 4.16 and Figure 4.19, minimum time gap values during manual driving drop below 1 s, whereas this is not observed to the same extent in scenarios where PA or ACC were active. Time gap values below 1 s are considered unsafe (Viti et al., 2008). Furthermore time gaps below 0.5 s can be identified for manual driving which are considered critical values (Lyu et al., 2018). The spikes observed in the PA and ACC plots can be explained by the fact that the driver sets a distance to the target vehicle.

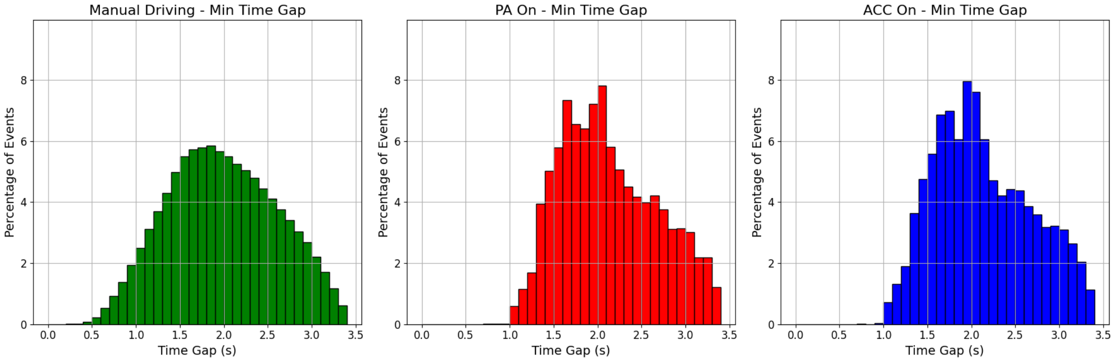

Figure 4.16: Distribution of minimum time gap for each car approaching scenario, with the 0 - 3.5 s interval highlighted.

Figure 4.17 shows the distributions as lines for easier comparison.

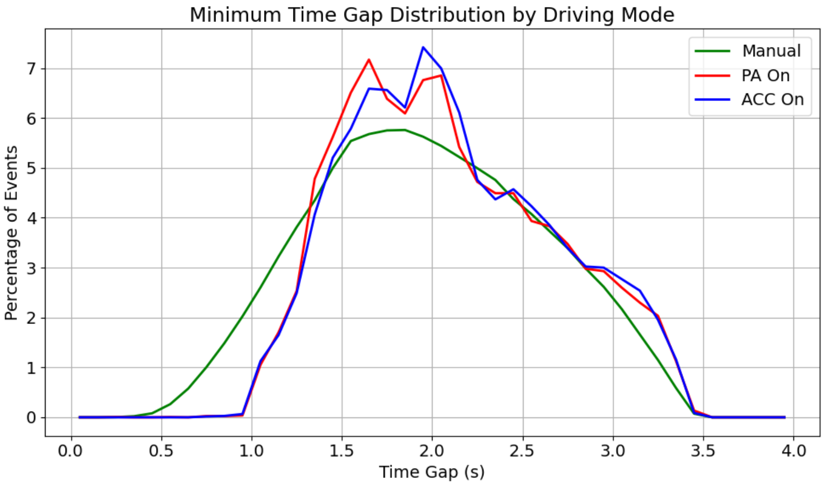

Figure 4.17: Distribution of minimum time gap illustrated as a line across driving modes, with the 0 - 4 s interval highlighted.

The distribution of mean time gaps in Figure 4.18 and Figure 4.19 further shows that higher time gap values are more common during PA and ACC driving compared to manual driving.

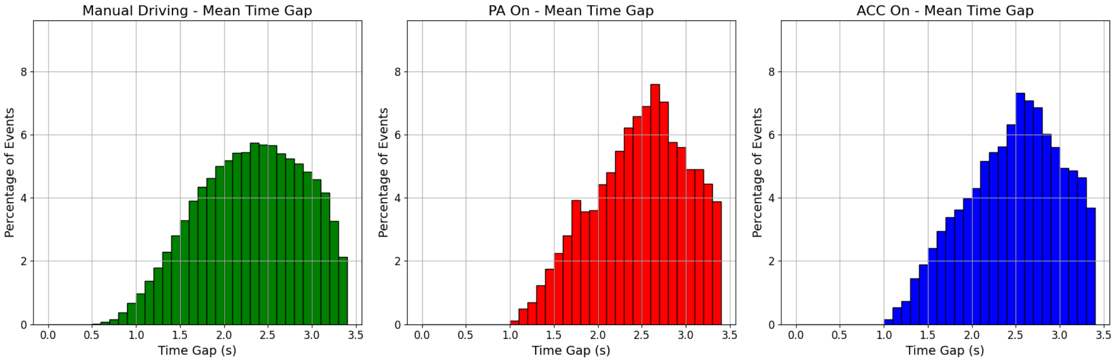

Figure 4.18: Distribution of mean time gap for each car approaching scenario, with the 0 - 3.5 s interval highlighted.

Figure 4.19 shows the distributions as lines for easier comparison.

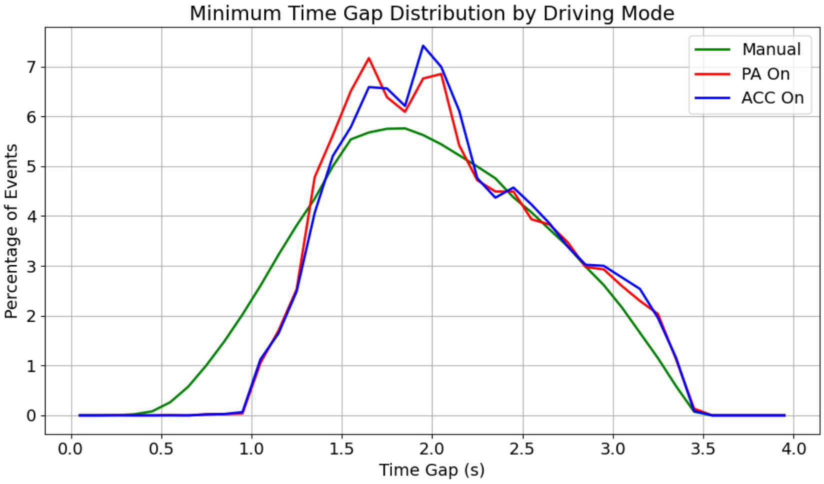

Figure 4.19: Distribution of mean time gap illustrated as a line across driving modes, with the 0 - 4 s interval highlighted.

Table 4.4 and Table 4.5 present the results of the Mann-Whitney U tests comparing the distributions of minimum and mean time gaps, respectively. The results indicate a significant difference in time gap distributions between manual driving and both PA and ACC driving. However there is no significant difference in mean time gap between PA and ACC.

Table 4.4: Mann-Whitney U test comparing the distributions of minimum time gap during car approaching scenarios with significance level = 0.017.

Comparison	**p-value**	**Result**
Manual vs PA	< 0.001	Significant difference
Manual vs ACC	< 0.001	Significant difference
PA vs ACC	< 0.001	Significant difference

Table 4.5: Mann-Whitney U test comparing the distributions of mean time gap during car approaching scenarios with significance level = 0.017.

Comparison	**p-value**	**Result**
Manual vs PA	< 0.001	Significant difference
Manual vs ACC	< 0.001	Significant difference
PA vs ACC	0.036	No significant difference

Figure 4.20 shows the minimum TTC values for the car approaching scenarios. TTC values below 4 s are considered relevant for safety (Singh and Kathuria, 2021), which is why this section of the histogram is highlighted. Although many values were recorded for car approaching scenarios above 4 s, these are considered less critical and are therefore less relevant to display. For the full distribution of minimum TTC, see Figure 4.24.

As illustrated in Figure 4.20, lower TTC values occur more frequently during manual driving. This indicates that drivers tend to get closer to the target vehicle during car approaching scenarios when driving manually.

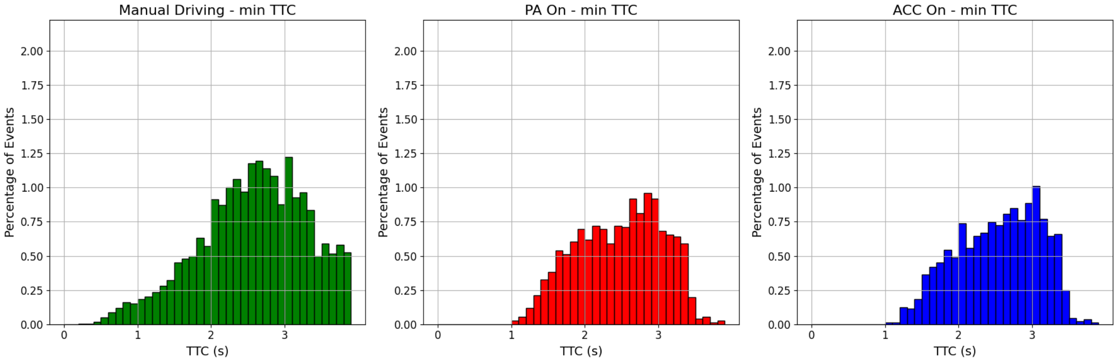

Figure 4.20: Distribution of minimum TTC for each car approaching scenario, with the 0 - 4 s interval highlighted.

Figure 4.21 shows the distributions as lines for easier comparison.

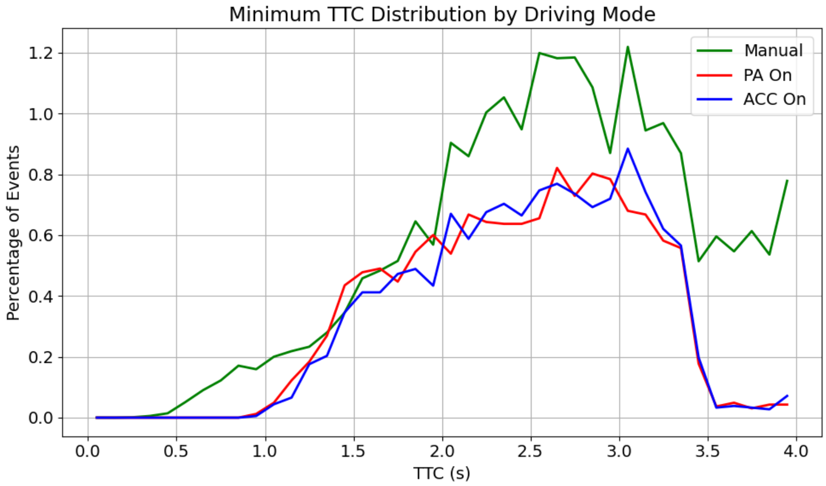

Figure 4.21: Distribution of minimum TTC illustrated as a line across driving modes, with the 0 - 4 s interval highlighted.

Table 4.6 list the result of the Mann-Whitney U test comparing the distribution of minimum TTC across the driving modes. It further supports that there is a difference in the distributions between manual driving and both PA and ACC driving.

Table 4.6: Mann-Whitney U test comparing the distributions of minimum TTC during car approaching scenarios with significance level = 0.017.

Comparison	p-value	Result
Manual vs PA	< 0.001	Significant difference
Manual vs ACC	< 0.001	Significant difference
PA vs ACC	0.0024	Significant difference

Figures 4.22, 4.23, and 4.24 show the distributions of minimum time gap, mean time gap, and minimum TTC as violin plots, with the mean and first quartiles illustrated at the center of each plot.

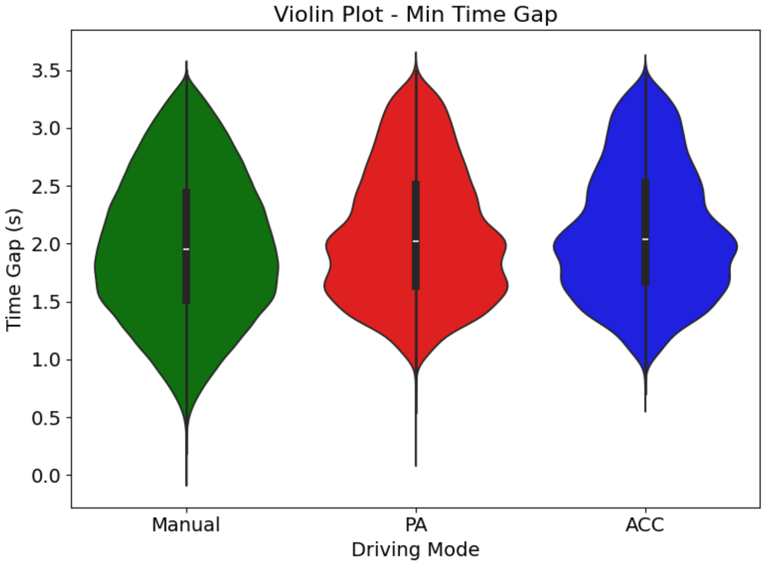

Figure 4.22: Violin plot illustrating the distribution of minimum time gap for each car approaching scenario.

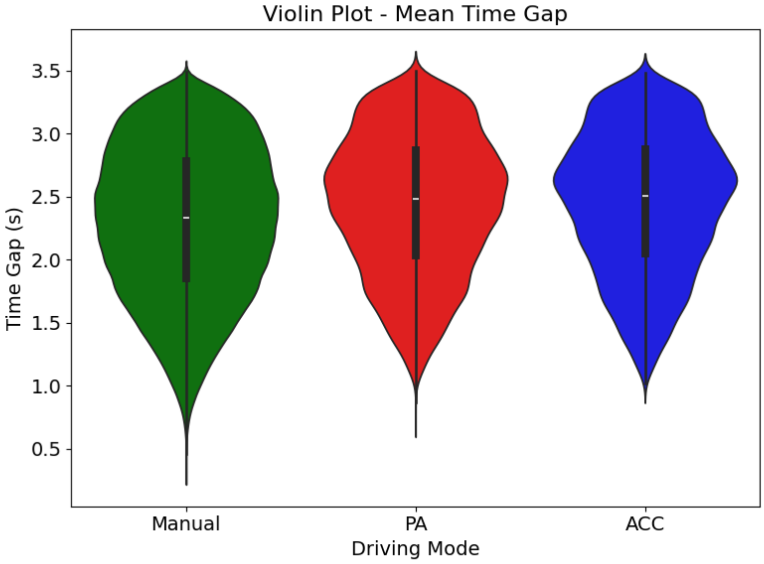

Figure 4.23: Violin plot illustrating the distribution of mean time gap for each car approaching scenario.

Figure 4.24 shows the full distribution of minimum TTC during car approaching scenarios. It can be observed that minimum TTC values are generally higher for PA and ACC driving compared to manual driving. The mean minimum TTC is also higher for both PA and ACC, 35.56 and 36.31 s respectively compared to 30.48 s for manual driving. Indicating that these systems maintain greater TTC margins.

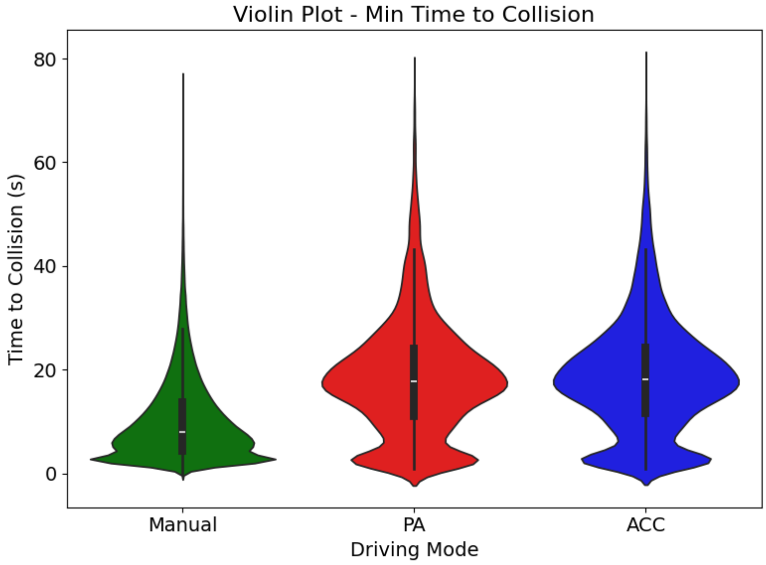

Figure 4.24: Violin plot illustrating the distribution of minimum TTC for each car approaching scenario.

4.3.2 Car Following

Similar conclusions to those in the car approaching analysis in Section 4.3.1 can be drawn for car following scenarios. As shown in Figure 4.25 and Figure 4.27, more scenarios with minimum time gaps below 1 s are observed during manual driving compared to when PA or ACC is active. This suggests that safer margins are more consistently kept when driving with PA or ACC.

The reason why there are scenarios with minimum time gap just below 1 s for PA and ACC active could be that the target vehicle rapidly decelerates and the system is not able to keep up which results in the time gap very briefly dropping below 1 s, see Figure B.2 in Appendix B. The driver is then most likely using the shortest distance setting, which also happens to be the most common distance setting during car following scenarios, see Figure 4.31. It is also important to mention the fact that ACC and PA need to sense a shift in time gap and cannot act precautionary by other cues such as target vehicle brake light onset, which drivers can during manual driving. Thus, the system has shorter time to react if the target vehicle begins to decelerate.

One important note is that the minimum time gap values in Figure 4.25 shows the minimum time gap that appeared for each car following scenario. This means that a single sample with a very low time gap could be reflected in the plot. It does not consider low time gaps for an extended time period. Therefore, it is relevant to look at the mean time gaps in Figure 4.27 which illustrates the mean time gap for each car following event.

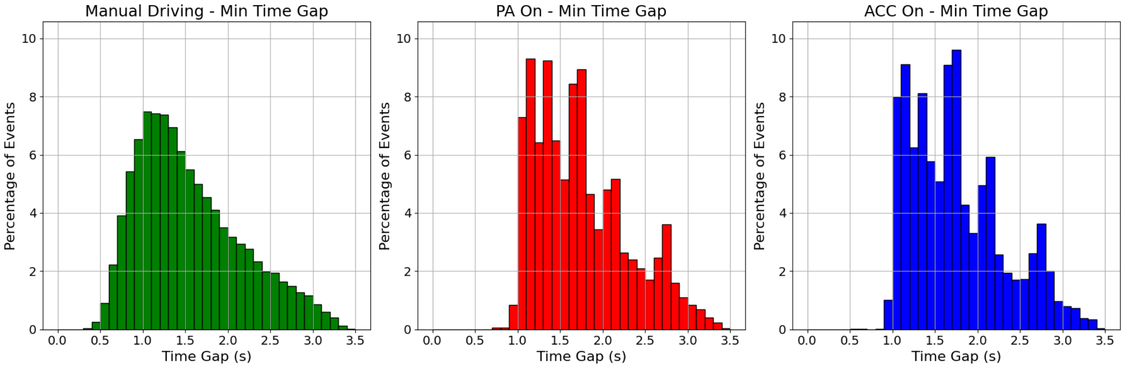

Figure 4.25: Distribution of minimum time gap for each car following scenario, with the 0 - 3.5 s interval highlighted.

Figure 4.26 shows the distributions as lines for easier comparison.

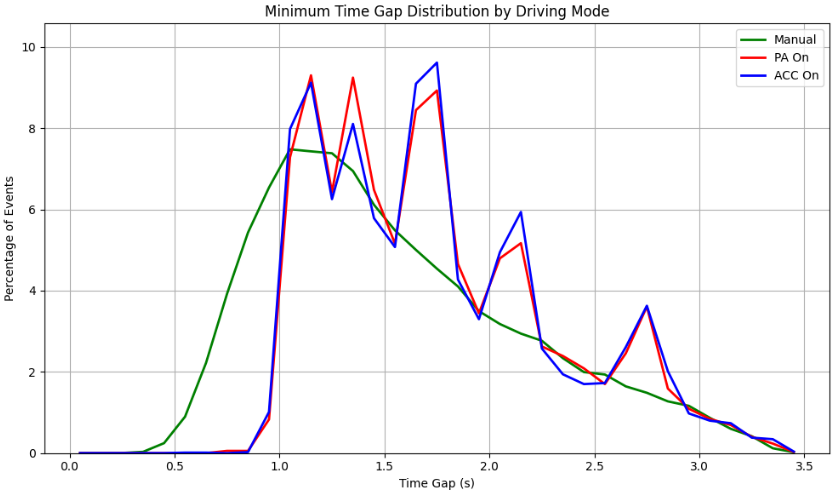

Figure 4.26: Distribution of minimum time gap illustrated as a line across driving modes, with the 0 - 3.5 s interval highlighted.

It is evident by examining the distribution in Figure 4.25 and Figure 4.28 that there are significantly more car following scenarios during manual driving, compared to PA- and ACC driving, in which the time gaps below 1 s are recorded, which as mentioned previously under Section 4.3.1 are considered unsafe. There are also scenarios with time gaps under 0.5 s which are considered critical (Lyu et al., 2018). By examining Figure 4.27 and Figure 4.28 one can see that the mean time gap values are higher for PA and ACC driving compared to manual driving.

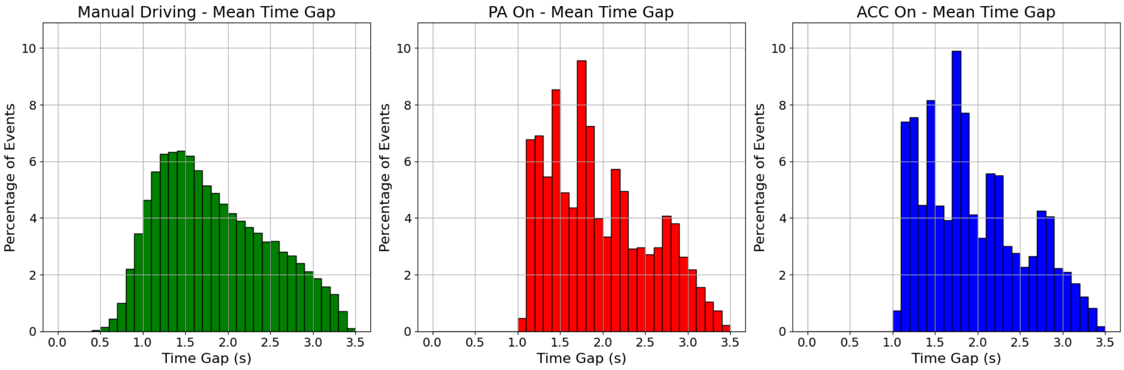

Figure 4.27: Distribution of mean time gap for each car following scenario, with the 0 - 3.5 s interval highlighted.

Figure 4.28 shows the distributions as lines for easier comparison.

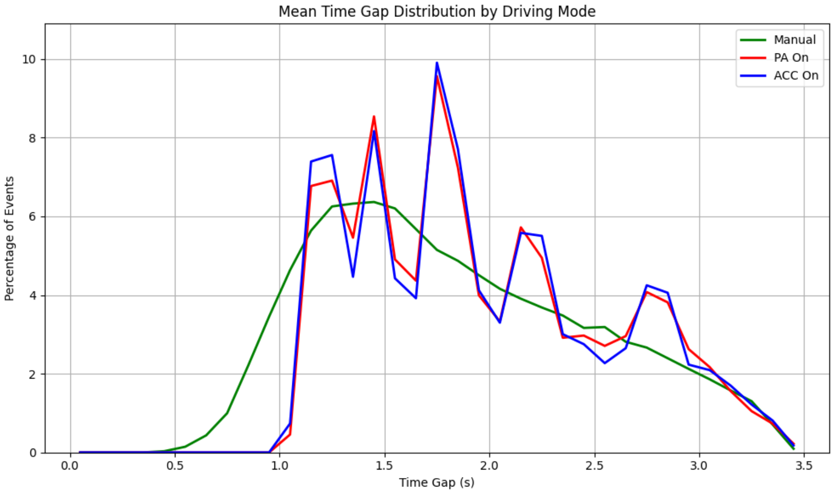

Figure 4.28: Distribution of minimum time gap illustrated as a line across driving modes, with the 0 - 3.5 s interval highlighted.

Table 4.7 and Table 4.8 present the results of the Mann-Whitney U tests comparing the distributions of minimum and mean time gaps, respectively. The results indicate a significant difference in time gap distributions between manual driving and both ACC and PA driving and no significant difference between the PA and ACC distributions.

Table 4.7: Mann-Whitney U test comparing the distributions of minimum time gap during car following scenarios with significance level = 0.017.

Comparison	p-value	Result
Manual vs PA	< 0.001	Significant difference
Manual vs ACC	< 0.001	Significant difference
PA vs ACC	0.56	No significant difference

Table 4.8: Mann-Whitney U test comparing the distributions of mean time gap during car following scenarios with significance level = 0.017.

Comparison	**p-value**	**Result**
Manual vs PA	< 0.001	Significant difference
Manual vs ACC	< 0.001	Significant difference
PA vs ACC	0.76	No significant difference

Figure 4.29 and Figure 4.30 shows the minimum time gap and mean time gap distributions in the form of violin plots. From the violin plots it is further clear that more low time gap events occur during manual driving while greater time gap margins are more common during PA and ACC driving.

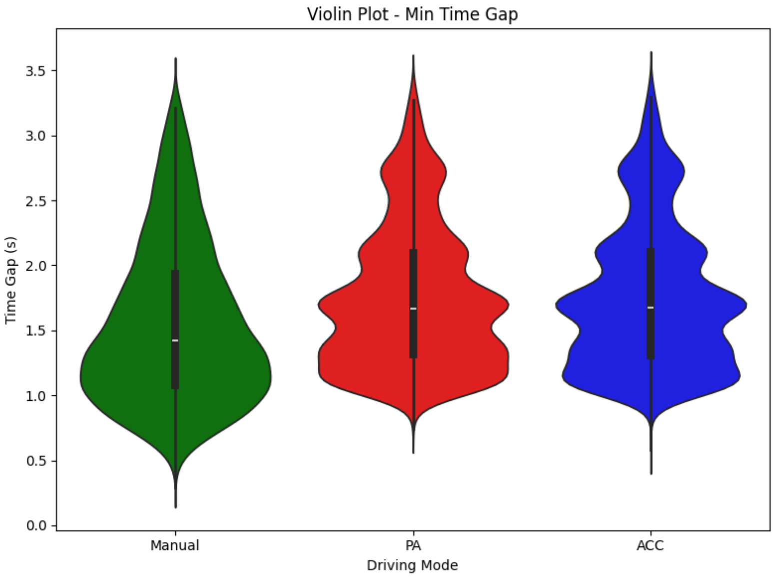

Figure 4.29: Violin plot of the distribution of minimum time gap for each car following scenario.

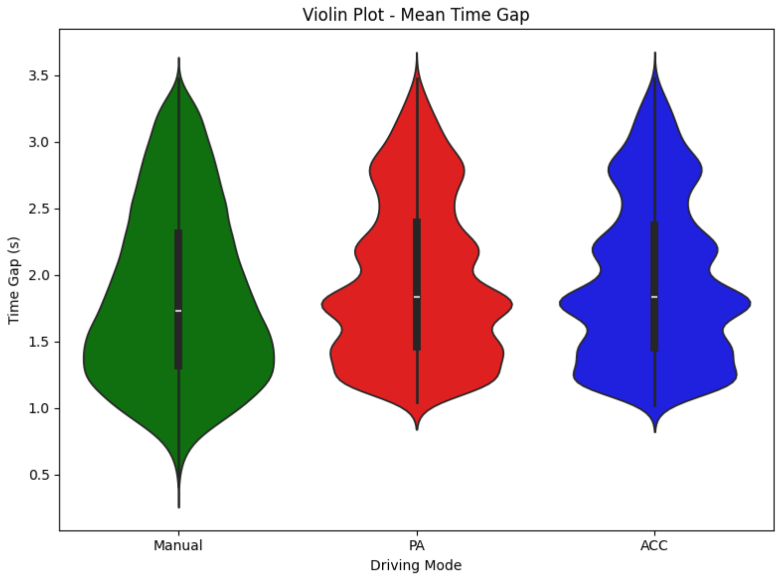

Figure 4.30: Violin plot of the distribution of mean time gap for each car following scenario.

Spikes corresponding to the different distance settings can also be observed in Figure 4.25 and Figure 4.27 as well as in the violin plots in Figure 4.29 and Figure 4.30. These align closely with the most commonly selected distance setting among drivers, as shown in Figure 4.31. It is also evident that drivers tend to prefer lower distance settings with 1 being the most common setting followed by 3 which is the default setting.

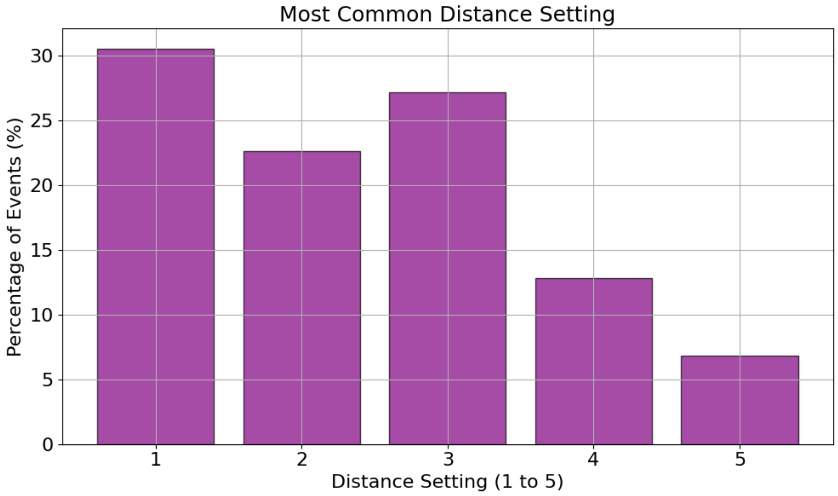

Figure 4.31: Most common distance setting among the drivers during car following scenarios.

4.3.3 Cut-in

Figure 4.32 shows the minimum longitudinal accelerations, i.e largest decelerations, for the cut-in scenarios. The mean values of the distributions of minimum longitudinal acceleration were -0.43, -0.51, and -0.52 m/s^2 for manual driving, PA, and ACC driving, respectively.

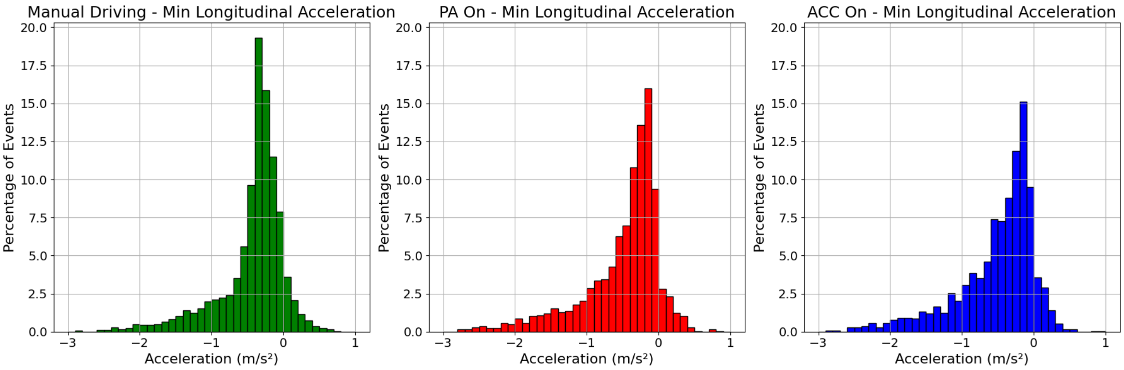

Figure 4.32: Distribution of minimum longitudinal acceleration for each cut-in scenario.

Figure 4.33 illustrates the time gap two seconds after each cut-in scenario. The distributions between the driving modes are similar. However, the mean values of the distributions are 1.86, 1.88, and 1.92 s for manual driving, PA, and ACC driving respectively, suggesting that the ADAS adjusts the time gap to slightly higher values after a cut-in has occurred.

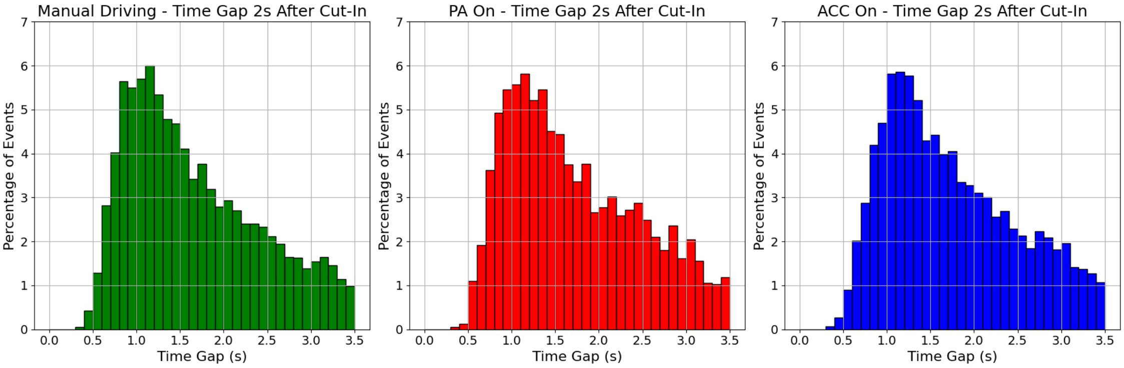

Figure 4.33: Distribution of time gap two seconds after each cut-in scenario, with the 0 - 3.5 s interval highlighted.

Figure 4.34 and Figure 4.35 illustrates the minimum time gap during cut-in scenarios. The distributions across the different driving modes are more similar compared to those observed in the car approaching and car following scenarios, as shown in Figure 4.16 and Figure 4.25. Figure 4.36 and Figure 4.37 shows the mean time gap during cut-in scenarios for the different driving modes, and the distributions appear very similar in this plot as well.

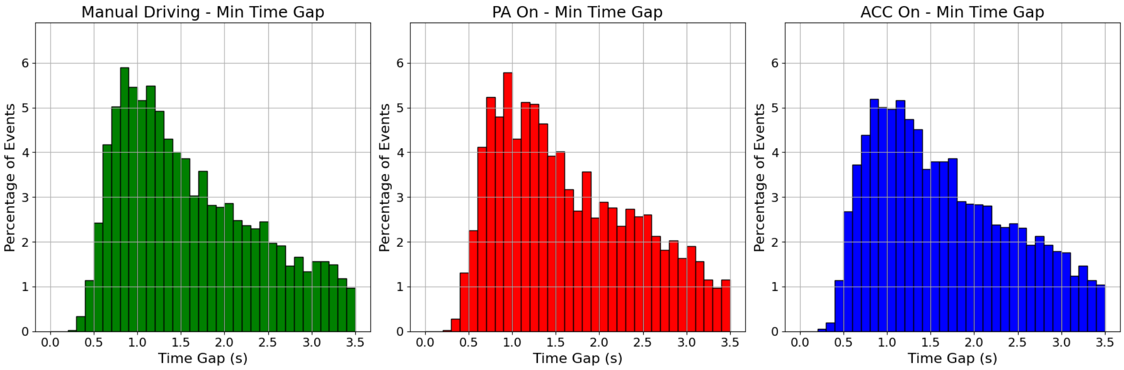

Figure 4.34: Distribution of minimum time gaps during cut-in scenarios, with the 0–3.5 s interval highlighted.

Figure 4.35 shows the distributions as lines for easier comparison.

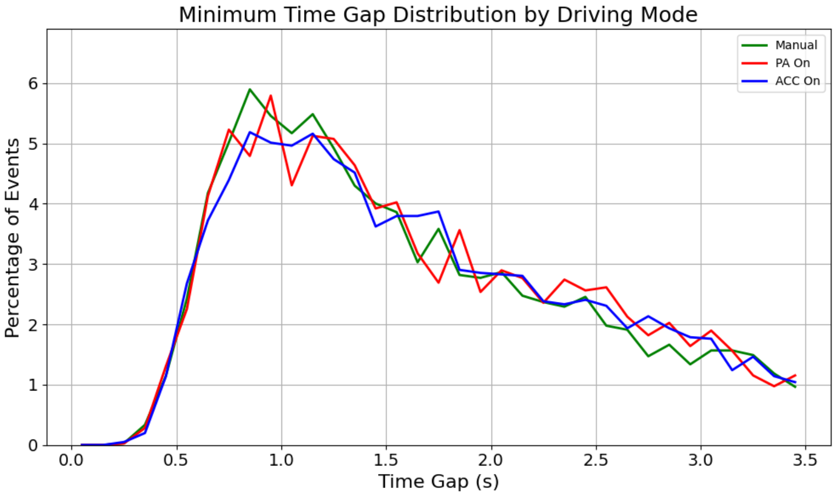

Figure 4.35: Distribution of minimum time gap illustrated as a line across all driving modes, with the 0–3.5 s interval highlighted.

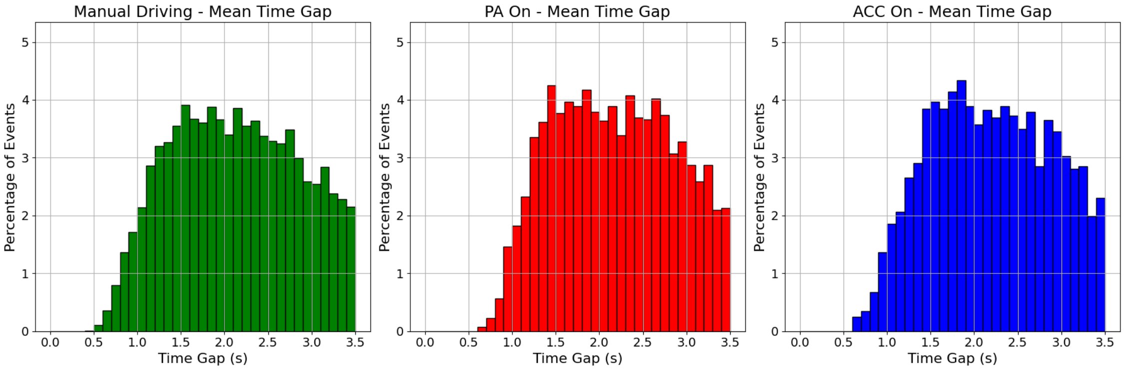

Figure 4.36: Distribution of mean time gap during each cut-in scenario, with the 0 - 3.5 s interval highlighted.

Figure 4.37 shows the distributions as lines for easier comparison.

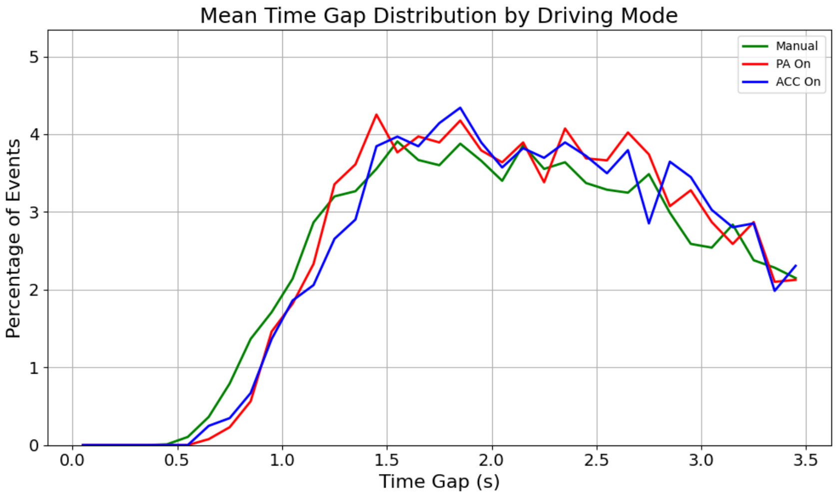

Figure 4.37: Distribution of minimum time gap illustrated as a line across driving modes, with the 0 - 3.5 s interval highlighted.

Table 4.9 and Table 4.10 present the results of the Mann-Whitney U tests comparing the distributions of minimum and mean time gaps, respectively. The results indicate no significant difference between manual driving and PA distributions and significant difference between manual driving and ACC driving.

Table 4.9: Mann-Whitney U test comparing the distributions of minimum time gap during cut-in scenarios with significance level = 0.017.

Comparison	p-value	Result
Manual vs PA	0.23	No significant difference
Manual vs ACC	< 0.001	Significant difference
PA vs ACC	0.22	No significant difference

Table 4.10: Mann-Whitney U test comparing the distributions of mean time gap during cut-in scenarios with significance level = 0.017.

Comparison	p-value	Result
Manual vs PA	0.95	No significant difference
Manual vs ACC	< 0.001	Significant difference
PA vs ACC	0.064	No significant difference

Figure 4.38 and Figure 4.39 illustrate the distribution of minimum time gap and mean time gap as violin plots.

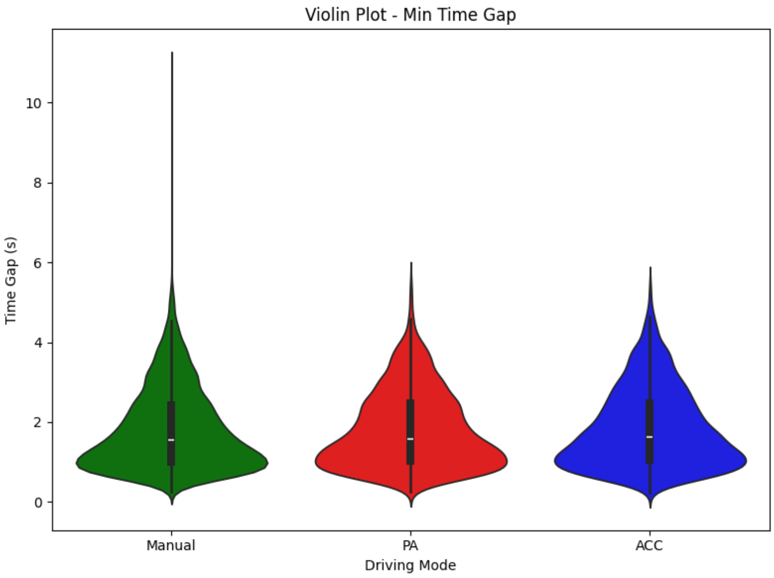

Figure 4.38: Violin plot of the distribution of minimum time gap during the cut-in.

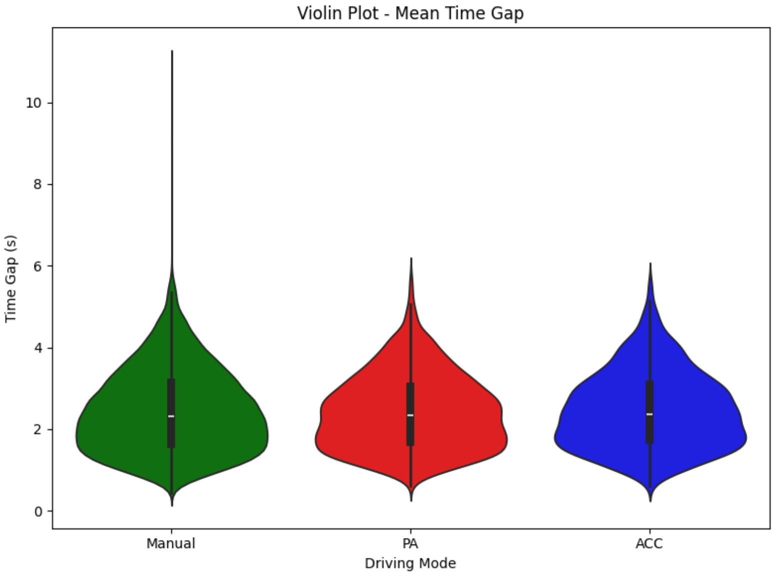

Figure 4.39: Violin plot of the distribution of mean time gap during the cut-in.

Figure 4.40 shows the distribution of minimum TTC values during the cut-in scenarios. The plot is limited to TTC values between 0 and 4 s, as this interval is most relevant from a safety perspective (Singh and Kathuria, 2021). A substantial number of scenarios had high and safe TTC values, which explains the relatively low percentages on the y-axis. As shown in Figure 4.40, the number of scenarios with critical TTC under 1 s are quite similar across all driving modes.

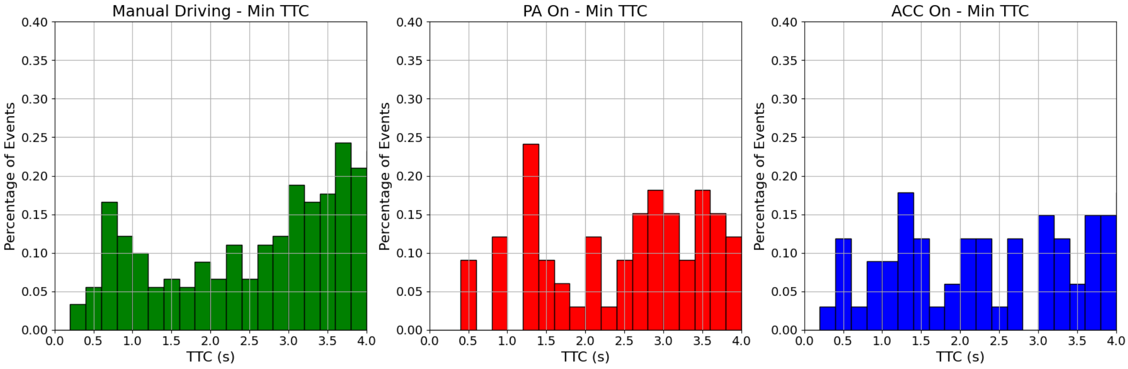

Figure 4.40: Distribution of minimum TTC reached during the cut-in scenarios, with the 0 - 4 s interval highlighted.

Table 4.11 presents the results of the Mann-Whitney U test comparing the distributions of minimum TTC across the driving modes. The results further support that there is a difference in distributions between manual driving and both PA and ACC driving.

Table 4.11: Mann-Whitney U test comparing the distributions of minimum TTC during cut-in scenarios with significance level = 0.017.

Comparison	p-value	Result
Manual vs PA	< 0.001	Significant difference
Manual vs ACC	< 0.001	Significant difference
PA vs ACC	0.9	No significant difference

Figure 4.41 illustrates the minimum TTC distribution in the form of a violin plot. The TTC values across a wider range can be seen and it is evident that a large portion of the cut-in events had high TTC values across all driving modes.

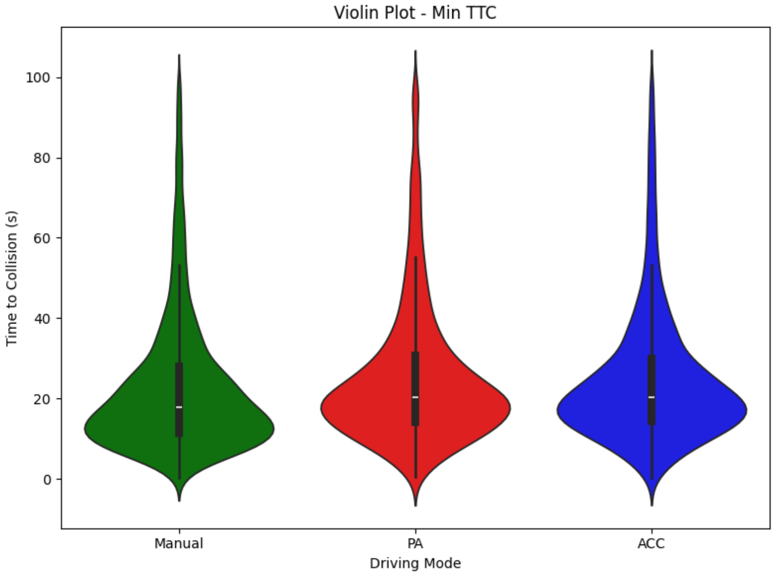

Figure 4.41: Violin plot of the distribution of minimum TTC reached during the cut-in scenarios.

5

Discussion

The following section discusses the results related to general ADAS usage, scenario-based analyses, lane positioning, and usage pattern analyses, including distance setting preferences and system deactivation.

5.1 General Usage

From Figure 4.1 and Figure 4.3, it is clear that drivers are more likely to use PA or ACC on roads with higher speed limits, which aligns with findings from previous research (Perez et al., 2024; Orlovska et al., 2020). Figure 4.5 and Figure 4.7 also indicates that the drivers preferred to use PA and ACC on expressways and highways compared to rural roads. The data also indicate that ACC is the more commonly used option across several speed categories and across all road types. One possible explanation is that some drivers may find the steering assistance from PA to be intrusive or uncomfortable, making ACC a preferred alternative (Orlovska et al., 2020).

In the study by Orlovska et al. (2020), drivers also completed surveys in which they reported a preference for using PA on open roads and highways, particularly under low traffic density conditions. In contrast, in urban environments, where frequent braking is required, drivers found that they had to engage and disengage the system more often. This increased interaction was considered inconvenient, leading to reduced system usage in such contexts. This trend is also reflected by the drivers in Figure 4.1 and Figure 4.3, where ADAS usage at lower speed limits, typically associated with urban areas, is lower.

In urban areas, extensive roadworks are often more common, which can result in sudden changes to the roadway, such as when lane markings no longer indicate the correct path. This is also noted by Volvo as a key limitation of PA and similar systems (Volvo Car Corporation, 2024), leading many drivers to avoid using the system in such environments. Similar limitations are present in other ADAS systems as well, such as GM's Super Cruise, which also relies on clear lane markings and mapped roads for proper functionality (GMC, 2025). This behavior is reflected in the reduced usage observed on lower-speed roads, as shown in Figure 4.1 and Figure 4.3.

Furthermore, Figures 4.5 and 4.7, which show ADAS usage grouped by road type, adding to the finding that PA and ACC are primarily used on highways and expressways, and to a lesser extent on rural roads. This is consistent with previous studies, such as Masello et al. (2022), which attribute lower usage in rural areas to factors like road curvature and poor lane quality. PA is less effective in providing support in these conditions, particularly when sharp curves or faded lane markings are present. Volvo also highlights these limitations, noting that under such circumstances, steering assistance may struggle to keep the vehicle centered or may be temporarily deactivated (Volvo Car Corporation, 2024).

Figure D.1 and Figure D.2 in Appendix D shows low usage of ADAS during traffic jams, which in this thesis are defined as situations where the vehicle is traveling at speeds below 60 km/h on roads with posted speed limits above 100 km/h (see Equation 3.6), i.e., highways. The total PA and ACC usage in percentage in terms of time were only 16.25% and 14% respectively. This finding aligns with previous results by Perez et al. (2024), which suggest that drivers are more likely to engage ADAS during free-flowing traffic and stable maneuvering conditions.

The paper by Orlovska et al. (2020) also notes that drivers preferred using PA during traffic jams and queuing situations, as the system handled stop-and-go traffic effectively. However, some drivers felt that the time gap maintained by PA during these situations was too long, which often encouraged other vehicles to cut in front of them. To address this, drivers may override the system to reduce the time gap to the vehicle ahead, thereby discouraging cut-ins. As previously mentioned, override statistics per car were collected from the data, including the total number of overrides and overrides per hour, see Section 3.5.4. The data showed that some vehicles had a high frequency of overrides during traffic jams which could be due to above reasoning, see Figure E.3 in Appendix E.

5.2 Distance Settings

The results regarding the most commonly used distance settings show that Setting 3 is the most popular, followed by the two shorter settings as can be seen in Figure 4.8. This is expected, as Setting 3 is the factory default which explains its high usage. Some drivers may not even be aware of the possibility to adjust the distance setting or may find it inconvenient to need to switch it repeatedly. This can be seen that only 21.81 % of drivers change settings during a trip. This default bias contributes significantly to Setting 3's high usage rate.

The fact that the shorter settings (1 and 2) are used more often than the longer ones (4 and 5) indicates that many drivers find the default time gap too long. As previously mentioned, the research from Orlovska et al. (2020) showed that large following distances tend to invite other vehicles to merge into the lane, interrupting the flow and requiring repeated deceleration. Therefore, one possible reason drivers opt for shorter distance settings is to reduce such interruptions and maintain smoother driving and better lane control.

Our hypothesis was that drivers that use a lower distance setting for ACC and PA would also tend to drive manually with a lower time gap. The results as can be seen in Figure 4.9 and Figure 4.10 supports the hypothesis. This suggests that time gap preferences are driver-dependent traits, rather than only a reaction to the automation system's behavior. In other words, drivers who select a shorter time gap likely have a general comfort with, or preference for, closer car following behavior. This alignment between manual and assisted driving reinforces the idea that personalization of distance settings could enhance user satisfaction and acceptance of driver assistance systems.

5.3 System Deactivation

Figure 4.11 illustrates how users typically choose to deactivate the system. The results indicate that deactivations through the button and through braking occur with nearly equal frequency, suggesting that users are comfortable using both methods depending on the situation. This was somewhat surprising, as it was anticipated that one method might dominate. However, the balanced use suggests that both methods are perceived as intuitive or convenient by users.

A hypothesis was that the brake is pressed more often for deactivations that occur closer to a vehicle in front. Figure 4.12 and Figure 4.13 shows the distribution of deactivations for different time gaps. The result is showing a higher percentage of low time gap deactivations for brake inputs compared to button presses for both PA and ACC, which is in line with the hypothesis. One possible explanation is that when drivers encounter sudden or ambiguous traffic situations, the natural reflex is to press the brake pedal, as it provides an immediate sense of control by slowing down the vehicle. However, braking may decelerate the car more abruptly than necessary. In contrast, using the button allows drivers to deactivate the system without significantly affecting vehicle speed, thereby maintaining comfort and minimizing disruption to traffic flow. The driver can also still press the brake after deactivation if needed.

5.4 Lane Positioning

The results in Figure 3.1 show that PA consistently leads to lower mean lane deviation from the center of the lane compared to both ACC and manual driving across all road types. This indicates that PA helps maintain a more centered lane position.

When looking at each road type, highways showed the most centered positioning, especially for PA (mean = 0.115 m), likely due to the presence of clear, consistent lane markings and less curvature which has been previously reported as factors affecting the LCA performance (Wang et al., 2025; Utriainen et al., 2020). Expressways showed the second most centered lane positioning, while rural roads had the highest deviations, with manual driving reaching a mean deviation of 0.267 m and ACC at 0.240 m. These roads often feature sharper curves and less visible lane markings, which can challenge both drivers and automation. The positioning metric is based on the vehicle's position relative to lane markings as detected by the car's sensors. If the lane markings are missing or unclear, the data is excluded from the analysis, which may bias the results toward better-performing segments.

Both ACC and manual driving provide no steering assistance to drivers, which would indicate that they are very similar. Interestingly, ACC tends to have slightly lower mean lane deviation than manual driving on highways (0.231 m vs. 0.239 m), expressways (0.219 m vs. 0.237 m), and rural roads (0.240 m vs. 0.267 m). It could be that drivers do not use ACC when driving in sharp corners as the system in the cars used in this analysis does not adapt to curvature (Masello et al., 2022; Wang et al., 2025; Lyu et al., 2018). However, the differences between ACC and manual driving are relatively small compared to the difference between either and PA. This suggests that the addition of lateral support in PA contributes to improved lane centering performance.

However, a higher mean lane deviation does not necessarily imply unsafe or poor driving. Drivers do not always aim to drive exactly in the center of the lane. For example, On rural roads, which often have smaller lanes and oncoming traffic, drivers may intentionally position the vehicle slightly more to one side in the lane to feel more safe. Such behavior can result in a consistent lateral offset, which would register as increased lane deviation in the data, even if it reflects a reasonable driving strategy rather than inattention or poor control.

To better understand how steadily drivers maintain their lateral position, the standard deviation of lane deviation was also analyzed. Figure 4.15 shows a similar trend as seen for the mean: PA has the lowest variability, followed by ACC, and then manual driving. However, the differences are less pronounced than in the mean deviation. One possible explanation for this smaller difference is, as previously mentioned, that drivers do not necessarily aim to stay exactly in the center of the lane. Instead, they may adopt a consistent lateral offset based on comfort or road conditions. PA still helps drivers maintain more stable lateral control than ACC or manual driving, even if the advantage is smaller when measuring consistency rather than average position.

Finally, Lane Keeping Aid could influence the lane deviation for both the ACC and manual driving. If the car is about to departure the lane, LKA can provide corrective steering to bring the car back inside the lane. This could therefore lead to a lower lane deviation value as the system steers the car back into the lane. The system can be turned on or off by the driver, although it is typically not changed during a trip since the controls are not directly accessible as for PA and ACC.

5.5 Safety Effects of ADAS Systems

Based on Figure 4.16 and Figure 4.18 it is evident that using PA or ACC resulted in generally higher time gaps compared to manual driving during car approaching scenarios. The time gap distributions from car following scenarios, see Figure 4.25 and Figure 4.27, also show that time gaps were generally higher when PA or ACC is active. Furthermore, the distributions of both minimum and mean time gap between manual driving and either PA or ACC driving were found to be significantly different according to the Mann-Whitney U test, see Table 4.4, 4.5, 4.7, and 4.8.

The significant differences in minimum time gaps between PA and ACC driving during car approaching scenarios, see Table 4.5, are somewhat unexpected, given that both systems are designed to handle car approaching scenarios through similar longitudinal control. Possible reasons to why the test shows significant difference might be due to differences in driver behavior. Further investigation showed that the most common distance settings differed between PA and ACC, see Figure F.1 and Figure F.1 in Appendix F. For instance distance setting 1 was more common during PA driving for instance compared to ACC driving. These differences could be one explanation to why there is significant difference between the time gap distributions. Furthermore, as can be seen in Figure 4.5 and Figure 4.5 the usage differs slightly between PA and ACC in different posted speed limits and road types. The difference in driving context might also effect the distance settings and hence the mean time gap distributions.

More scenarios had unsafe time gap values below 1 second during manual driving compared to PA- and ACC driving, with some manual driving scenarios even showing time gaps below 0.5 seconds. When the time gap drops to these levels, the risk of a critical safety event increases significantly. Lyu et al. (2018) state that certain events are strongly associated with traffic risk, such as near-crash situations when the THW is critically low. The results from the car approaching and car following analyses in Section 4.3 indicate that exposure to such events is reduced when PA or ACC is active.

For cut-in scenarios, the distributions of minimum and mean time gap were much more similar across the different driving modes, as shown in Figure 4.34 and Figure 4.36. The Mann-Whitney U test confirmed that there was no significant difference between the distributions for manual driving and PA, as shown in Table 4.9 and Table 4.10. Since cut-ins are initiated by another vehicle merging in front of the ego vehicle, there is limited action that the PA or ACC systems can take to mitigate the resulting low time gap. Consequently, the differences between the driving modes are not as pronounced in this scenario. However, the mean of the distribution of minimum longitudinal acceleration was slightly lower for PA and ACC. This suggests that decelerations were generally stronger during PA and ACC driving, indicating that the ADAS responded more aggressively to cut-ins compared to manual driving. Moreover, the distributions of minimum TTC, shown in Figure 4.41, indicate that PA and ACC generally resulted in higher minimum TTC values.

Contrary to manual vs PA driving, the Mann-Whitney U Test in Table 4.9 and Table 4.10 also surprisingly showed that there was significant difference between manual and ACC driving. This might be due to the over representation of certain users in the dataset. Some drivers may only use either PA or ACC and select a preferred distance setting. If the driver contribute a substantial portion of the data, their individual preferences could skew the overall distribution. However, as we did not have information on driver level, we could not investigate this further.

Overrides were also prominent among many of the vehicles in the dataset. A large number of total overrides and high override frequencies were identified in car following and car approaching scenarios, see Figure E.1 and Figure E.2 in Appendix E. This may be because drivers perceive the time gap set by the PA or ACC system as too long, prompting them to override the system to reduce the gap and follow more closely. As shown in Figure 4.31 the most common distance setting during car follow scenarios were 1 which indicates that drivers preferred shorter time gaps to the target vehicle. Another possible explanation is that the target vehicle ahead signals an intention to exit the road and begins to decelerate. In such cases, the ADAS in the ego vehicle responds by slowing down to maintain the set time gap. However, the driver may judge that it is safe to maintain speed and accept a slightly shorter time gap for a brief moment, overriding the system to prevent unnecessary deceleration before the target vehicle exits. It could also be that the driver intends to overtake the target vehicle and therefore begins to accelerate, overriding the ADAS system before initiating the overtaking maneuver.

5.6 Limitations and Future Research

The cars involved in this thesis are mainly driven by Volvo employees and, in some cases, by their family members. Therefore, it was not possible to know the driver at any given time so one cannot be certain about the driver information. This makes it difficult to make any behavioral analysis regarding different type of drivers. Some patterns could however be identified, but on a vehicle level (distance setting and override). Recommendation for future research would be to include driver information to be able to make driver-based pattern analyses.

Since the drivers are mainly Volvo employees it is possible that they are more familiar with vehicle functions such as ACC and PA compared to other drivers. This can influence the result on ADAS usage. Previous studies have shown that a large population is unaware of these limitations (McDonald et al., 2018) and for future work it would be interesting to include these types of drivers to see if this affects the usage patterns.

The fleet of cars is primarily driven in and around Gothenburg. The characteristics of Swedish roads and road users differ from those in other countries (Carsten et al., 2017), which could influence ADAS usage. Well maintained, generally safe, and high quality roads may enable drivers to use ADAS more frequently.

The data provided did not include any GPS or location information, which made it more challenging to determine the geographical context in which the vehicles were operated. Instead, other signals such as FRC and posted speed limits were used to identify the road type. If GPS data had been available, it would have been easier to identify the road types more accurately, and the reliability of other signals, such as the number of lanes and posted speed limit, could have been verified through comparison with GPS data.

For future research, a more extensive dataset including fleets from other countries could yield more generalizable and robust results, as the data would cover a wider range of road types and traffic situations. Moreover, integrating demographic information about the drivers into the analysis could provide valuable insights. Since no data about the individual drivers was available for this thesis, it was not possible to analyze ADAS usage patterns at the driver level or to compare driving behavior between different drivers. This limitation restricts the scope of the analysis. With access to driver information, it would be possible to identify different types of drivers based on their driving behavior and ADAS usage patterns.

Furthermore, this thesis does not include an analysis of ADAS usage in relation to different weather conditions. Weather is a factor that has been shown to influence the use of ADAS (Perez et al., 2024; Orlovska et al., 2020), and PA performance may be affected by certain weather condition, such as in rain, snow, slush, or fog with poor visibility (Volvo Car Corporation, 2024). This aspect was not considered in the thesis mainly because the signals identified to determine weather conditions were either unreliable or lacked sufficient data.

6

Conclusion

This master thesis investigated how Advanced Driver Asstisance Systems (ADAS), specifically Volvo's Pilot Assist (PA) and Adaptive Cruise Control (ACC), are used in everyday driving. The general usage patterns showed that PA and ACC were more commonly used on highways and expressways, particularly on roads with posted speed limits of 100 km/h and above. This trend was evident both in terms of time spent with the systems active and the distance driven while they were engaged. During traffic jams the usage of PA and ACC were low.

The results showed that overall deactivation patterns using the brake or the deactivation button were quite similar. However, in situations involving lower time gaps (0–4 seconds), brake deactivations were more frequent.

Furthermore, the result showed that drivers who prefer lower distance settings for PA and ACC also tend to maintain short time gaps during manual driving. Similarly, those who prefer to use higher distance setting also tend to maintain higher time gaps during manual driving.

Mean lane deviation were lower with PA activated across all road types compared to ACC and manual driving. PA driving on highway showed the lowest mean lane deviation, followed by expressway, and rural road. Highest mean lane deviations was observed for manual driving on rural roads.

Regarding the safety effects of PA and ACC, an analysis of key safety metrics, TTC and time gap, revealed notable differences across driving scenarios. In both car approaching and car following scenarios, time gaps were generally shorter during manual driving, with some cases falling below 0.5 seconds, indicating a critical safety risk. In contrast, when PA or ACC were active, larger time gaps were consistently maintained, reducing the likelihood of critical situations by increasing the distance to the vehicle ahead. Similarly, minimum TTC values tended to be higher with PA or ACC engaged, while TTC values below 1 second, considered critical, were primarily observed during manual driving. These findings suggest that PA and ACC can give positive safety effects by maintaining safer following distances and reducing the likelihood of critical situations.

For cut-in scenarios, the distributions of safety metrics, including minimum and mean time gap, were much more similar across all driving modes. However, since the short distance to the target vehicle in such scenarios is typically caused by the vehicle cutting in front of the ego vehicle, there is limited opportunity for the ADAS to prevent the abrupt reduction in distance.

Overall, this thesis demonstrates how naturalistic driving data can be used to evaluate the real-world use of ADAS. While these systems are not without limitations, the findings suggest that PA and ACC can support safer driving behavior, particularly in maintaining longer distances to the target vehicle.

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A

Appendix 1

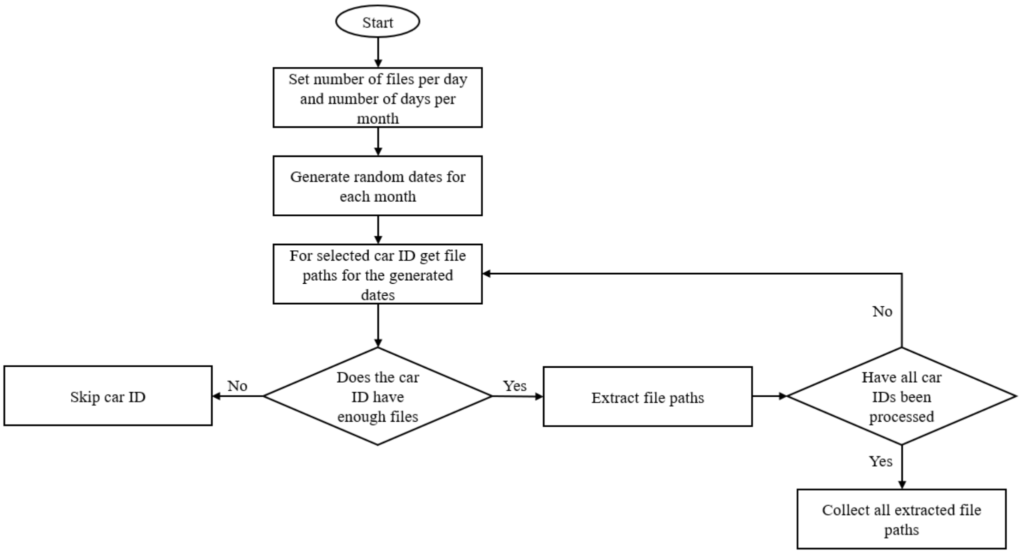

Figure A.1: Flowchart illustrating the algorithm behind the selection of files to be processed for the analyses.

B

Appendix 2

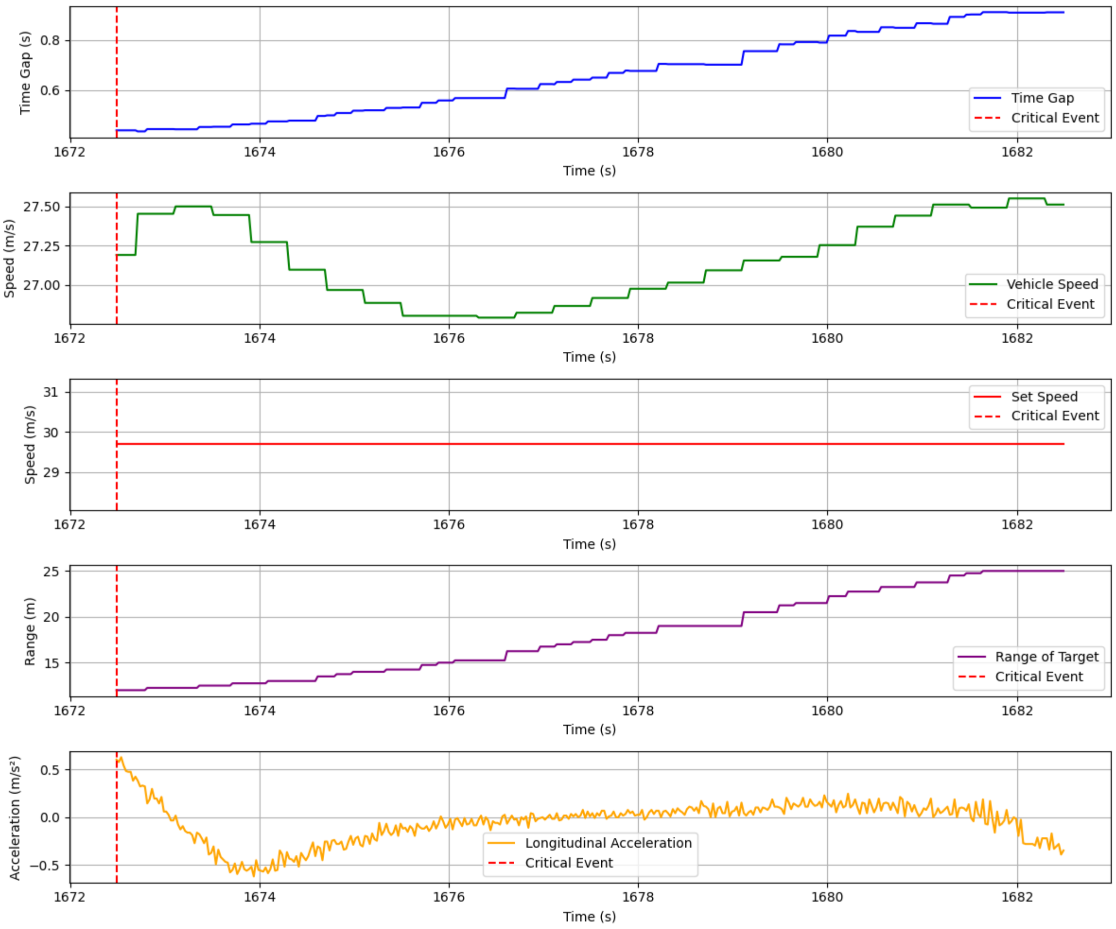

Figure B.1: Time gap (s), vehicle speed (m/s), set speed for CC (m/s), range of target (m), and longitudinal acceleration (m/s^2) for a car following event with minimum time gap below 1 second at the start of the car following event. The time shown on the x-axis represents the timestamp of the individual event, measured from the start of the trip. Critical event line represent the point at which the time gap reaches below 1 second.

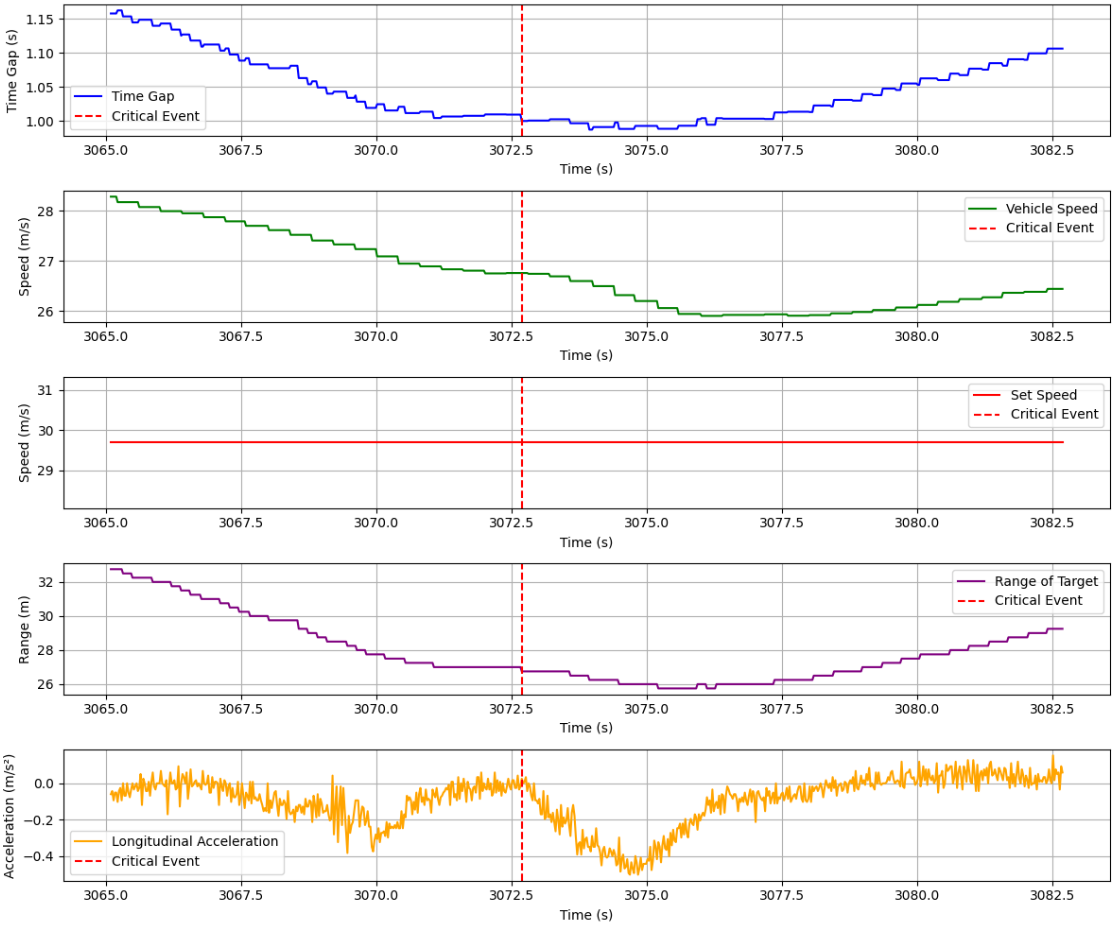

Figure B.2: Time gap (s), vehicle speed (m/s), set speed for CC (m/s), range of target (m), and longitudinal acceleration (m/s^2) for a car following event with minimum time gap below 1 second. The time shown on the x-axis represents the timestamp of the individual event, measured from the start of the trip. Critical event line represent the point at which the time gap reaches below 1 second.

C

Appendix 3

Table C.1: Percentage of distance setting switches.

Transition	**Percentage**
1.0 → 2.0	10.14 %
2.0 → 1.0	9.14 %
2.0 → 3.0	8.74 %
3.0 → 1.0	7.51 %
3.0 → 2.0	7.51 %
1.0 → 3.0	7.24 %
5.0 → 1.0	5.58 %
3.0 → 4.0	5.14 %
1.0 → 5.0	4.98 %
4.0 → 5.0	4.35 %
4.0 → 3.0	4.03 %
3.0 → 5.0	3.98 %
5.0 → 3.0	3.84 %
5.0 → 4.0	3.67 %
4.0 → 1.0	2.81 %
1.0 → 4.0	2.56 %
4.0 → 2.0	2.37 %
2.0 → 4.0	2.33 %
5.0 → 2.0	2.10 %
2.0 → 5.0	1.98 %

D

Appendix 4

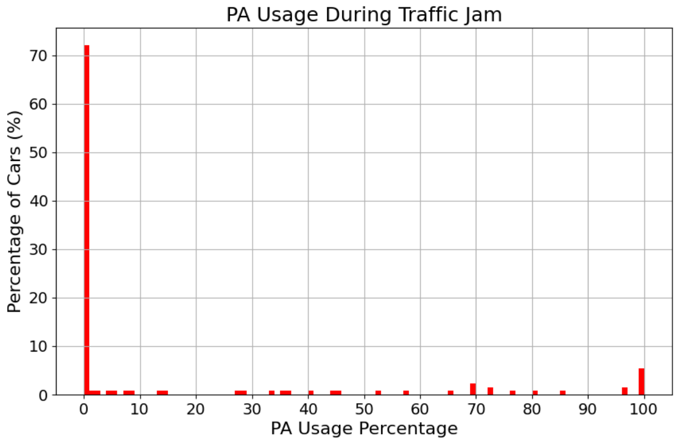

Figure D.1: Percentage of cars that used PA during traffic jams. The x-axis represent the PA usage in terms of percentage of time the car spent in traffic jams with PA activated.

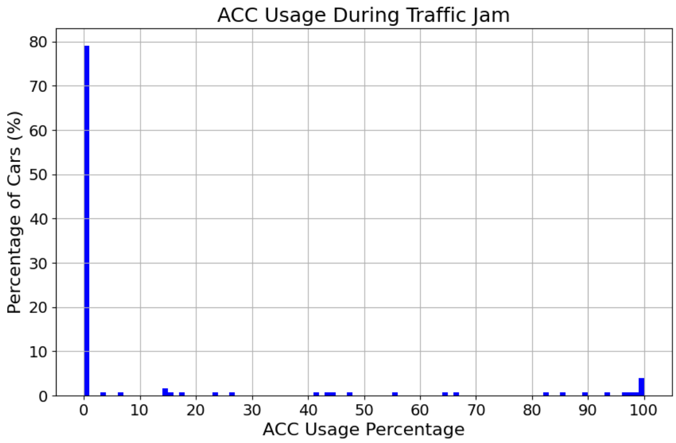

Figure D.2: Percentage of cars that used ACC during traffic jams. The x-axis represent the ACC usage in terms of percentage of time the car spent in traffic jams with ACC activated.

E

Appendix 5

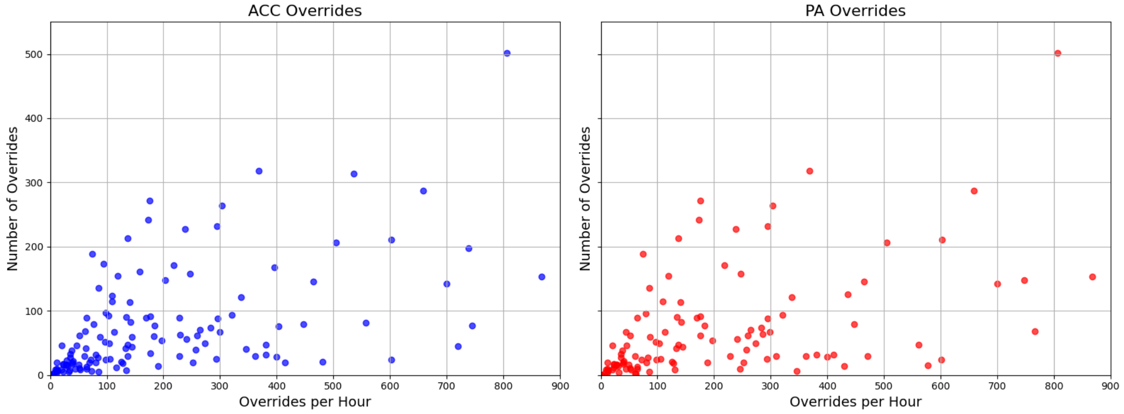

Figure E.1: Override events during car approaching scenarios in terms of total number of overrides and overrides per hour for each car in the data.

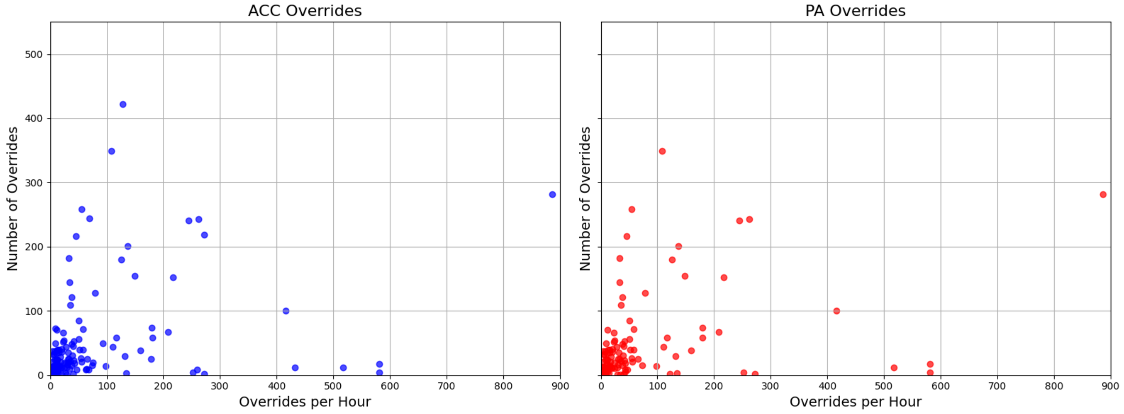

Figure E.2: Override events during car following scenarios in terms of total number of overrides and overrides per hour for each car in the data.

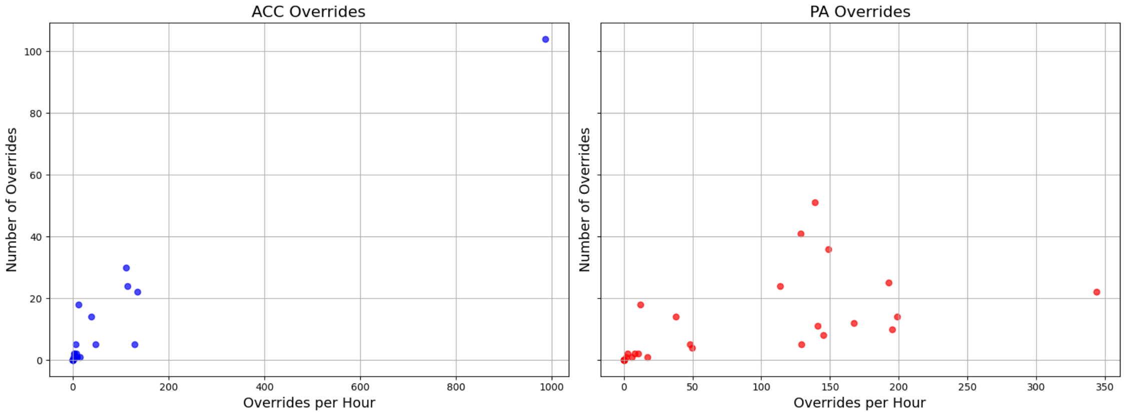

Figure E.3: Override events during traffic jam in terms of total number of overrides and overrides per hour for each car in the data. It is important to note that there was significantly less data available for traffic jam situations compared to scenarios like car approaching and car following, which explains the lower number of data points (cars) shown in the figure.

F

Appendix 6

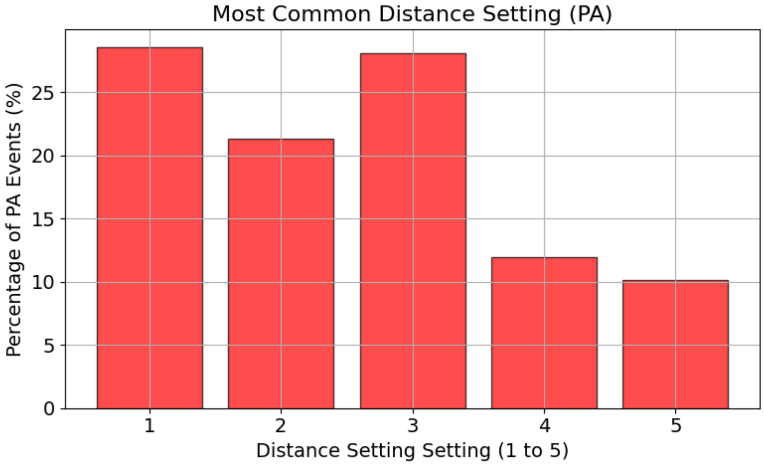

Figure F.1: Most common distance settings for PA driving during car approaching scenarios expressed as the percentage of total PA driving car approaching scenarios.

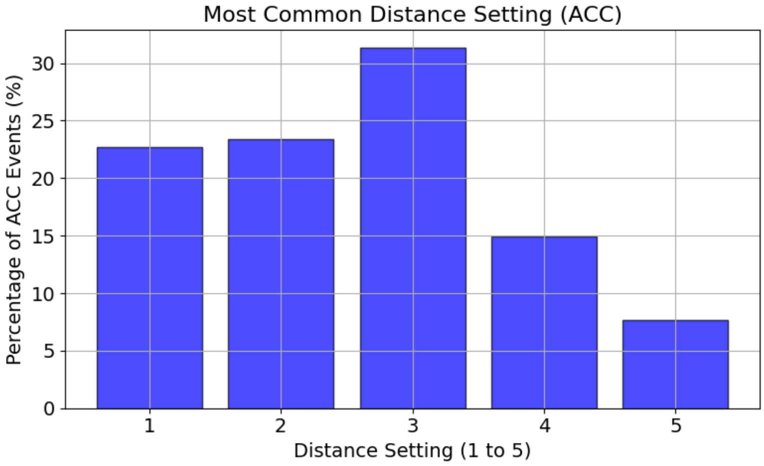

Figure F.2: Most common distance settings for ACC driving during car approaching scenarios expressed as the percentage of total ACC driving car approaching scenarios.

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