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Analyzing the override strategy for collision avoidance functions

Master's thesis in Applied Data Science

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Cover:Volvo safety functionalities (*Volvo Cars safety features* n.d.)

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Abstract

The automotive industry has been shifting towards leveraging intelligent software solutions to ensure safety and ease of use. However, ensuring safety during execution heavily depends on how the human user interacts with these automated systems. In particular, one of the most commonly used safety features in current vehicles is called Automatic Emergency Braking (AEB). Although this automatic function has been proven effective in practice, there still exists an option for the driver to override the functionality as needed. This motivates the question of understanding the underlying intention of the driver when performing an override, as this knowledge can further improve the system's safety when encountering edge cases. In this work, we analyze the driver behavior using unsupervised machine learning models and demonstrate an effective overriding strategy for AEB, through which undesired AEB intervention can be overridden faster by an average of 0.5 seconds. If verified, the new strategy would directly impact vehicle safety and enhance the user experience.

Keywords: Collision Avoidance, Driver behaviour, Data science, Driver override, K-means clustering, Time series clustering, Unsupervised learning

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1 Introduction

The global vehicle population is increasing rapidly day by day. The number stood at 1.32 billion vehicles (cars and trucks only) in 2016. As in 1996 the number was 670 million, in 20 years, this number has enlarged by almost two times (Petit 2017). The latest report from the European Automobile Manufacturers' Association (ACEA) (2021) states that in 2019 there were 242.7 million passenger car fleets on the road in Europe. This indicates an increment of 1.8% compared to 2018.

Statistically, the expansion of the vehicle population has led to an upsurge in the number of collisions on the roads. Alone in Europe, 22,660 lives were lost in road accidents in 2019. The substantial number of road accidents has made safety an important principle in the automotive industry.

When discussing safety in vehicles, two main categories are discussed; Passive safety and active safety. Passive safety refers to the safety systems meant to reduce the fatality rate in case an accident occurs. For example, airbags, seat belts and possibly other structural properties in the car that reduces the severity of injuries to the passengers in the event of an accident (Hojjati-Emami et al. 2012).

Active safety, or Advanced Drivers Assistance Systems (ADAS), on the other hand, refers to the systems in a place whose purpose is to prevent an accident from happening. ADAS uses the input given to sensors and cameras on the vehicle, which are in turn used to detect a potential accident. Technologies like crash detection, lane-keeping aid, automated braking, blind-spot detection and many more are all systems that are in place in modern cars to help prevent accidents (Hojjati-Emami et al. 2012).

1.1 ADAS

As safety is a core value at Volvo Car Corporation (VCC), the company utilizes innovative technologies to assist drivers in many ways. One of such is the ADAS. It uses various vehicle sensors to detect obstacles on the vehicle's drive path. Such obstacles can be pedestrians, bicycles and other cars.

The system provides a revolutionary change in a low-speed rear-end collision compared to higher speed scenarios. The engagement of the brake can mitigate the collision's damage significantly in high-speed scenarios.

Figure 1.1 is an overview of ADAS functions. This project focuses only on the Collision Mitigation System (CMS) subsection. The CMS is a function that gets triggered when the car's sensors notice a threat in front of the vehicle which has the potential to create a dangerous situation (Euroncap 2020).

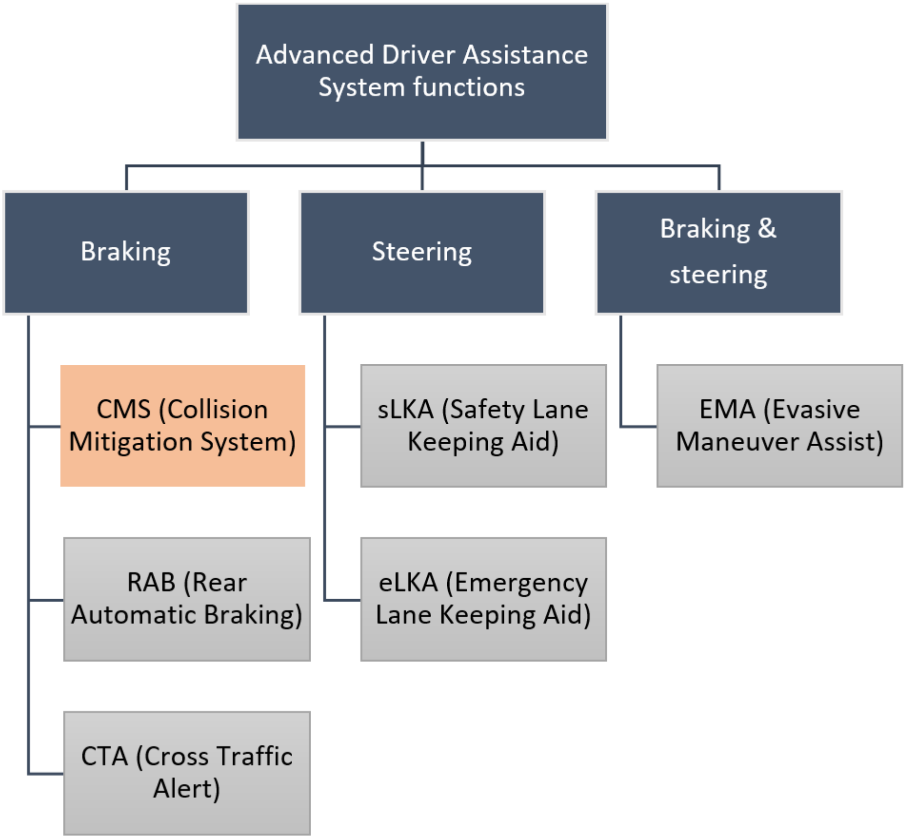

Figure 1.1: ADAS functions (*Driver assistance systems | Volvo Cars* n.d.).

CMS is a combination of two subfunctions:

1. Forward Collision Warning (FCW): This function is a warning system always applied before the brakes are engaged.

2. Collision Mitigation by Braking (CMbB): The function applies when the driver is not active or the brake implemented by the driver is not sufficient enough. The CMbB can also be referred to as Autonomous/Automatic Emergency Braking (AEB).

The goal of the CMS function is to help the driver avoid or mitigate a collision and not disturb the driver in typical driving scenarios. Keeping the balance between these two goals defines the success of this function.

Systems like AEB have decreased the collision rates significantly; Much research and studies have supported the statement. For example, the Filippo Caracciolo Foundation Council (2020) explored the real-world effectiveness of AEB. The study focused on rear-end crashes and the effect of the AEB on them. The results showed that implementing AEB enhances safety considerably. In vehicles younger than three years old, the AEB system resulted in a 45% reduction in collisions. The system prevented almost one of every two crashes. Notably, VCC was the only vehicle manufacturer whose AEB system could detect cyclists on the road since 2013 (European-Commission 2016).

The results of a study conducted by Cicchino Cicchino (2017) on the effectiveness of FCW and AEB show that these systems reduced rear-end crashes by 43% and the injured rate in these crashes by 45%.

The efficiency of AEB in different nations has been assessed using a meta-analysis. When compared to a sample of identical vehicles, vehicles equipped with low-speed (generally under 30 kph) AEB exhibited a 38% reduction in rear-end collisions (Fildes et al. 2015).

1.2 Driver override

Although the AEB systems have been able to reduce the rate of crashes significantly, the delinquency of these systems should also be considered. Below are two examples of the misjudgments of the systems:

- The car is approaching a threat on the drive path, but the system does not send the FCW and does not apply the brakes (false negative), which will result in a collision if the driver does not take necessary action.

- If the car is not approaching any threats on the drive path, but the system wrongly sends an FCW and applies the brakes (false positive), the car might be put in a dangerous situation and cause a collision with the cars behind.

The override function has been introduced to overcome the system's delinquency. This function allows the driver to prevent the brake system from making automatic decisions and keep the driver in charge of the vehicle (Coelingh et al. 2007).

VCC is currently using two different overriding strategies. The first strategy is mostly used during high-speed scenarios, e.g., highways. From now on, this strategy will be referred to as *strategy 1*. On the other hand, the second strategy is mostly used in somewhat lower-speed scenarios, e.g., traffic jams. From now on, this strategy will be referred to as *strategy 2*.

The override strategy's activation to overrule the auto-braking system's decision is normally dependent on an input parameter from the driver to the car. This means that the overriding strategy must be defined based on the reactions and behaviors that drivers usually have in precarious situations.

The accelerator pedal acts as the main trigger to activate the overriding strategy from the driver to cancel the AEB. For instance, pressing the accelerator pedal can indicate that the driver is in control of the situation. As a result, the car's initial decision of activating the AEB will be overridden by the driver. On the other hand, the release of the accelerator pedal by the driver indicates that the driver is avoiding any additional acceleration and thus it can be assumed that the driver acknowledges the risk of a collision (Coelingh et al. 2007). These two examples can demonstrate why the accelerator pedal is used as an input to override the automatic braking by the car.

In such systems, it is important to investigate how the considered threshold for the accelerator pedal can be improved to be accurate enough to capture all the events when the driver had the intention to override the false activation of the auto-braking function.

The lack of a precise trigger or threshold to activate the strategy can cause nuisance interruptions while driving. For example, a false FCW, which is then followed by a false AEB activation can be distracting. Also, a false positive AEB in a traffic jam can increase the risk of rear-end collisions. Hence, the drivers must be confident that in case of a need to change the car's automatic decision, they can override it safely.

1.3 Goal

The primary goal of this thesis is to analyze how the drivers act in a critical situation after the activation of the AEB function. In addition, this thesis aims to propose a refinement of the overriding strategies currently used at VCC. An efficient overriding strategy can release the driver from an unnecessary auto braking situation. The outcome of this research can contribute to traffic safety and enhance the customer experience when using the system.

1.3.1 Research questions

1. What is the typical driver reaction to an activated AEB intervention?
2. Can the existing override strategies at VCC be improved?

1.4 Data description

The data used in this thesis project is provided by VCC, consisting of statistics from customers' vehicles in Sweden over three years (2017 - 2020). This period has been divided into 13 quarters, starting from the first quarter in 2017 to the first quarter in 2020. Each quarter contains several event occurrences. The number of events that occurred can vary in each quarter. It is also worth mentioning that for each event, there are multiple corresponding Comma Separated Values (CSV) files that show the vehicle's state in case of an *event* occurrence.

The events can be described as different groups, i.e., activation of different safety functionalities such as auto-braking and emergency lane-keeping aid systems. This thesis will mainly focus on the events related to the activation of the AEB (also known CMbB) and the corresponding data files. Each data file consists of more than 250 signal values in an eight-second time interval (four seconds before and after the event occurrence, e.g., AEB activation), capturing a sample at the frequency of 5 Hz. These datasets will be referred to as the *Sensors datasets* in this report.

Sensor	Sample 1	Sample 2	...	Sample 39	Sample 40
Cruise control	1.0	1.0		1.0	1.0
Vehicle's Speed	23.56	19.48		20.19	5.51
Brake pedal pressed	0	1.0		1.0	1.0
...	...	...		...	...
Vehicle's motion	5.0	5.0		5.0	5.0

Figure 1.2: Sample from the sensors - the Sensors dataset.

In addition to the data files described above, a *summary* file has been provided by VCC. This file will be referred to as the *Summary dataset*. The Summary dataset has derived measurements calculated from 40 sample values of each signal. Instances of these measurements are the vehicle's speed when the CMbB function gets activated. That said, each row represents an event, and each feature is a qualitative analysis of relevant signals to the driver's behavior. In other words, the Summary dataset has the information from all the events in the Sensors datasets in an accumulative format. However, the Summary dataset needs modifications to be utilizable. A list of some of the features in this dataset is attached as appendix A. Figure 1.3 demonstrates an example of the Summary dataset.

Index	Event	Vehicle TYPE	Vehicle Speed at CMbB	Above Speed Limit	Target Present At Beginning of Scenario	Speed Reduction by CMbB
1	Event 001	Car	20.48	NO	YES	15.45
2	Event 002	Car	25.95	NO	YES	0.0
3	Event 003	Car	21.80	YES	YES	17.15
...	...	...	...	...	...	...
49836	Event YZ	Car	55.94	YES	NO	35.17
49837	Event ZZ	Car	25.39	NO	NO	5.12

Figure 1.3: A sample of the Summary dataset.

It is worth mentioning that there have been minor system updates within the period in which the data was collected. As the main goal of these updates is to fix the current bugs, the probability of having a CMbB activation is not affected on a large scale. Furthermore, an event does not affect the occurrence of the next event.

That said, the observations are independent of each other.

The dataset in this project is based on signal information retrieved from the vehicles. Therefore, there is no specific labeling in the Sensors datasets. However, the Summary dataset contains information regarding if the activation of the CMbB function was true-positive, false-positive or nuisance:

- True-positive: The system has correctly detected the danger and activated the function.
- False-positive: There was an error in the system's detection. Thus, the CMbB function was activated incorrectly.
- Nuisance: The system has correctly detected the danger. However, the activation of the CMbB function could be delayed as the severity was low.

These labels in the Summary dataset are good indicators for the correctness of the AEB function itself, however cannot assist to classify the drivers into different behavioral groups.

1.5 Boundaries

This research is based on the data gathered from the cars' signals captured at the time of an event. The data is not capable of demonstrating the drivers' personal feelings or intentions at the time of the intervention. There are no images or similar content to help conduct a ground truth for understanding the driver's intentions in regards to overriding the AEB activations. An experiment can be conducted using Volvo's test fleets to simulate an AEB event. Further, during the experiment, the drivers can be interviewed about their intention, which could not be captured by the signals. However, this is out of the scope of this master thesis and thus will be proposed as a potential future work to VCC.

The data is collected at the frequency of 5Hz. This frequency can cause potential latency in the data recorder and, as a result, data loss in some samples. The logs are captured in eight-second intervals. In the case of having a longer time interval, better judgments could be drawn about the drivers' behaviors.

Furthermore, this master thesis will focus on the overriding strategy and the driver behavior in response to the AEB activation. It will not consider the accuracy or effectiveness of the false/true positive AEB activations.

2
Background

In this chapter aims to introduce and discuss the related concepts and work in the automotive field and driver behavior.

2.1 Human-computer interaction

Human-computer interaction is a bridge between computer technology and human psychology. This science focuses on the interaction between humans (i.e., system users) and the computers to fulfill users' necessities. Although the field initially dealt only with computers, it gradually included information technology design in almost all its forms. For example, as the automotive industry is becoming software-driven, human-computer interaction plays an essential role in system designs (Bansal & Khan 2018).

Analyzing and understanding human-computer interaction and human behavior becomes a critical point in developing and improving active safety. Knowing how a driver reacts, interacts and makes decisions when driving, results in more accurately predicting that behavior to prevent an accident.

2.2 Driver behavior

Previous research on driver behavior can be considered to limit the relevant variables for behavior analysis. The papers reviewed in this section have inspected quantitative variables such as acceleration/deceleration and speed. The studies done by these papers can be grouped into two categories: (1) The studies which claim that the driver behaviors can be in the form of longitudinal and lateral control (Macadam 2003, Qu et al. 2014, Li et al. 2003, Zheng 2014). (2) Studies regarding the application of the Internet of Vehicles (IoV) for driver assistants, based on data-driven methods (Dua et al. 2014, Jing-Lin et al. 2014, Yang et al. 2014). An example of such is an iPhone app (Drive Safe) introduced at the 2014 IEEE conference that can give feedback and points to drivers by detecting inattentive behaviors (Bergasa et al. 2014).

Consequently, considering that the driver can take control of the vehicle both longitudinally and laterally, it can be said that behaviors can be divided into four main categories: speeding, acceleration/deceleration, braking and steering (Zfnebi et al. 2017).

The findings here have been used to create scenarios for the descriptive analysis part of this thesis. This technique is addressed in more detail in chapter 4, *Methods*.

2.3 Driver/human reaction time

Categorizing the drivers based on how long it takes them to react to a hazardous situation depends on various parameters such as age, driving experience, road, traffic conditions (Hugemann 2002). Hence, previous research in this area has grouped drivers into different types. For example, McGehee et al. (2000) has examined the driver reaction time in possible collision situations in an intersection, both in a simulator and on the test track, using a 95% confidence interval. Table 2.1, retrieved from this paper, shows the results of this experiment comparing the drivers in the Iowa Driving Simulator (IDS) and on the test track.

Table 2.1: The results of an experiment conducted by McGehee et al. (2000), comparing the means and standard deviations of the measurements done by drivers in the IDS and on the test track.

	IDS	Test Track
Initial Accelerator Release	Mean : 0.96 sec Std: 0.21	1.28 sec 0.29
Total Brake Ratio (to max brake)	Mean : 2.2 sec Std: 0.44	2.3 sec 0.46
Time to Initial Steering	Mean : 1.64 sec Std: 0.49	1.67 sec 0.46

McGehee et al. (2000) justify the differences in the average time for the accelerator pedal to be released between the two groups by the fact that the drivers who were on the test track had seen the in-coming car in the intersection three times before the actual attack. Additionally, the car was not moving during the three prior events. Thus, it can be explained that the test track drivers would respond later. Furthermore, McGehee et al. (2000) mention that although the time for releasing the accelerator pedal differed between the two groups, it can be claimed that this is a sign of acknowledging the danger. After the acknowledgment, the further actions taken by the drivers should not differ.

As mentioned earlier, the driver's reaction time can depend on several factors. One of the factors that can make a distinction in the reaction time is the driver's attention to the road. Wolfe et al. (2020) have conducted a study in a situation where drivers did not pay full attention to the road at the time of danger. Two groups of drivers (20-25 years) and (55-69 years) participated in this study. The test results show that the younger group can detect the danger at an average of 220 milliseconds and respond to it within an average of 388 milliseconds. The older group needed 403 milliseconds to detect and 605 milliseconds to respond to danger.

Another study conducted by Green (2000) has categorized the reaction time in three primary methodologies:

- Simulator studies, where the subjects are placed in either a simulator of a car or the cabin of an actual vehicle. The driver is then asked to react, by braking, to simulated events occurring in front of them. The goal is to measure the braking reaction time of the driver.

- Controlled road studies, where the subjects were driving on a public or private road with the researcher as a passenger, aware that they were being monitored for research purposes. The reaction time was measured by analyzing the driver's reaction to unexpected events.

- Naturalistic observation, where drivers were being placed in traffic situations unaware they were being monitored. A recording equipment is recording their reaction time to cars braking ahead of them.

The results show that expectancy is the most significant factor for short reaction times. The interpretation is that in situations where a driver expects something to happen, reaction times are shorter. When the expectancy was high and uncertainty was low, the reaction time was the best. The driver's response time was about 0.70 to 0.75 seconds in these situations. Urgency seemed to significantly impact reaction times if a sense of urgency was present. A better reaction time was recorded if the time-to-collision was low. Although it should be noted that the results varied considerably across the studies, making it difficult to pinpoint a single value or even an extensive range of values.

The age factor was also relevant as older people generally had a slower reaction time of 0.1 to 0.3 seconds on average. One crucial factor is a high cognitive load. If a driver is overwhelmed with the unfamiliarity of the roads or is distracted by a cellphone, the reaction time is significantly increased.

The outcome of this research seems to be that no single study can capture all aspects of what affects the reaction time in a driver, since human behavior is quite complex and extremely sensitive to environmental factors and changes. This forces the research to lean toward some intuition since the full spectrum of human behavior cannot be explained mathematically.

2.4 Forward collision warning for AEB

Although drivers' reaction times can vary depending on their age or level of attention while driving, the automotive industry has implemented the FCW function to warn drivers who do not take precautions.

FCW uses cameras and radars to detect stationary or moving objects in front of the vehicle. This system is activated when the distance from the host to the target vehicle is decreased and a possibility of a collision is detected. In the case of activation, the driver receives an audible and visual warning on the windshield (Yue et al. 2021). The FCW allows the driver to manually avoid the collision before the AEB activation. Thus, where an essential reaction is taken by the driver in response to the FCW, the AEB/CMbB functions will no longer take place.

FCW timing can have an impact on drivers' response to AEB/CMbB activation. Abe & Richardson (2006) have shown that the FCW warning time has a greater influence on drivers' confidence in the vehicle safety system than the improvement of the AEB system itself. In addition, the study shows that alarms that occur after AEB activation are considered delinquent alarms by drivers. This article concludes that drivers expect to receive an FCW warning before the AEB intervention. By considering this, further study is done on the impact of FCW timing on the drivers' AEB override in this master thesis.

2.5 Adaptive cruise control (ACC)

One of the essential factors in increasing the safety of cars and reducing accidents is to maintain a proper distance from the vehicles in front while driving. Although the driver can follow this vital principle, car companies have added ACC to their vehicles. ACC can intelligently reduces the vehicle's speed when approaching a car in front to add safety for the drivers who are not following this principle.

ACC is a new generation of speed cruise controls. Prior to ACC, in normal cruise control, the driver could adjust the car's speed to a certain value. Although the normal cruise control provided comfort for drivers to drive for a long time, it was not able to reduce or increase the car's speed due to its inability to detect obstacles in front of it. Thus, the driver was personally responsible for this task.

The new generation of cruise control, ACC, has a more efficient system. The system combines a road scanning radar, motion sensors and a vehicle computer or Electronic Control Unit (ECU) that can change vehicle speeds depending on road conditions. Therefore, the car can increase or decrease its speed without the driver's intervention by analyzing the variables in front of it (Volvo Cars 2018).

Using the car's adaptive cruise control, the driver controls the lateral movement of the vehicle (steering) and gives longitudinal control to the vehicle. However, the driver still has the power to accelerate further to increase the chosen speed by the ACC.

3

Theory

This chapter discusses the theory behind the methodology used in this research.

3.1 Quantitative data analysis

A dataset consisting of number-based information which can be measured and counted can be referred to as quantitative data (Sheard 2018). Having a dataset with a numerical nature makes the mathematical calculations such as the mean, the variance and other statistical indicators possible for the observations.

One of the datasets used in this master thesis i.e., the Sensors datasets includes numerical values obtained from the vehicle signals. Since the observations were captured in the form of continuous and discrete values, it can be said that this data is quantitative. Thus, quantitative data analysis on such data can be used for assessing various scenarios such as the distinction between groups (conducted from samples), the relationship between features in the data and testing hypothesis (Watson 2015).

The quantitative data analysis is carried out in the form of descriptive statistics, which is described in the chapter 4, *Methods*.

3.1.1 Descriptive statistics (DS)

DS describes the characteristics and contents of a smaller, more detailed and limited proportion of data called *samples*. The samples are subsets of a bigger group in the data, referred to as *population*. The population forms an entire set of observations for the study (Berndt 2020). In this thesis, the population is all the drivers in the world who have experienced an AEB/CMbB activation and the samples are the drivers in Sweden whose data is available and used in this project, and who had the same experience.

Furthermore, DS does not focus on making predictions based on the data but on finding detailed statistical knowledge of the chosen sample. This detailed information is used to get both a macro and a micro overview of the data. Moreover, by observing the statistics from each sample, possible errors in the data can be spotted e.g., an abnormal variation in a specific signal value in similar scenarios. To solve an issue in an unknown system or come up with an improvement for it, it is required to have an insight into the nature of events, groups and humans interacting with it. It would be impossible to understand this type of system data without insight into it. These understandings are the necessary bases for applying other methodologies such as inferential statistics or machine learning modeling (Siedlecki 2020).

3.2 Machine learning

Machine learning uses data to learn and derive meaningful insights based on the given input. It attempts to design a machine using algorithms so that it can learn and work without explicitly dictating each action. Machine learning algorithms are mainly classified into supervised and unsupervised types. The data used to be fed into the models determines the type of the algorithm (Mahesh 2020).

- Supervised: The data is labeled, and the labels assign each observation to a specific group. A supervised machine learning algorithm can leverage the labels in the data to learn and make predictions. Supervised models analyze a training dataset and then produce an inferential function to make predictions about output values (Berry et al. 2019).

- Unsupervised: The input data is not labeled. Unsupervised algorithms attempt to find hidden patterns and structures without the need for human intervention or involvement of a target label (Berry et al. 2019).

Given the dataset and goals of this project, an unsupervised machine learning algorithm is used. Thus, the theory in this area is focused on this type of algorithms.

In unsupervised learning, the algorithm must look for finding structures in the data. Mathematically speaking, unsupervised learning refers to when there are only input variables X and no output variables Y in the dataset. Unlike supervised learning, there is no correct answer given to the algorithm to learn from and the model itself must look for the answer. Unsupervised learning can be divided into clustering and association tasks.

- Association: The goal is to discover the relationship between the variables in the data. For example, a person who buys X will most likely buy Y.

- Clustering: When there is an intention to discover intrinsic groups (data that are inherently in a particular group) in the data, e.g., grouping customers based on their buying behavior.

To answer the first research question, machine learning can be used to group the drivers into different groups. Thus, more investigation is done on clustering algorithms and how they are used to group behavioral data.

3.2.1 Data scaling

The features in the Summary dataset have different ranges concerning the variance. Therefore, feature scaling is needed to ensure that the observations are within the same range. The scaling of the data can have a large impact on the result of the machine learning algorithms. If the features' ranges differ significantly, the model will be biased towards the larger range. The model assumes that the features with a larger range have a more significant impact on the outcome (Patel & Kushwaha 2020).

In this project the removal of outliers results in a significant loss of data. Thus, *robust scaling* can be used. Robust scaling uses the interquartile range to scale the data so that it is robust to the outliers. The formula below is explaining this scaler where Q1 and Q3 represent the first and third quartile of the data accordingly and Q2 is the median of the data:

$$\frac{x_i - Q_1(x)}{Q_3(x) - Q_1(x)} \tag{3.1}$$

3.2.2 Feature reduction with principal component analysis (PCA)

Feature selection plays a significant role in unsupervised learning models. The amount of data required can increase exponentially in high-dimensional datasets. Therefore feature selection is used to extract the columns that are primarily contributing to the desired outcome (Jamal et al. 2018).

PCA is one of the commonly used dimensional reduction methods. PCA is used when the input data has a high dimension of features and the goal is to compress the dataset into a smaller number of features. The cost of the dimension reduction in a dataset is the accuracy reduction. Therefore, PCA is recommended exclusively if the dimension reduction technique trades a little accuracy for higher simplicity in the data (Kondo et al. 2019).

3.2.3 K-means clustering

The k-means algorithm is an unsupervised machine learning model. The purpose of the model is to divide the data points with one or multiple dimension into K number of clusters. The algorithm is centroid based which means each cluster has its own centroid. The objective of the model is to minimize the sum of distances of data points within the same cluster, which is reachable when the centroids are located in the most optimized positions. The model reaches to this goal by performing repetitive calculations for the positions of the centriods (Hartigan & Wong 1979).

In this method, the chosen number of clusters will each have a representative, namely a centroid. Each observation will be grouped in a cluster with the shortest Euclidean distance to its centroid. New centroids can be calculated for each iteration by averaging the data and re-assigning the data to new clusters. This process continues until the groups are no longer changed (Saxena et al. 2017).

3.2.4 K-means clustering for time-series data

3.2.4.1 Time series data

A sequence of data collected over a period of time forms a time series. These data reflect the changes in a phenomenon over time. Therefore, these values (changes) can be considered as a time-dependent vector. If X is a vector, the time series can be represented as follows where t represents time and X is a random variable

$$X(t), t = 0, 1, 2, \ldots \quad (3.2)$$

According to this definition $t = 0$ is the time of occurrence of a phenomenon or when the first information was recorded. Hence, $X(t)$ defines the random variable X in time of t. The observed values of this random variable have an order that indicates the time of occurrence of each observation (Hamilton 2020).

A time series model is *univariate* if created based on only one property (i.e., feature) of a phenomenon. On the other hand, if several features are used to create a time series model, the model is called *multivariate*.

3.2.4.2 Tslearn

Tslearn is a python package specially made for analyzing time series data. The package is built on top of three other packages; Numpy, Scikit-learn, and Scipy (Tavenard et al. 2020).

3.2.4.3 Dynamic time warping (DTW)

DTW is an algorithm that can measure the similarity between two time series that may differ in speed or time. This algorithm can be used to overcome the weaknesses of the Euclidean distance in capturing similarity between two sequences, which may only differ in time but have a similar pattern. In a study Wang et al. (2013) have experimented and compared nine different similarity measures on time series data. Wang et al. (2013) claims that DTW has higher accuracy than Euclidean distance in small datasets. Wang et al. (2013) further adds that limiting the warping window size in DTW can reduce the cost in computation while outperforming the Euclidean distance.

The time complexity of DTW is $O(NM)$, where N is the length of the first sequence and M is the length of the second sequence. Different techniques can be used to increase the computational speed of DTW. Wang et al. (2013) has investigated the effect of *LB Keogh* (Keogh & Ratanamahatana 2005) and reported that it has a positive impact on reducing DTW computational cost.

Hoseini et al. (2021) have conducted a study to annotate scenarios to find driver behavior based on transitive relations. In this study, Hoseini et al. (2021) have presented the use of DTW in finding similarities between trajectories with different lengths in time.

3.2.5 Cluster evaluation

In an unsupervised machine learning model, unlike classification problems, there is no ground truth (i.e., labels) in the data to verify the quality of the clustering result. Therefore, the need for appropriate criteria, both to evaluate the efficiency of a clustering method in cluster retrieval and to compare the performance of different clustering methods, is necessary. There are two types of criteria for evaluating clustering results:

- Internal criteria: The purpose of examining internal criteria is to evaluate the structure of clusters created by clustering algorithms. These criteria measure the similarity of members within a cluster and the dissimilarity between clusters.

- External criteria: There is a real label (benchmark) for all the observations in external criteria, mapping each observation to a belonging cluster. On the other hand, there are clustering labels, which are unique labels for each cluster with observation within it. External criteria is the mapping between these two labels to assure the goodness of the clustering algorithm (Saxena et al. 2017).

3.2.5.1 Silhouette score

The silhouette score is an example of internal criteria. It is a metric used for evaluating the quality of the clusters. This criterion depends on the cohesion within the clusters and their degree of separability. The silhouette score for each point measures the extent to which it belongs to its cluster relative to the adjacent cluster. This metric can have the maximum and minimum values of +1 and -1, respectively. An interpretation of the silhouette score is as follows (Shahapure & Nicholas 2020):

- +1: The clusters are well distinguished and separated from each other.

- 0: The clusters are similar, or the distance between them is not considerable.

- -1: Each observation is wrongly assigned to its cluster.

The silhouette score can be calculated using the formula below, where a is the average distance between each observation within a cluster and b is the average distance between clusters (Shahapure & Nicholas 2020). The highest silhouette score can be used to determine the number of clusters (i.e., k) for the K-means algorithm.

$$score = \frac{(b-a)}{\max(a,b)} \tag{3.3}$$

3.2.5.2 Cluster Stability

Silhouette score is not the only method for selecting the number of clusters in the K-means algorithm. Another proposed methodology is using the *cluster stability* as a technique for finding the optimal k value. It can be said that an algorithm produces stable clusters if the clustering results remain identical even after re-sampling the data from the same distribution (Von Luxburg 2010). This methodology has introduced new ways of finding the optimal number of clusters. A recent paper from Mourer et al. (2020) claims that only stability cannot be adequate in determining the number of clusters since it cannot identify if the determined number of k is sufficient or too low.

Mourer et al. (2020) has proposed a new internal criterion validation methodology that overcomes the previous weaknesses. In this technique, a good cluster is defined based on two characteristics: (1) the cluster needs to be stable, and (2) within each cluster, there should not be a stable partition. This method validates the clustering results on stability within clusters and between clusters. They have introduced an index which stabilizes the trade-off between the *within cluster* and *between cluster* stability, called *Stadion*. Stadion stands for "stability difference criterion." Stadion also provides a visualize stability path which is the growth of stability as a function of ϵ (ϵ-Additive Perturbation).

Furthermore, Mourer et al. (2020) has performed a comparison between Stadion and other internal-based evaluation metrics such as the Silhouette score. The comparison shows that Stadion is outperforming these metrics in K-means clustering.

4 Methods

This chapter aims to describe the methodologies used to answer the two research questions.

Question 1: *What is the typical driver reaction to an activated AEB intervention?* This question is answered by studying the drivers' behaviors using two methods, descriptive analysis and K-means clustering. These three methods are addressed in sections 4.1 and 4.2. In all three methodologies, the data has been split into three main categories: (1) *No overriding*, (2) *Overriding with strategy 1* and (3) *Overriding with strategy 2*.

Question 2: *Can the existing override strategies at VCC be improved?* This question could be answered based on the derived results obtained from question 1. A new strategy has been investigated to answer the second research question which is addressed in section 5.3, *New strategy*.

The driver can influence the car in two main ways, laterally and longitudinally. The lateral control is related to steering, the longitudinal control is related to acceleration/deceleration and braking (Zfnebi et al. 2017). Section 2.2 of this report has addressed this categorization in detail. Additionally, section 2.3 has mentioned the importance of reaction times. Hence, these four parameters (steering, acceleration/deceleration, braking, and reaction time) are the main focus for the drivers' behavioral analysis.

4.1 Descriptive statistics for behavioral analysis

Regarding the longitudinal control, the vehicle's speed, acceleration and braking signals have been considered. Furthermore, signals correlating with the steering wheel, such as the *steering wheel angle*, are studied. The mean, median, standard deviation, and skewness of data are considered to analyze the results. These parameters make the analysis of different groups comparable. The variables in the signal-based data could not directly be used for analysis. To get valuable insights from this type of data, it was necessary not to manipulate the variables, but to make meaningful combinations and groups before statistically analyzing them. In the following sub-sections the detail of how these groups and combinations were shaped is described.

The drivers can have different behaviors in different situations; Although the recorded signals' values are informative, they cannot provide exact information about the drivers' conditions and their intention. The events have been categorized into different groups several times to study the drivers' behaviors. The categorization is based on the four primary behavioral groups mentioned in the beginning of this section (steering, acceleration/deceleration, braking, and reaction time). In the following section, each scenario is described in detail. This way, the problem can be divided into smaller segments to make the analysis more efficient. The analysis result of each scenario can be found in chapter 5, *Results*.

4.1.1 Data pre-processing: the Sensors datasets

The behavioral analysis using the descriptive statistics is performed using the *Sensors datasets*. The Sensor datasets were created using four raw data files (for each event) provided by VCC. Data from these files were merged, sorted alphabetically, and transposed to create a file with 40 samples per event as rows, and signals collected as columns. The 40 samples correspond to 4 seconds before the event and 4 seconds after the event. The data were then filtered to get only the events related to the CMbB function, thus all other events were discarded. The filtering was carried out in two steps. The first step is checking the status of the *Collision Reduction by Braking Post Status Arbitration* signal, a status signal for the automatic braking function, to be in a *pre-brake* or a *full-brake* state. The second step is checking the *Vehicle Motion Status* signal to assure the vehicle was not stationary and was moving forward at the time of the intervention.

Figure 4.1 illustrates the data pipeline. The total number of events was 153,154 which got reduced to 49,850 events after filtering. The final datasets, namely, the Sensors datasets will be used for further analysis in this section of the thesis.

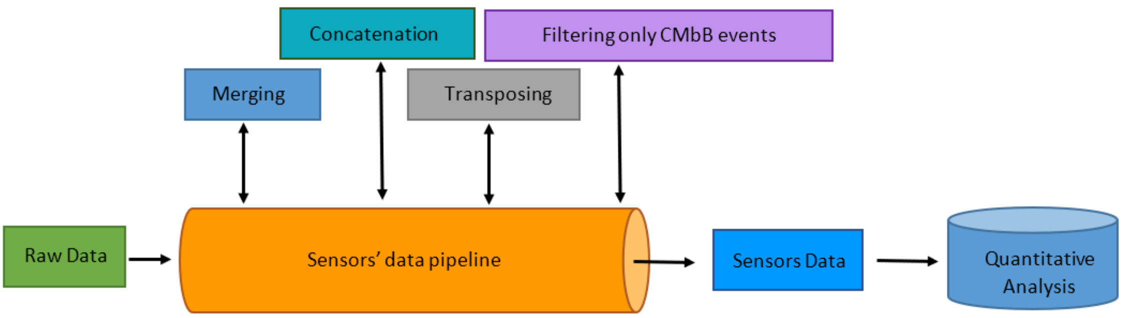

Figure 4.1: Pipeline to convert the raw data into sensors dataset.

4.1.2 Investigating the distribution of the overriding drivers

The drivers who have experienced a CMbB activation have been categorized into two groups; Group one consists of the drivers who have overridden the CMbB intervention, and group two consists of the drivers who have not. The *Collision*

Reduction by Braking Post Status Arbitration signal, a status signal for the automatic braking function, was used to create these two groups. Each value of this signal is an indicator of the type of CMbB activation.

Furthermore, considering different existing thresholds and conditions for triggering each overriding strategy (strategy 1 and 2), the drivers were grouped into two additional groups. Group one consists of drivers who overrode the intervention using strategy 1 and group two consists of the drivers who have overridden the CMbB using strategy 2.

Figure 4.2 is provided to give a better indication of how the categorization is done in this particular scenario.

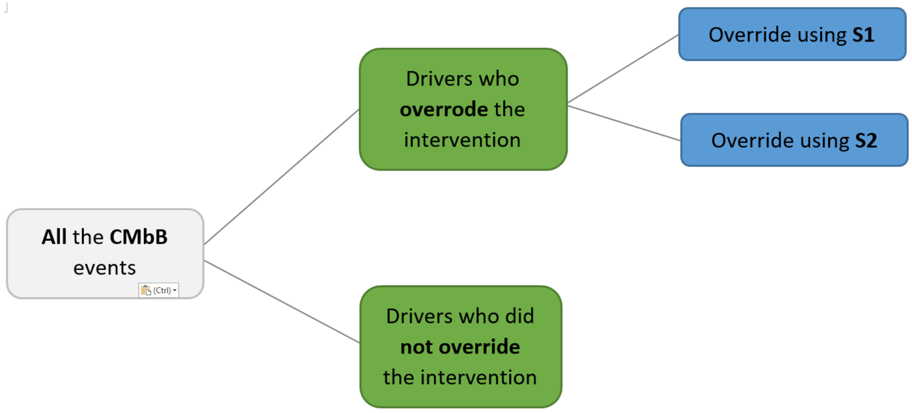

Figure 4.2: Grouping the drivers based on whether they overrode the CMbB activation. Furthermore, grouping based on different strategy used to override the intervention. Each compared pairs are having a matching color.

4.1.3 Speed investigation at the time of intervention

The drivers' speed behavior is investigated in three different scenarios using the *Vehicle Speed Longitudinal* signal, indicating the host vehicle's speed.

- The overall speed distribution of the drivers at the time of the CMbB intervention. This shows the speed the drivers had when entering the intervention.

- Using the categorization done in the previous scenario where the drivers were grouped by two different overriding strategies, the speed distribution in each strategy group was investigated.

- By further looking into the speed distribution of each overriding strategy, the distribution of the vehicles that fully stopped during the intervention was studied. This stopping can be occurred by either the driver and/or the braking of the CMbB function.

Figure 4.3 gives a better illustration of how the three described scenarios above are distributed.

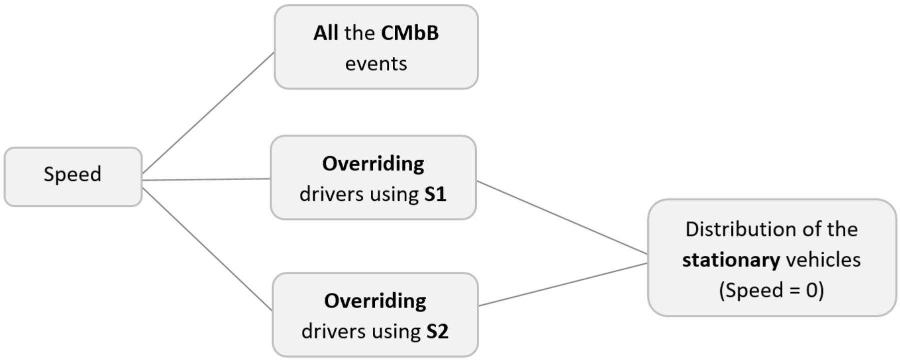

Figure 4.3: The groups created to investigate the speed at the time of CMbB intervention. The groups are addressing the speed of : (1) all the drivers experiencing CMbB intervention, (2) drivers overriding with strategy 1, (3) drivers overriding with strategy 2 and (4) all the drivers who overrode the intervention whose vehicle became stationary during the CMbB.

It should be noted that the data recorder latency was considered in all the described scenarios above.

4.1.4 Investigating the relationship between the FCW and the driver override

One question that can be asked, as Abe & Richardson (2006) also points out, is whether the timing of giving warning to the driver can affect the level of attentiveness. In other words, is FCW one of the reasons for successfully overriding a CMbB intervention as it alerts the driver before the intervention? To answer this question, the *Warn Request* signal, a signal indicating the activation of FCW, was investigated. It is also studied at which sample in the Sensors datasets this signal gets triggered.

The hypothesis was that the drivers who overrode the intervention might have had an earlier FCW than those who did not override the intervention. To prove the hypothesis, the duration between FCW initiation and the beginning of the CMbB intervention was calculated.

Furthermore, the same comparison was made between the drivers who overrode the CMbB intervention with different strategies. Each overriding strategy (i.e., strategies 1 and 2) gets triggered under different conditions; Strategy 1 is for higher speed, and strategy 2 is for lower speed scenarios. Thus, comparing the effect of FCW in these two groups can reveal the potential difference concerning the timing of the warning between these two overriding groups.

Having this information will lead to a more profound understanding of the effectiveness of FCW in regards to the driver override, as well as the relative time of activation of this function based on the time of the CMbB intervention.

Figure 4.4 shows how the different scenarios are created for investigating the effect of FCW timing in overriding the intervention.

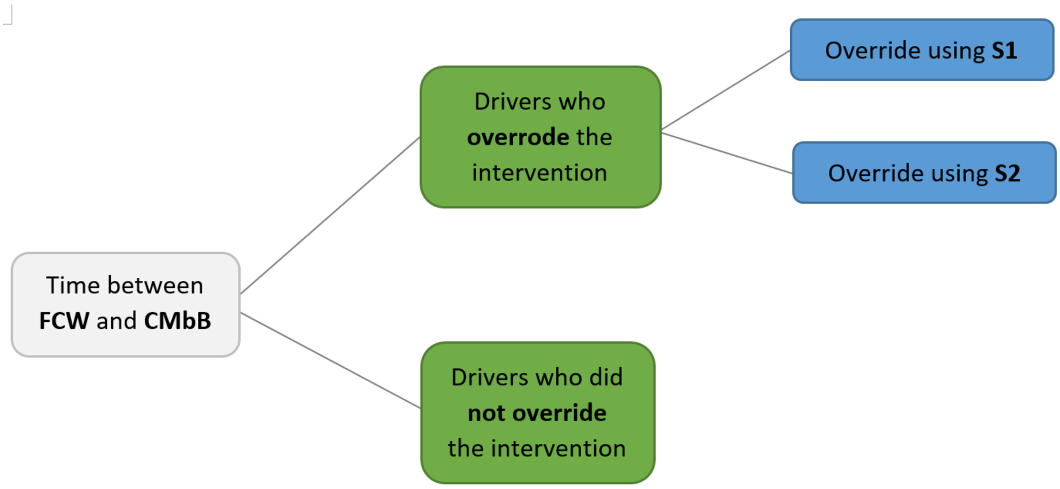

Figure 4.4: Scenarios to be compared in regards to the timing between the FCW and CMbB activation. The groups with matching colors are compared with each other.

4.1.5 Investigating the relationship between the length of intervention and the driver override

A new question to be answered is whether the length of intervention makes an apparent difference between the drivers who have overridden and those who did not. This question was answered by by investigating the length of intervention in isolation. The duration of CMbB intervention was measured and it was studied how the duration affects the chance to override.

Since there are two different strategies, strategy 1 for high speeds and strategy 2 for low speeds, it would be interesting to investigate if the length of intervention contributes to the speed distinction in different scenarios. Thus, it was investigated how the length of intervention differs among overriding drivers using different strategies.
Figure 4.5 shows a clear illustration of how two different comparison groups are conducted.

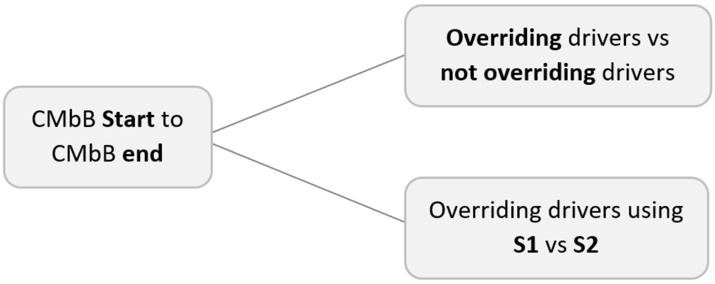

Figure 4.5: Comparison between different groups in regards to the length of intervention.

4.1.6 Investigating the driver reaction time concerning the usage of ACC

Based on the characteristics of ACC discussed in section 2.5, the CMbB events in which the driver was using ACC were selected in this scenario. Additional rounds of filtering were carried out which are described as follows:

1. ACC = "ON" and "ACTIVE"
2. No further acceleration by the driver during the activation of the ACC
3. Length of intervention > 0.8 seconds
4. Acceleration by the driver during the time of CMbB intervention

When analyzing an outcome of an event, it is essential to consider what has happened prior to the event. As the drivers can, if wanted, accelerate even further than the ACC, it was verified that the drivers were not accelerating (further) by themselves while ACC was activated. This increases the probability of resting the feet behind the pedals. Thus, the probability of capturing undesired accelerations due to body inertia from braking would be less.

Further, the length of intervention has an important impact on overriding an event. Hence, it was ensured that the length of the intervention was long enough (more than 0.8 seconds) to be felt by the driver.

Finally, as this investigation aims to measure how long it takes for the drivers to react to a CMbB intervention, the events in which the driver has accelerated during the intervention were selected. Having the reaction time of the driver considered, depressing the accelerator after a certain time is a good indicator for measuring the reaction time of the driver.

4.1.7 Investigating the overriding drivers' reaction time concerning the deceleration request impact

The deceleration power from the CMbB function can impact the drivers differently; A harsh deceleration request, i.e., full-brake, is much more noticeable for the driver than a pre-brake. That said, considering how hard the CMbB has interfered is essential and can result in different reactions from drivers.

Further, to better understand the driver's behavior, one vital factor is the reaction time. Therefore, it was mainly studied when and how drivers start interfering with the system concerning different CMbB deceleration requests.

The information gathered from this investigation can help to have a better understanding of how drivers are involved in the overriding process and how the deceleration request has an impact on this involvement. This can be useful when discussing improvements or new strategies.

This investigation has been carried out in three groups. In each group, different periods have been measured. Figures 4.6 explain and demonstrate the time spans for this investigation.

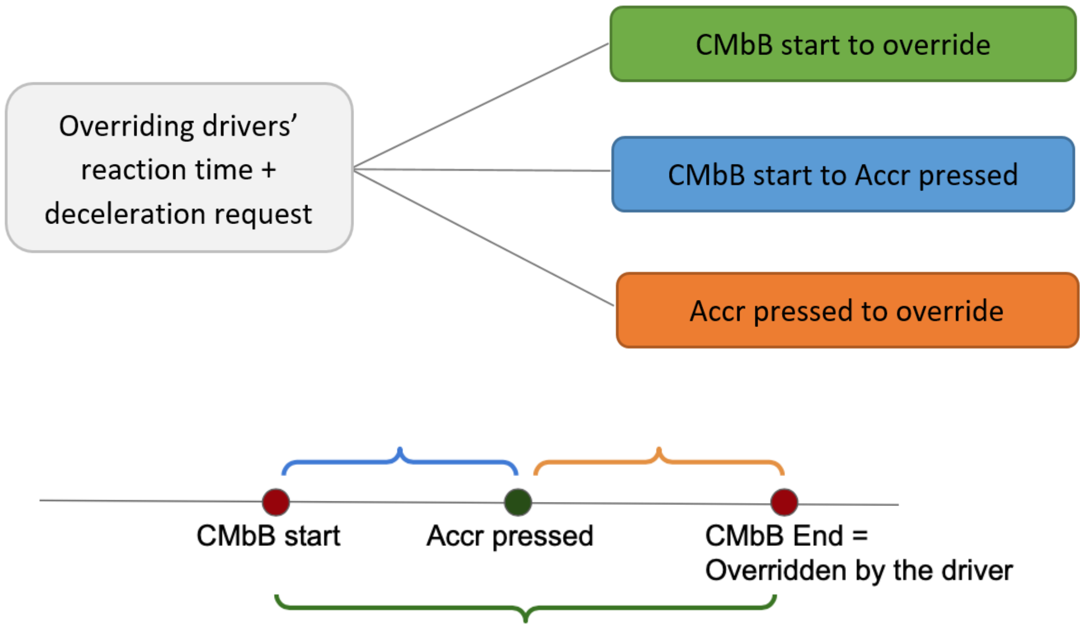

Figure 4.6: Created grouping of the overriding drivers' reaction times concerning the deceleration request.

In the first group, the time between the CMbB intervention and pressing the accelerator pedal by the driver was measured. The second group measured the time between a pressed accelerator pedal and the end of the intervention (i.e., override by the driver). Finally, in the last group, the duration of the intervention, from the start to the time overridden by the driver, was measured. In all three groups, the comparison was made between the overriding drivers who (1) experienced a full-brake versus (2) who had experienced a pre-brake followed by a full-brake from the CMbB function.

4.1.8 The maximum slope of accelerator pedal's ratio during the CMbB intervention

The term *slope* refers to the difference between the ratio (how much (in percentage) the accelerator pedal is pressed) of the accelerator pedal in two sequential samples. Figure 4.7 gives an illustration of the slope in the accelerator pedal. Depressing the accelerator pedal by the driver is an indication of gaining speed. The higher the slope, the harsher the pedal is pressed by the driver. This factor has been investigated among three groups of drivers: Drivers who did not override, drivers who overrode the intervention using strategy 1 and using strategy 2.

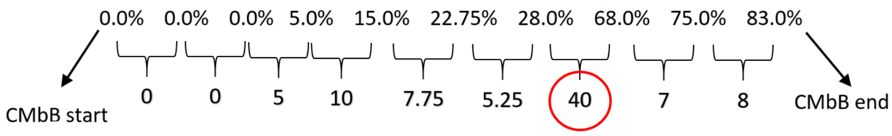

Figure 4.7: The pedal ratio shown in percentages, indicates the pressure by the driver on the accelerator pedal. The numbers on the bottom row show the slope (difference) between two sequential samples. The red circle shows the maximum slope between all the calculated slopes.

The distribution of the maximum slope of the accelerator pedal for drivers who did not override the CMbB intervention is projected in figure 4.8. The distribution for the drivers who overrode the CMbB intervention with strategy 1 and with strategy 2 are projected in figures 4.9 and 4.10, accordingly.

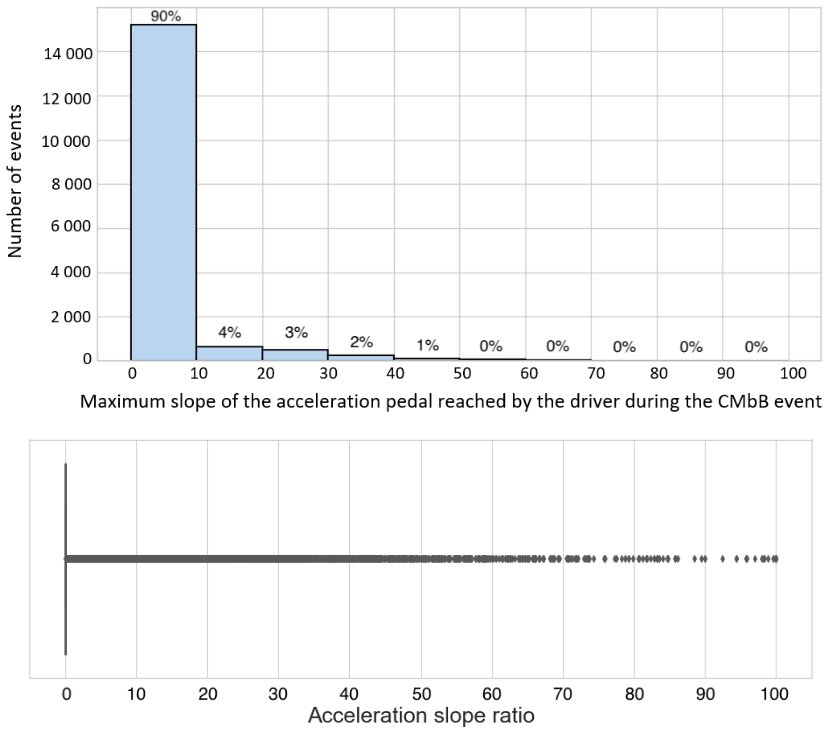

Figure 4.8: Distribution of maximum accelerator slope reached by the drivers who did not override the intervention.

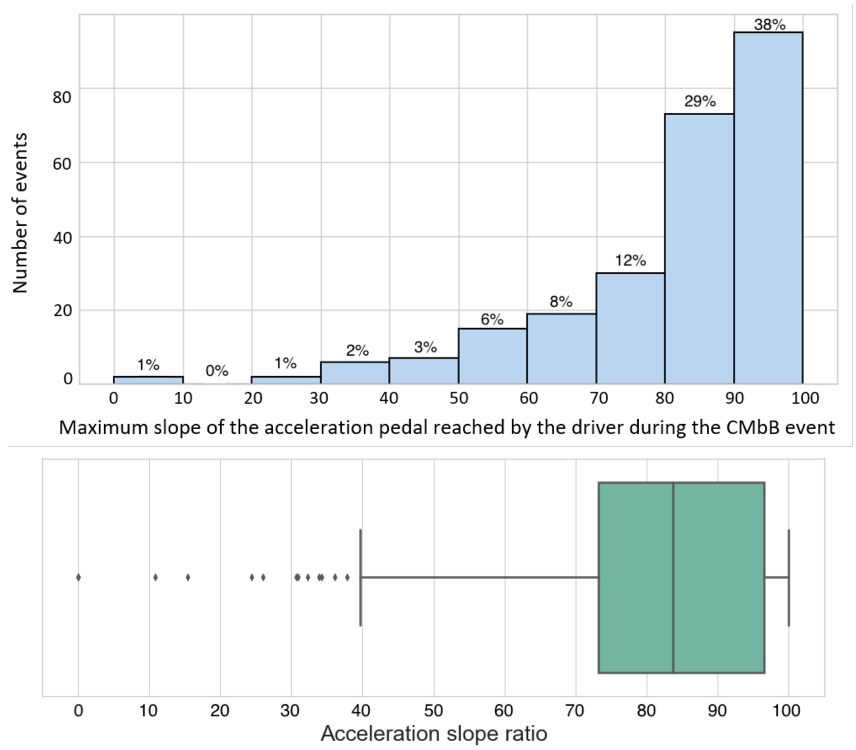

Figure 4.9: Distribution of maximum accelerator slope reached by the drivers who overrode the intervention using strategy 1.

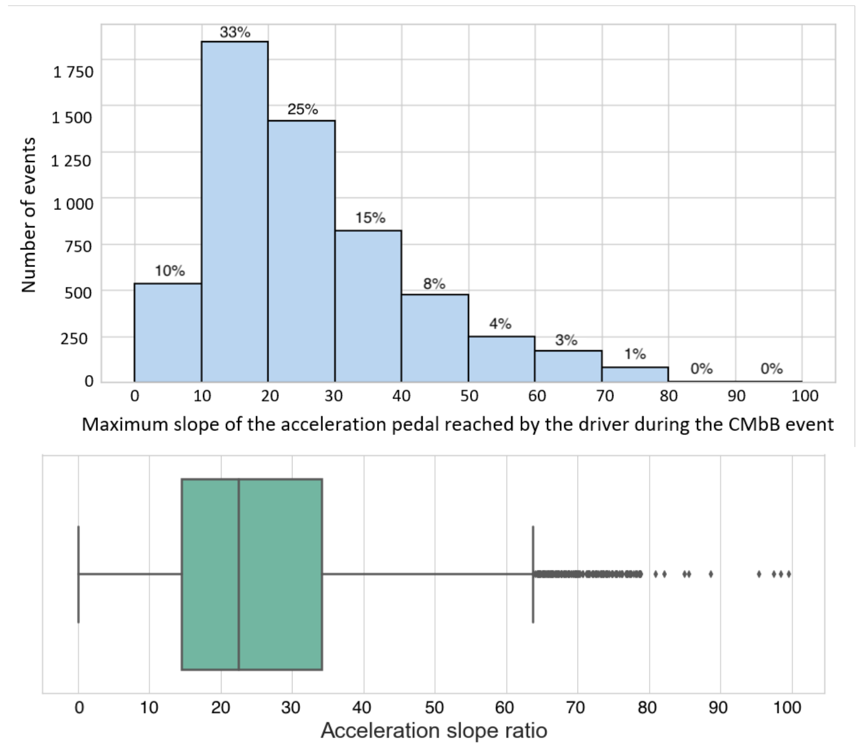

Figure 4.10: Distribution of maximum accelerator slope reached by the drivers who overrode the intervention using strategy 2.

Most drivers in the not overriding group either did not press the accelerator pedal during the CMbB, or only performed a light depress on the pedal (less than 10% change in the slope); As the figure 4.8 projects. While the majority of the drivers who overrode the intervention using strategy 1 (79%) performed a sharp depress on the accelerator pedal as shown in figure 4.9.

Furthermore, figure 4.10 shows almost 75% of the drivers who overrode the CMbB using strategy 2 had a maximum slope of 10 to 40. It can be concluded that the acceleration pedal slope can be used as an indicator for the drivers who intend to override.

4.2 Unsupervised machine learning for behavioral analysis

4.2.1 Data pre-processing: the Summary dataset

As mentioned earlier, the Summary dataset is created based on the sensors' data. Figure 4.11 shows an overview of the pipeline used to create the Summary dataset. The Summary dataset is the data file that is fed into the first K-means implementation. For the time series K-means, the Sensors datasets are used.

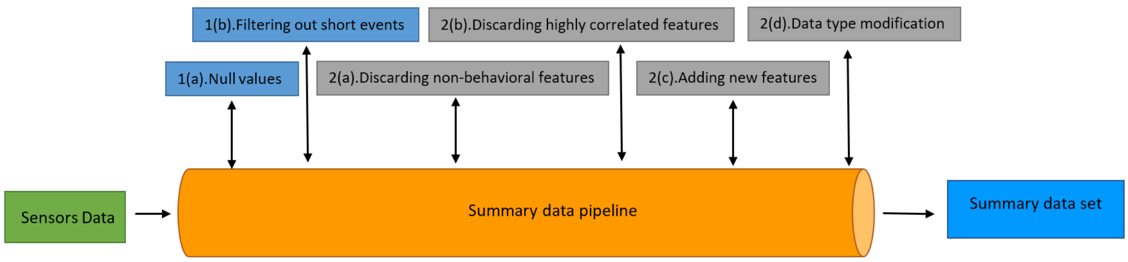

Figure 4.11: Pipeline to convert the sensors data into summary dataset. Blue boxes represent data filtering processes. Gray boxes represent feature reduction/increment processes.

1. **Data Filtering**

   (a) Null values: 16 out of 49,850 events, contained null values. Considering that they do not make a significant change in the total number of observations (Lokesh 2021), they were dropped from the dataset.

   (b) Discarding short-length events: Based on the investigation done during the quantitative analysis and studies addressed in section 2.3 e.g., (Green 2000), the drivers don't have a chance to react to the events shorter than 0.8 seconds. Therefore, the events which have a CMbB length of intervention shorter than this time have been discarded from this dataset. After this filtering the number of rows in the Summary dataset is reduced to 21,598 events.

2. **Discarding irrelevant features, adding relevant features**

   (a) Discarding the irrelevant features to the driver behavior: The Summary dataset contains many features that do not contribute to this project's goal. Therefore, the irrelevant columns to driver's behavior are removed from the dataset.

   (b) Highly correlated features removal: A heat-map of correlations between the columns has been created to remove redundant features. The columns with high correlations (regardless of having positive or negative correlation) are not taken into consideration.

(c) Adding new behavioral features to the dataset: The Summary dataset initially had 78 features, some of which are the results of the driver's behavior. However, not all the driver behaviors (specially the important factors found in the descriptive analysis) were originally found in the Summary dataset. Therefore, using the Sensors datasets, new features have been created and added to the Summary dataset for each event. The newly computed features could be beneficial in showing a pattern among different behaviors in different groups. These new created features are described below:

   i. Override status: Shows how a CMbB intervention ended. It is a categorical column that takes three values, *NO* for events in which the driver did not override the CMbB. *S1* and *S2* if the driver overrode the event using strategy 1 or strategy 2, accordingly.

   ii. The maximum accelerator pedal's ratio during the CMbB intervention: Shows the maximum ratio of the acceleration pedal (in percentage) reached by the driver, as a result of depressing the pedal.

   iii. The maximum slope of accelerator pedal's ratio during the CMbB intervention: Represents the change of accelerator pedal ratio between two sequential samples (see section 4.1.8 for calrification).

   iv. Brake pedal interaction time: Shows the time it took the driver to interact with the brake pedal after the CMbB starting point.

   The number of remaining features is reduced to 28 columns after the feature reduction/increment process. The list of features is provided in appendix A.

(d) Data type modification: A large part of memory can be occupied due to the implicitly of Python. Thus, the data types were adequately modified to save a good amount of memory and boost the processing speed. For example if only two digits are used to represent a value. the data type changed from int64 which occupies eight bytes to int8 which occupies only one byte.

4.2.2 Principal component data frame

The result of having seven principal components is approximately 86% variance ratio of the Summary dataset. The feature's with the majority of contribution in each principal component is shown in table 4.1.

Table 4.1: Features ratio as per principal component.

Component 1	Ratio
CMbBDecelRequestMax	92%

Component 2	Ratio
DriverDecelRequestMax	81%
SpeedReduction	30%

Component 3	Ratio
MaxPedalRatioDuringCMbB	75%
MaxSlopeAccrPedal	56%

Component 4	Ratio
TimeBrakingBeforeIntervention	94%

Component 5	Ratio
TimeBrakeOnset	65%
TimeBetweenCMbBEndAndDriverAcc	42%
LengthOfIntervention	30%

Component 6	Ratio
SpeedLimit$_{R}SI$	77%
MaxSteeringAngle	36%
TimeBetweenCMbBEndAndDriverAcc	34%

Component 7	Ratio
TimeBetweenCMbBEndAndDriverAcc	72%
TimeBrakeOnset	44%
DriverBrakingAtCMbBStart	40%

4.2.3 Data I.I.D-ness

Most machine learning algorithms, supervised or unsupervised, assume the data is independent and identically distributed (i.i.d). The two characteristics that make the data i.i.d are:

- Independence: An event does not affect the occurrence of the next event. That said, the observations are independent of each other.

- Identically distributed: A dataset can be claimed identically distributed if the samples come from the same distribution (Clauset 2011).

The events are divided based on six software versions. The most important features of data (based on the PCA results) are chosen to be compared in different software versions (V1 to V6). The chosen signals are the *max slope acceleration pedal ratio* (56% of principle component 3), *CMbB deceleration request max* (92% of principle component 1 and 81% of principal component 2), *time between CMbB end and driver acceleration* (42% of principle component 5) and *time brake onset* (65% of principle component 5 and 44% of principle component 7).

The comparison is carried out using the two-sample Kolmogorov-Smirnov test. The null hypothesis is that the two given samples are from the same distribution. The null hypothesis can be rejected by a p-value lower than the significance level (α) using a 95% confidence interval. Meanwhile, the null hypothesis fails to be rejected if the p-value is higher than α.

The tables below are the results of these comparisons.

Table 4.2: MaxSlopeAccrPedal

	V1	V2	V3	V4	V5	V6
V1	-	0.811	0.678	0.822	0.374	0.948
V2	0.811	-	0.999	0.673	0.080	0.976
V3	0.678	0.999	-	0.387	0.057	0.954
V4	0.822	0.673	0.387	-	0.131	0.978
V5	0.374	0.080	0.057	0.131	-	0.675
V6	0.948	0.976	0.954	0.978	0.675	-

Table 4.3: CMbBDecelRequestMax

	V1	V2	V3	V4	V5	V6
V1	-	0.068	0.266	0.034	0.194	0.397
V2	0.068	-	0.971	0.679	0.764	0.623
V3	0.266	0.971	-	0.490	0.810	0.632
V4	0.034	0.679	0.490	-	0.646	0.555
V5	0.194	0.764	0.810	0.646	-	0.923
V6	0.397	0.623	0.632	0.555	0.923	-

Table 4.4: TimeBetweenCMbBEndAndDriverAcc

	V1	V2	V3	V4	V5	V6
V1	-	0.113	0.094	0.733	0.250	0.730
V2	0.113	-	0.987	0.649	0.999	0.933
V3	0.094	0.987	-	0.289	0.930	0.942
V4	0.733	0.649	0.289	-	0.988	0.910
V5	0.250	0.999	0.930	0.988	-	0.970
V6	0.730	0.933	0.942	0.910	0.970	-

Table 4.5: TimeBrakeOnset

	V1	V2	V3	V4	V5	V6
V1	-	0.586	0.411	0.595	0.791	0.735
V2	0.586	-	0.934	0.873	0.909	0.868
V3	0.411	0.934	-	0.491	0.983	0.923
V4	0.595	0.873	0.491	-	0.699	0.684
V5	0.791	0.909	0.983	0.699	-	0.896
V6	0.735	0.868	0.923	0.684	0.896	-

As the results in tables 4.2 to 4.5 show, the null hypothesis fails to be rejected as the p-value in all the comparisons (except for one comparison in listing 4.3 (V1 vs. V4)) is higher than the significance level. Therefore, the distribution in the compared signals in six different software versions is identical.

Additional comparison was made comparing the three years in which the data was collected from using Quantile-Quantile (QQ) plots. In one year there can be more than one software update. By comparing years with each other, we are comparing multiple software versions.

As shown in figure 4.12, the *Host speed at CMbB activation* feature distribution is compared within three years. As a result, it can be seen that they follow an almost identical distribution. It can be observed that the distribution of the feature is the same within the three years. Therefore, it can be concluded that the data has the characteristic of being identically distributed. The vehicle's speed feature is just a representative of all other features used. The feature has been used more than any other feature during the project. Therefore it is selected for the QQ plot analysis.

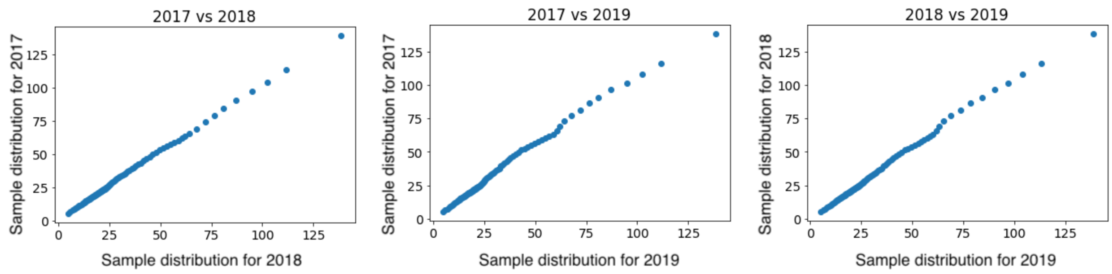

Figure 4.12: QQ plots of the host speed compared in three years.

4.2.4 K-means

The unsupervised machine learning model applied to the Summary data is K-means. Three clusters have been chosen based on the Stadion method addressed in the *Theory* chapter. Centroids are initiated using K-means++. The number of initiation is 20, and the maximum number of iterations in each initiation is 300.

Stadion was used to assure that the chosen number for k, results in stable clusters. This metric shows the trade-off between the *within cluster* and *between clusters* stability scores for the value of k, from 1 to 10. The score obtained for each k is illustrated in table 4.6. Figure 4.13 shows the Stadion stability path. The plot shows the growth of stability as a function of ϵ.

Table 4.6: Stadion-max score for k = 1 to 10.

k = 1	[0.28488226]
k = 2	[0.]
k = 3	[0.29960903]
k = 4	[0.26545708]
k = 5	[0.14988901]
k = 6	[0.04547995]
k = 7	[0.08103329]
k = 8	[0.06439307]
k = 9	[0.08592891]
k = 10	[0.11595334]

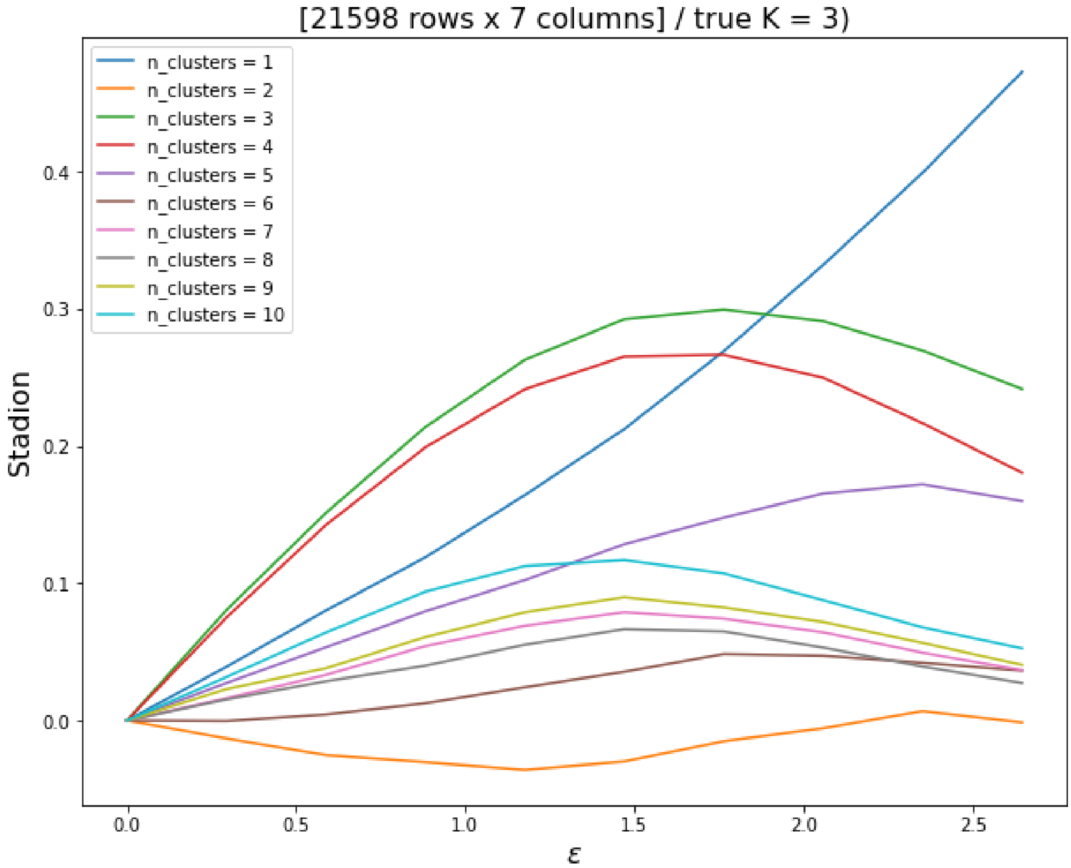

Figure 4.13: Stadion stability path to determine the number of clusters.

4.2.5 K-means clustering for time series data

K-means clustering for time series data has been implemented using the Senors datasets to find different drivers' behavior and answer the first research question. This algorithm was implemented using the *tslearn* package. As mentioned earlier, the driver behavior can be explained by acceleration/deceleration, braking, and steering actions. Thus, to describe the driver behavior, four behavioral categories are considered which are:

1. Accelerating behaviors
2. Acceleration slope
3. Steering behaviors
4. Braking behaviors

Accordingly, the optimal number of clusters and iterations chosen are 3 and 10. The distance metric used to find similarities between sequences is the DTW. Furthermore, the considered window size (w) is 5 and the LB Keogh is used to optimize the processing time.

5

Results

This chapter demonstrates and discusses the results of the methodology discussed in the previous chapter.

5.1 Descriptive analysis

5.1.1 The drivers who overrode the CMbB activation and their distribution in the two different strategies

The drivers were splitted into two groups based on the two overriding strategies. Table 5.1 demonstrates the distribution of the drivers in each strategy out of the total of 5,996 overrode CMbB activation events.

Table 5.1: The distribution of the events in each overriding strategy

	Number of events	Distribution (%)
Strategy 1	277	4.6
Strategy 2	5746	95.4

Table 5.1 indicates that the majority of the drivers have overridden the CMbB activation using the second strategy. This denotes that mostly the drivers were driving in lower speed scenarios, e.g., in traffic jams, city traffic where the speed limit is below 50 kph, were the ones who did an override.

5.1.2 Speed distributions

5.1.2.1 All vehicles experiencing the CMbB activation

The speed was monitored at one sample before the intervention of the CMbB function. Figure 5.1 shows how the speed is distributed in intervals of 20 kph. As shown below, the data is highly skewed right, which means the majority of the events were when the drivers had lower speeds. The minimum and maximum speeds observed were 1.01 kph and 224.88 kph, respectively. The percentages shown at the bottom of each bin in figure 5.1 are the share of events in the corresponding speed range based on the total number of events.

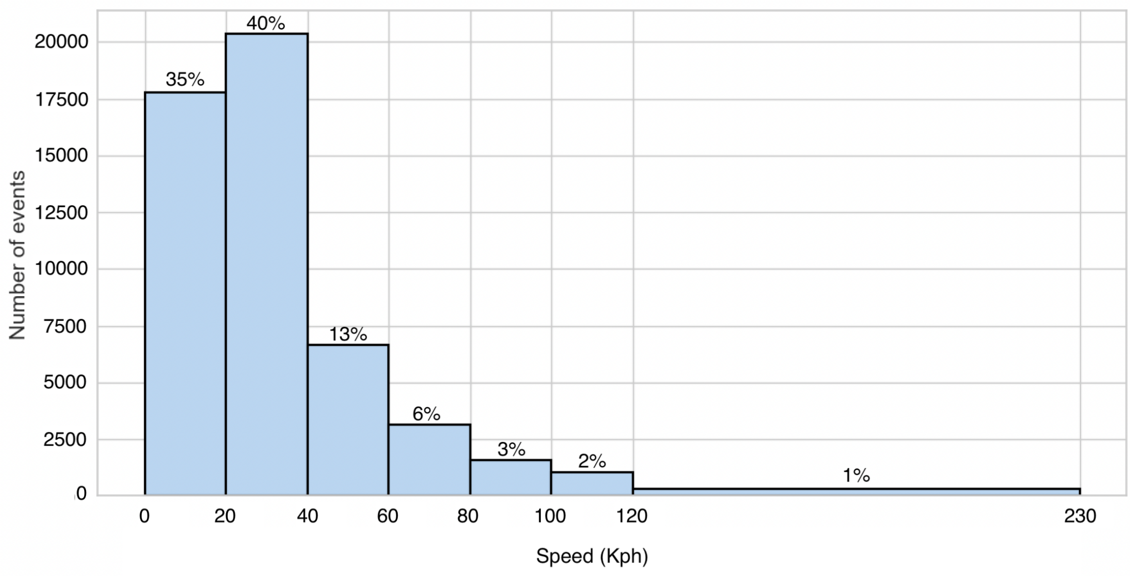

Figure 5.1: The speed distribution of vehicles at the time of CMbB intervention.

As the box plot in figure 5.2 projects, 75% of the data have a speed lower than 40 kph. The median is at 24 kph and the vehicles with more than 74.25 kph are considered outliers. The Interquartile range (IQR) is from 17 to 40 kph.

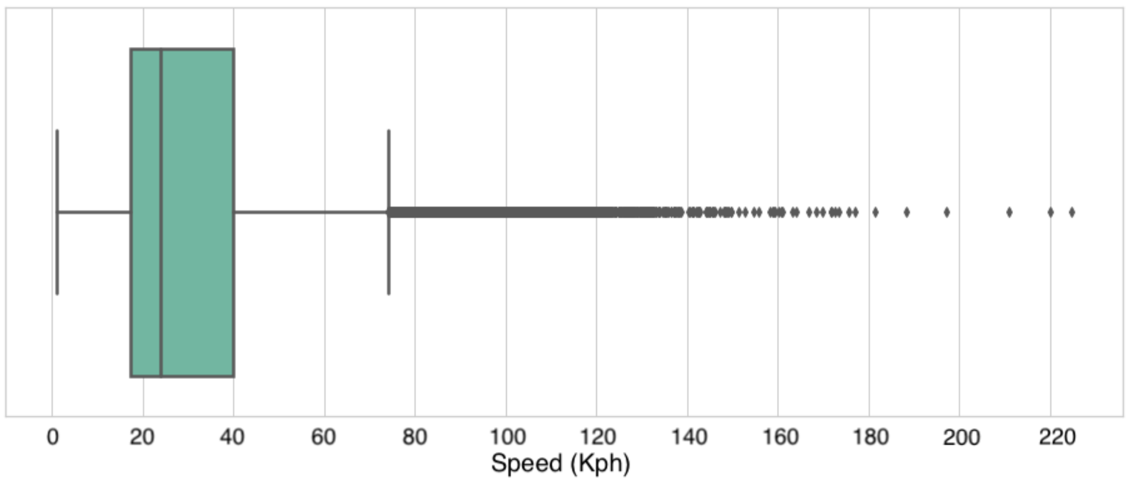

Figure 5.2: The box plot of vehicles' speed, 0.2 seconds before activation of the CMbB function.

5.1.2.2 Drivers overriding with strategy 1

Majority of the drivers overriding with strategy 1 have entered the CMbB intervention with a speed below 60 kph. Figure 5.3 displays the vehicle speed distribution of the drivers who overrode the CMbB intervention using strategy 1. The percentages shown at the bottom of each bin are the share of events in the corresponding speed range based on the total number of events where the driver overrode the CMbB using strategy 1. The distribution is skewed right while the first bin is lower than the second and third bins, where 62% of the data lie.

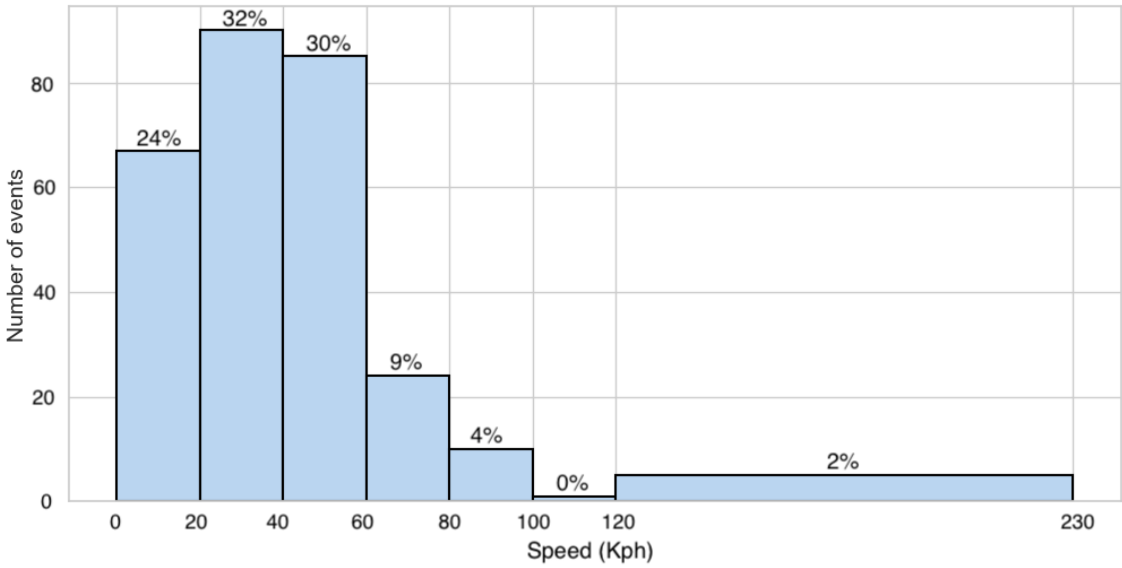

Figure 5.3: The speed distribution of vehicles at the CMbB intervention when the driver has overridden the CMbB function with strategy 1.

5.1.2.3 Drivers overriding with strategy 2

The majority of the drivers overriding the CMbB using strategy 2, have entered the CMbB intervention with a speed below 40 kph. In figure 5.4, the distribution of overridden scenarios with strategy 2 is plotted. The percentages shown at the bottom of each bin are the share of events in the corresponding speed range based on the total number of events in which the driver overrode the CMbB using strategy 2. The plot still follows the right-skewed pattern similar to the figure 5.3. However, it is notable that 91% of the data are within the first two bins. Only 1% of the vehicles had more than 60 kph, which clearly shows the use of this strategy in lower-speed scenarios.

By comparing figures 5.3 and 5.4, it is concluded that the speed range for the drivers overriding with strategy 1 is relatively higher than the drivers overriding with strategy 2.

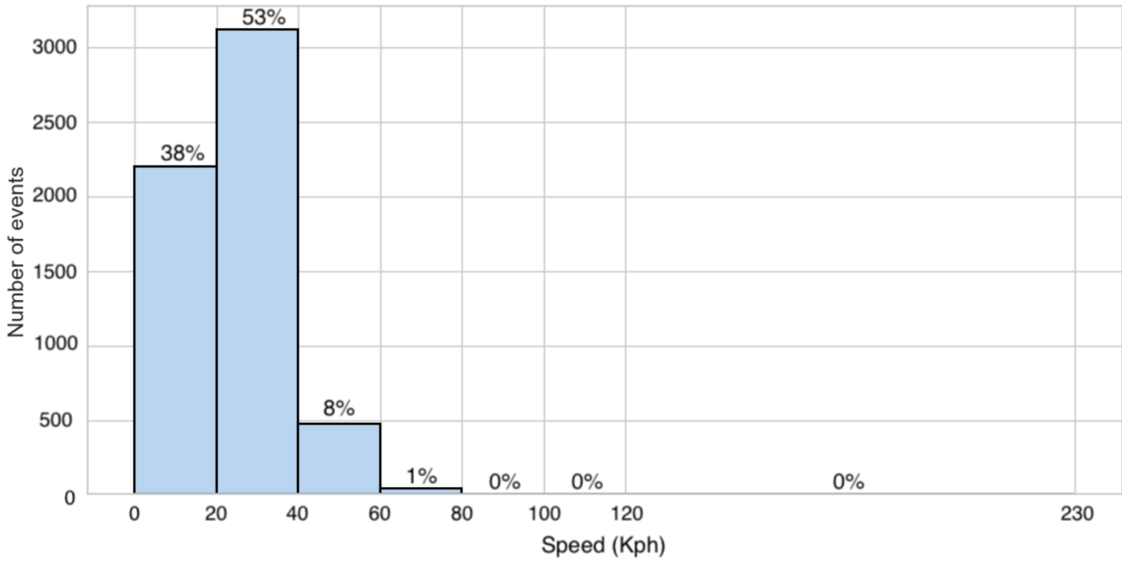

Figure 5.4: The speed distribution of vehicles at the of the CMbB intervention when the driver has overridden the CMbB function with strategy 2.

5.1.2.4 Stationary vehicles in strategy 1 and 2

By investigating the number of vehicles that have reached a stationary state during the CMbB intervention and combining the founding of different speed distribution in sections 5.2.2 and 5.2.3, it can be seen that the number of stopped vehicles in strategy 2 is more than strategy 1.

Table 5.2 projects the distribution of the events in which the host vehicle speed has been reduced to zero. In other words, the host vehicle became motionless/stationary. For example, during a CMbB intervention, in strategy 1, almost 25% of the vehicles reached a zero speed, while the ratio for strategy 2 is 66%.

It can be concluded that most of the events which are overridden with strategy 1 are in lower speed scenarios where it is more likely for the car to reach a stationary state. On the other hand, the events overridden using strategy 2 are more likely to be in higher speed scenarios, e.g., on highways, where reaching zero speed is not as feasible.

Table 5.2: The ratio between two override strategies when the vehicle's speed becomes zero during the CMbB intervention.

	Fully stopped (%)	Did not stop (%)
Strategy 1	26.2	73.8
Strategy 2	61.6	38.4

5.1.3 Impact of the FCW concerning overriding an intervention

Figure 5.5 compares the distribution of the drivers who overrode the CMbB activation and the drivers who did not, concerning the time they had between FCW and the CMbB intervention. The x-axis displays the time (in seconds) between the FCW and the start of the CMbB intervention. It can be observed that the difference between these two is negative on some rare occasions. That implies that the FCW in the sensor dataset was captured after the CMbB activation for its corresponding event. However, it should be noted that this can be because of the latency in the data recorder.

By looking at the two plots in figure 5.5, it can be noticed that the majority of the drivers in both groups have received the FCW very close to or slightly after the event (i.e., at the same time or 0.2 seconds after the event). A too early FCW can increase false-positive warnings received by the driver. This can justify why 42% of the drivers who overrode the intervention and 40% of the drivers who did not, have received the FCW simultaneously as the CMbB activation. Comparing the plots, it is clear that there is no significant difference between the two groups of overriding and no overriding drivers.

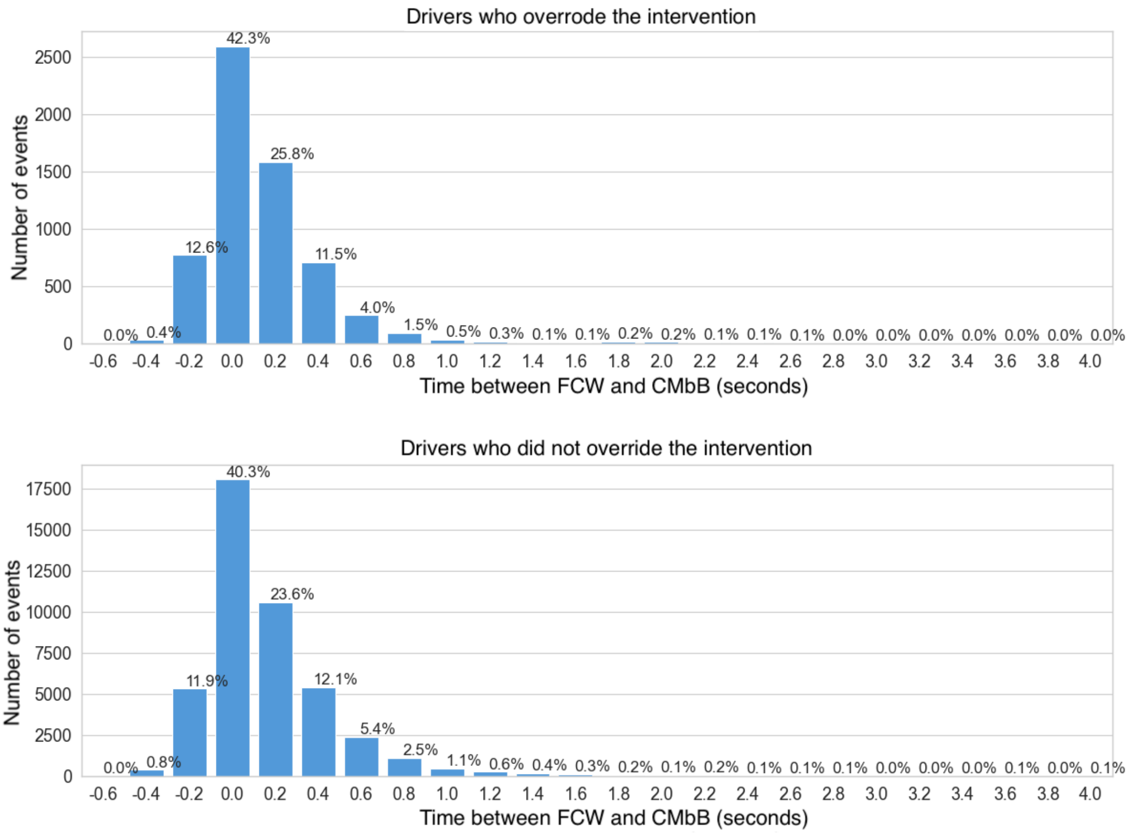

Figure 5.5: Comparing the time between the FCW and the CMbB activation, between the drivers who overrode and the drivers who did not override.

A similar comparison as in figure 5.5 is conducted in figure 5.6. However, in this comparison, the two groups were drivers who did an override using strategies 1 and 2. The two groups are following the same distribution approximately, except that the drivers in strategy 1 have received an earlier FCW.

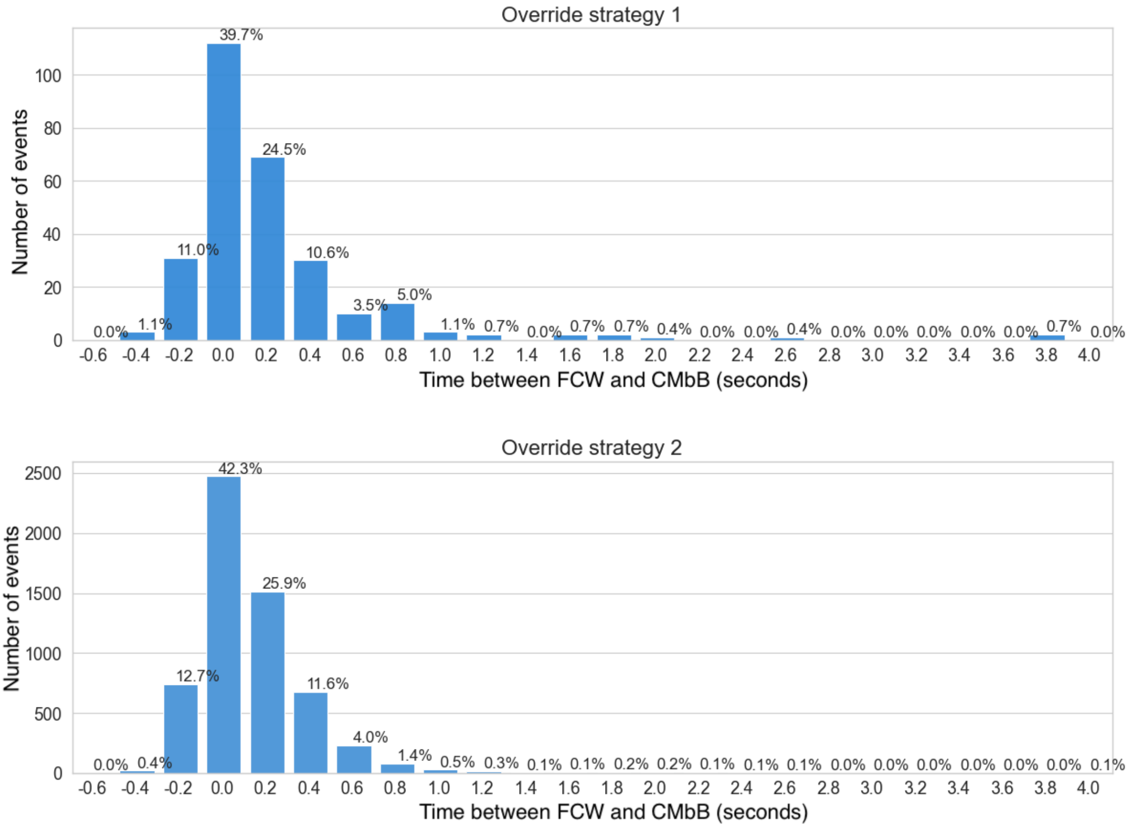

Figure 5.6: Comparing the number of samples in between the FCW and the CMbB activation, between the drivers overriding with strategy 1 and the drivers overriding with strategy 2

As the two distinct groups of the drivers who did an override and who did not are following the same distribution regarding the timing between FCW and CMbB activation (figure 5.5), it can be concluded that FCW's timing is not affecting the probability of overriding an event.

5.1.4 CMbB length of intervention

The investigation on the impact of the length of the intervention illustrates that the drivers who overrode the CMbB intervention had a relatively longer length of CMbB intervention. Considering the driver's reaction time, it is justifiable that a very short intervention will not give the driver the chance to react.

The distribution of the drivers in regards to the length of CMbB activation is shown in figure . By looking at the first plot in figure 5.7, it can be seen that the drivers who overrode the CMbB activation had a noticeably longer time of intervention.

On the other hand, the second plot in figure 5.7 shows that the majority of the non-overriding drivers experienced a very short intervention.

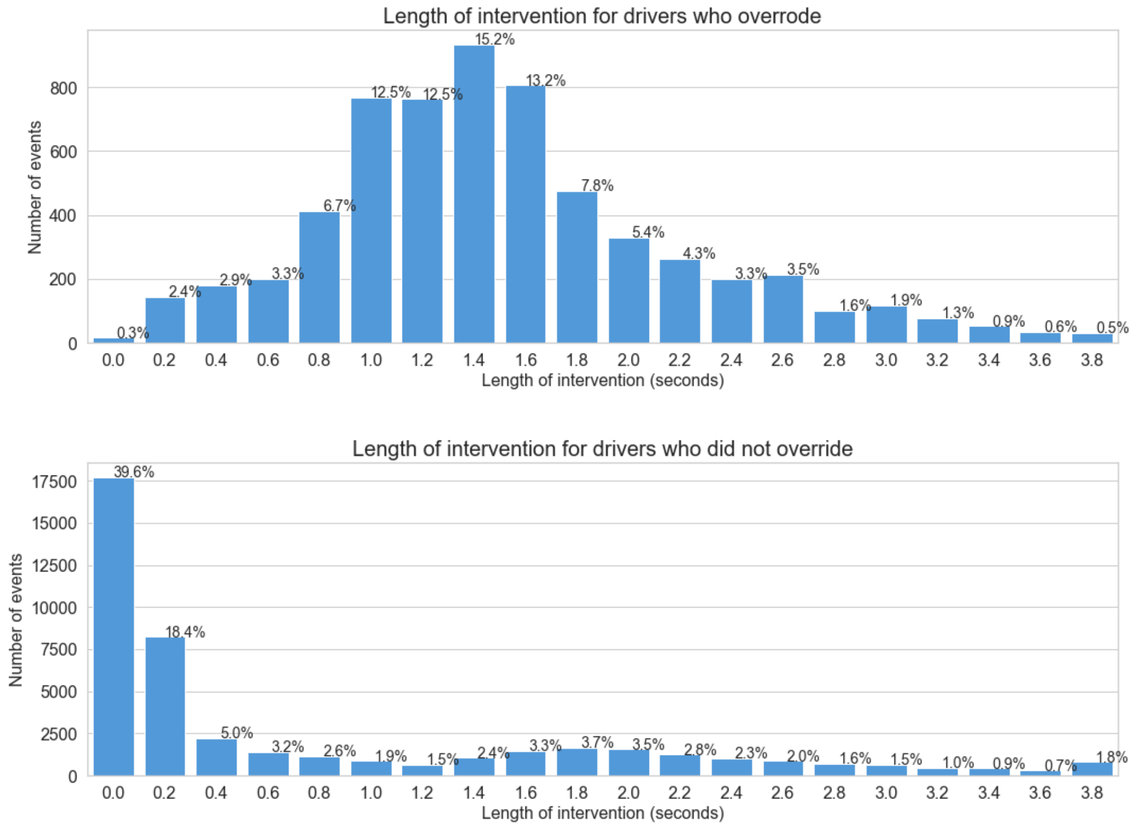

Figure 5.7: Comparing the length of intervention between the two group of overrode versus not overridden events

A similar experiment was conducted and presented, comparing the overriding strategies. Figure 5.8 illustrates how the length of intervention differs in strategies one and two.

The first plot in figure 5.8 shows how the length of intervention is distributed between the drivers overriding strategy one. The second plot in figure 5.8 shows the same for the drivers overriding strategy two. Comparing the two plots in figure 5.8, if dropping the extremes in the strategy 1 group, both plots follow a relatively normal distribution. No major difference can be seen between the two overriding groups.

It can be concluded that the length of intervention should be long enough for the driver to be able to acknowledge the car's automatic decision to intervene. Also, it should be noted that a very short CMbB cannot give the driver enough time to take action.

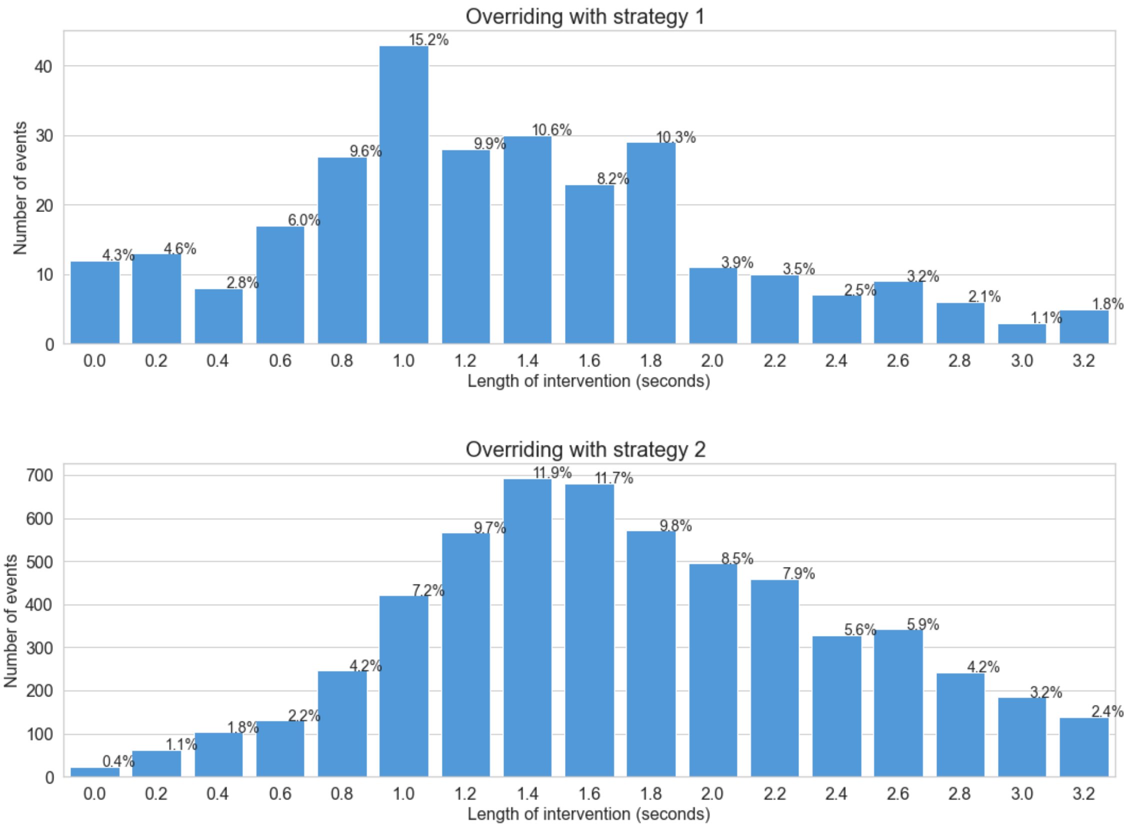

Figure 5.8: Comparing the length of intervention between the drivers overriding with strategy 1 and the drivers overriding with strategy 2.

5.1.5 Reaction time

5.1.5.1 Adaptive cruise control

The investigation shows that the reaction time of both groups of drivers (i.e., overriding and no overriding drivers) did not significantly differ from each other concerning the ACC involvement. Figure 5.9 shows the reaction times for the drivers who had the ACC activated and did not overrode the CMbB intervention. The majority of the drivers had reaction times between 1.8 to 2.4 seconds.

Figure 5.10 illustrates the distribution of the reaction times for the drivers who had the ACC activated and overrode the CMbB intervention. The majority of the drivers in this group had reaction times between 2.0 to 2.4 seconds.

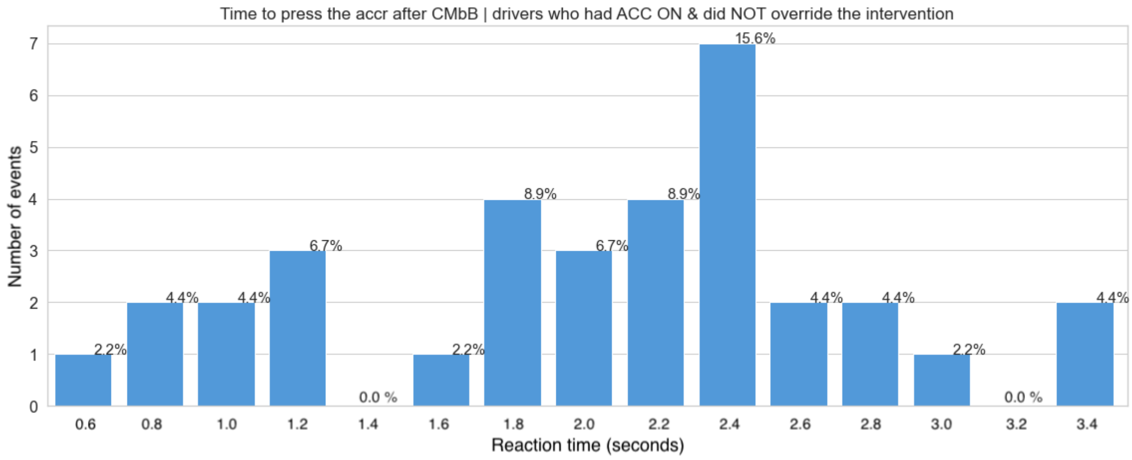

Figure 5.9: The reaction time of the non-overriding drivers when the ACC is activated before the intervention.

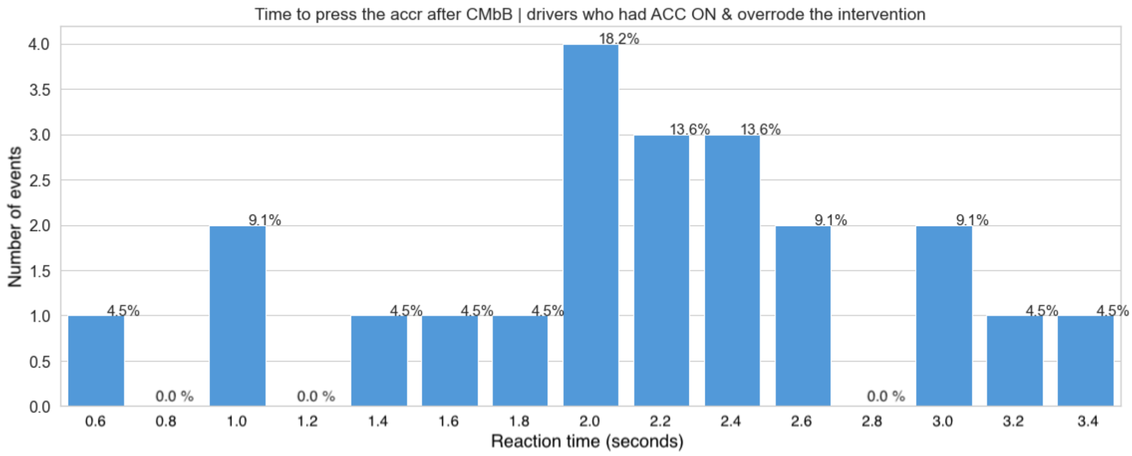

Figure 5.10: The reaction time of the overriding drivers when the ACC is activated before the intervention.

It can be concluded that no major difference was observed in the reaction times in regards to the ACC activation, between the overriding and no overriding drivers.

5.1.6 The reaction time of the overriding drivers concerning the impact of deceleration request

For this investigation, the group of drivers who have overridden the CMbB intervention were selected. This investigation is divided into three subgroups described in detail in section 4.1.7.

5.1.6.1 Time to press the acceleration pedal

The time it takes for the drivers to press the accelerator pedal from the start of the intervention was measured and compared in two groups. Group one was the drivers who experienced a harsher deceleration request (full-brake) from the CMbB function. Group two was the drivers who experienced a relatively lower impact deceleration request (pre-brake), followed by a full-brake. This comparison makes it possible to know *when* the human decides to interfere with the function.

It was seen that the distribution of reaction times in the first group is thinner than in the second group, which means that the variation in reaction times is lower and hence, more predictable in group one. On the other hand, the reaction time in the second group varied more.

A box plot of these two groups separately is illustrated in figure 5.11. On the left side, the box plot shows the distribution of drivers in group one. As it can be seen, the lower range, the upper range and the median for this group is 1 second, 1.6 seconds and 1.4 seconds, respectively.

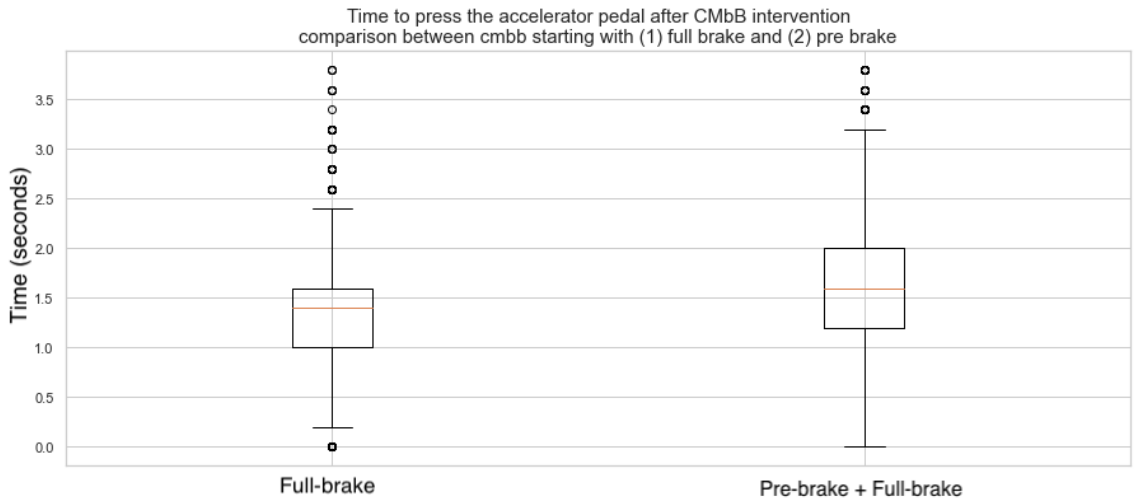

Figure 5.11: Reaction time of overriding drivers based on the type of deceleration request received from the CMbB intervention.

The right-hand side box plot in figure 5.11 shows how the reaction time for group two is distributed. It can be seen that this group has a higher range of variance in reaction times. The lower range, the upper range and the median for this group are 1.2 seconds, 2 seconds and 1.6 seconds, respectively.

The average reaction time for the left-hand side box plot is 1.27 seconds while for the right-hand-side is 1.57 seconds. The box plots are not capable of showing the mean of a distribution, therefore these average reaction times are calculated separately and is not presented in figure 5.11.

Considering the numbers shown in figure 5.11, it can be concluded that the deceleration request impacts how fast the drivers react to the CMbB function. It is essential to consider that due to the high deceleration request coming from a full-brake, the reaction times captured in the first group may also be from a sudden "panic" reaction to the function.

5.1.6.2 Time to override from the acceleration pedal pressed

This investigation measures the time it takes for drivers to successfully override the CMbB intervention from when the accelerator pedal is depressed. Figure 5.12 shows how the time between depressing the accelerator pedal by the driver and the CMbB overrode differs concerning the type of deceleration request from the CMbB function.

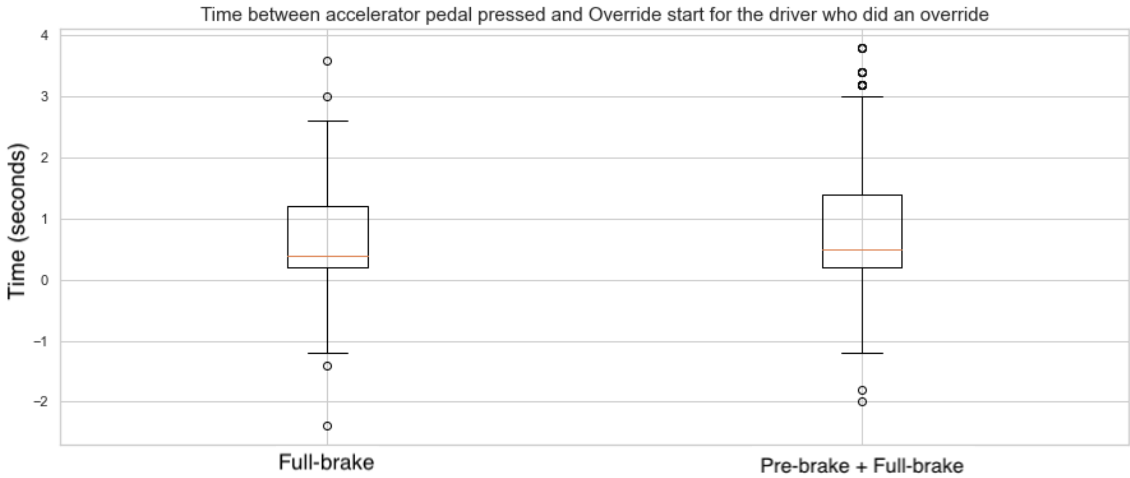

Figure 5.12: Time to override from when the accelerator pedal was pressed comparing the impact of the deceleration request in overriding drivers.

It can be seen that the distribution of time in both groups is positively skewed (i.e., skewed to the right) as the median is closer to the first quartile. However, the left box plot shows that the time distribution between depressing the pedal and overriding is thinner for the drivers who only received a full-brake. The time to successfully override the function for the majority of the drivers in this group lies between 0.2 seconds and 1.2 seconds while lying between 0.2 seconds and 1.5 seconds for the drivers who received a pre-brake before a full-brake.

A shorter time in this measurement can result from depressing the accelerator pedal harsher, thus reaching the overriding threshold faster and overriding the intervention faster. It can be concluded that the distribution in this investigation did not differ significantly concerning the deceleration request impact. However, the drivers who have received a full-brake have pressed the pedal harder and therefore overrode faster than the other group.

5.1.6.3 Length of intervention in overriding drivers

The duration of the intervention was investigated among all the overriding drivers comparing those receiving a full-brake and those receiving a pre-brake followed by a full brake during the intervention. Figure 5.13 displays two box plots comparing the mentioned two groups.

This figure concludes the result of the two previous sub-sections (shown in figures 5.12 and 5.11), as it demonstrates the entire duration of the intervention. The time from CMbB activation to the time overridden by the driver is calculated. The left box plot shows the distribution of overriding drivers who experienced a full-brake. The right box plot illustrates the overriding drivers who experienced a pre-brake which was later followed by a full-brake.

It can be seen that the duration of the CMbB is shorter for the group shown on the left box plot, with an approximate median of 0.3 seconds. The median for the group on the right-hand side does not differ significantly, and it is about 0.4 seconds. Both groups have a positive skewness (i.e., skewed to the right).

In conclusion, the deceleration request does not significantly affect the length of intervention among overriding drivers. However, most of the overriding drivers have experienced an intervention longer than 1 second. This is justified by considering the driver reaction time discussed in the *Background* chapter.

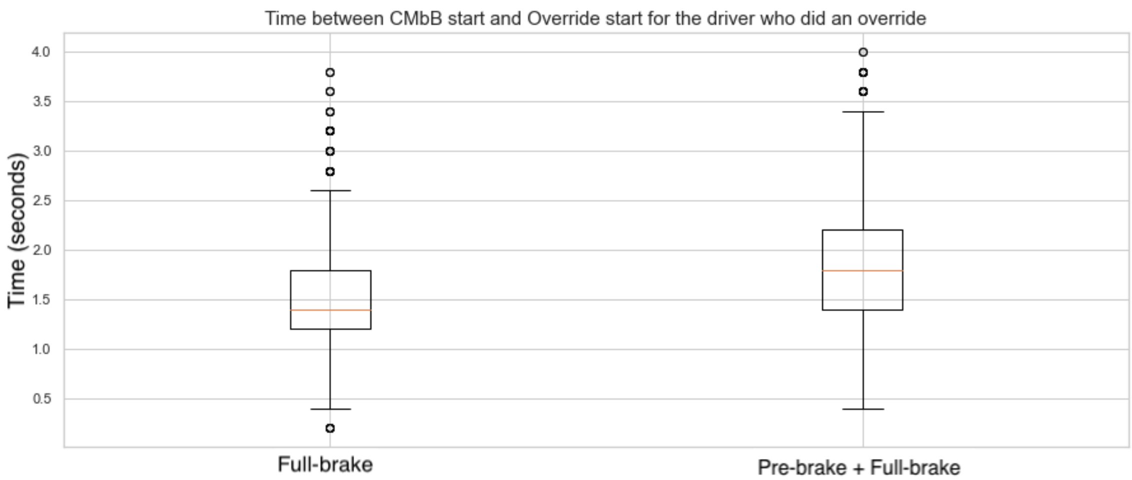

Figure 5.13: The length of intervention for overriding drivers who have experienced different deceleration requests from the CMbB function.

5.2 Clustering results

5.2.1 Result of the K-means clustering on the PCA dataset

Three clusters were made as a result of the implementation of the K-means algorithm. The categorization described previously in *Methods* (i.e., No overriding, Overriding with strategy 1, and Overriding with strategy 2) is used to analyze the clustering result. Table 5.3 shows the result of the cluster analysis.

The results from table 5.3 show that drivers using strategy 1 are significantly different than those using strategy 2 and the no overriding group; As 99.23% of drivers overriding with strategy 1 are in the first cluster. The remaining percentage

Table 5.3: Distribution of each category in each cluster.

	Cluster 1 (%)	Cluster 2 (%)	Cluster 3 (%)
Not overridden	6.06	62.03	31.90
Strategy 1	99.23	0.38	0.38
Strategy 2	29.45	47.55	22.98

of drivers overriding with strategy 2 are distributed in clusters 2 and 3.

The majority of the non-overriding drivers are in cluster 2 alongside the majority of the drivers overriding using strategy 2. This suggests that drivers using strategy 2 to override the intervention may have similar driving behaviour with drivers who do not override the intervention.

The drivers overriding with strategy 2 are distributed among the three clusters, with the majority (47.55%) in cluster 2.

Thus, it can be concluded that drivers who have overridden the intervention using strategy 1 behave entirely differently from other drivers. Furthermore, the drivers who did not override or overrode using strategy 2 behave similarly.

5.2.2 Result of the time series K-means clustering

5.2.2.1 Acceleration pedal ratio

Three clusters are made as the result of the K-means clustering on the time series data. 5.14.

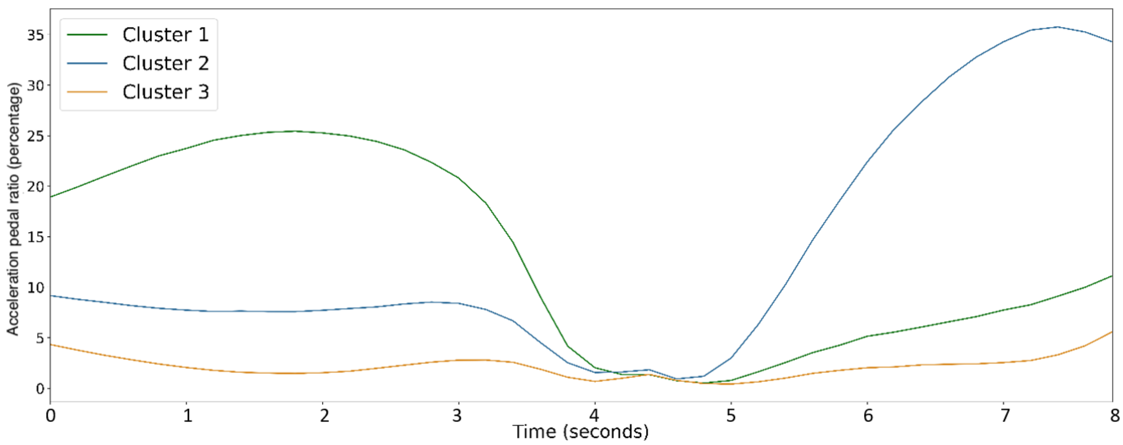

Figure 5.14: The centroid of each cluster in the time series data for the acceleration pedal ratio. The x-axis starts at the beginning of the event and ends at the end of the event, while the CMbB intervention takes place approximately at the fourth second on the x-axis.

The distribution of each group is presented in table 5.4. Almost half of the drivers who did not override the CMbB intervention are located in cluster 3, and the remaining are evenly distributed in clusters 1 and 2.

Cluster 2 can represent the drivers who overrode the CMbB intervention using strategy 1, as 78% of these drivers lay in cluster 2. The drivers who overrode the CMbB function using strategy 2 have a 51% population in cluster 3, and the remaining population is distributed almost evenly in clusters 1 and 2.

In conclusion, cluster 2 can be a good representative of overriding behavior, as 78% of overriding drivers using strategy 1 and 51% of drivers using strategy 2 are within this cluster. Furthermore, it can be observed that the acceleration behavior in overriding drivers starts to have a raise approximately after 0.8 seconds of the intervention (i.e., at about 4.8 seconds of x-axis). By connecting this finding to the driver reaction time studies addressed in Chapter 2, it can be justified why the difference in acceleration behavior between the overriding and no overriding drivers can be seen after 0.8 seconds of the intervention.

Moreover, by looking at the behaviors prior to the CMbB intervention, it can be seen that the overriding drivers (cluster 2) have a stable accelerating behavior. This is an additional indicator for assuring that the raise in the acceleration, after the CMbB intervention, is intentional. Thus, it can be concluded that a stable acceleration behavior prior to the event and a raise in the accelerating after the event is a good indicator of overriding intention. Furthermore, the difference between the overriding and non-overriding drivers starts to becomes explicit 1 second after the intervention. This means to separate these two groups of drivers, one can look for capturing differences even 1 second after the intervention.

Table 5.4: Distribution of each group in clusters.

	Cluster 1 (%)	Cluster 2 (%)	Cluster 3 (%)
Not overridden	29	28	43
Strategy 1	15	78	7
Strategy 2	28	51	21

5.2.2.2 Acceleration slope

The three drivers group (i.e., no overriding, overriding with strategy 1, and overriding with strategy 2) have been considered in this clustering. Most of the overriding drivers are located in cluster 1 (75% of overriding drivers using strategy 1 and 55% of overriding drivers using strategy 2). Thus, cluster 1 can be considered as representative of the overriding behavior. Cluster 3 mainly consists of the non-overriding drivers and cluster 2 is almost blended between all groups.

The results of the three conducted clusters show that the *slope* of the acceleration at the beginning of the series is almost similar between all the drivers. However, the difference between the overriding drivers versus the non-overriding driver is visible around 1.5 seconds after the intervention. By looking at figure 5.15, it can be seen that drivers in cluster 1 are reaching a higher slope 1.5 seconds after the intervention.

Furthermore, as the new strategy considers the acceleration slope, the findings from this clustering results and the acceleration ratio clustering results can be beneficial in setting a suitable time and threshold for activation of the new strategy.

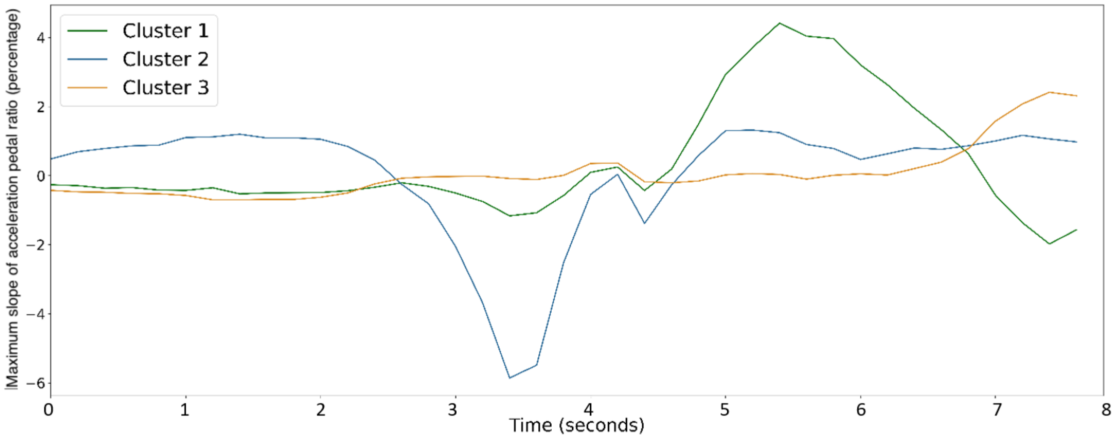

Figure 5.15: The centroid of each cluster in the time series data for the acceleration pedal slope. The x-axis starts at the beginning of the event and ends at the end of the event, while the CMbB intervention takes place approximately at the fourth second on the x-axis.

Table 5.5: Distribution of each group in clusters.

	Cluster 1 (%)	Cluster 2 (%)	Cluster 3 (%)
Not overridden	27	37	36
Strategy 1	75	21	4
Strategy 2	55	34	11

5.2.2.3 Steering behaviors

The variable considered for studying the driver's steering behavior is the steering angle speed. The sensor's value indicates how fast the driver turns the steering wheel in any direction. The positive values represent the turn clockwise, and the negative values represent the turn counter-clockwise. There is a considerable difference observed between each cluster centroid before the intervention (at about 4.0 seconds of the x-axis), as shown in figure 5.16. However, the difference between the clusters is not as substantial after the intervention.

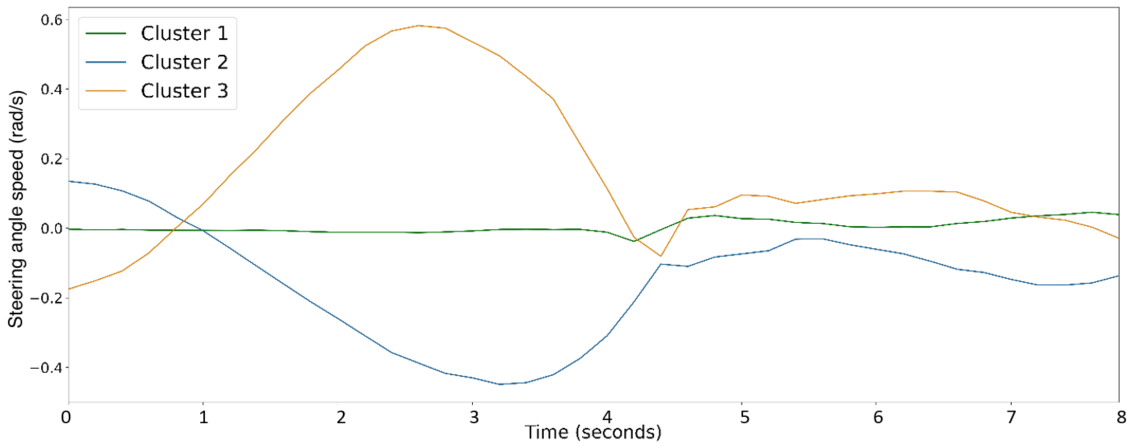

Figure 5.16: The centroid of each cluster in the time series data for the steering angle speed. The x-axis starts at the beginning of the event and ends at the end of the event. The CMbB intervention takes place approximately at the fourth second on the x-axis.

As shown in the table 5.6 the driver groups (i.e., those who do not override, those overriding with strategy 1, and those overriding with strategy 2) are almost distributed among all the clusters. That said, no specific conclusion can be drawn from clustering the steering behavior.

Table 5.6: Distribution of each group in the clusters.

	Cluster 1 (%)	Cluster 2 (%)	Cluster 3 (%)
Not overridden	55	25	20
Strategy 1	57	19	24
Strategy 2	45	32	23

5.2.2.4 Braking behaviors

Drivers' braking behavior is analyzed using the *Driver deceleration request* signal. This signal shows how much deceleration is requested due to depressing the braking pedal by the driver.

Figure 5.17 shows the time series clustering result on the mentioned signal in which the y-axis shows the value of the deceleration request by the driver. The braking behavior in the data has resulted in three clusters. In all three clusters, the deceleration reaches its peak around 0.5 seconds after the intervention (i.e., on the 4.5 seconds of the x-axis). Cluster three has the higher deceleration request with the peak at 6 m/s^2. Clusters one and two have their peaks at approximately 3.5 and 1.5 m/s^2, respectively.

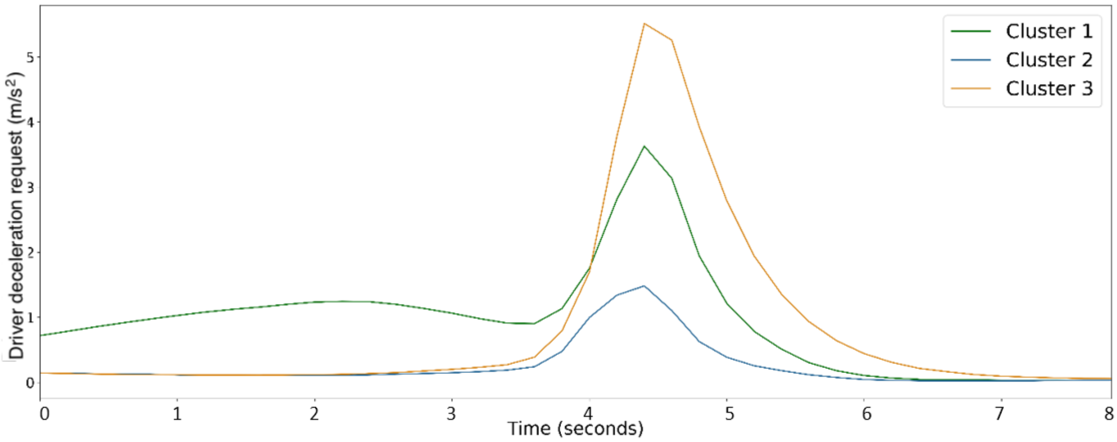

Figure 5.17: The centroid of each cluster in the time series data for the driver's deceleration request. The x-axis starts at the beginning of the event and ends at the end of the event, while the CMbB intervention takes place approximately at the fourth second on the x-axis.

Table 5.7 shows how the driver groups (i.e., those who do not override, those overriding with strategy 1, and those overriding with strategy 2) are distributed in each cluster. There is no significant difference among the driver groups in each cluster as they are blended in all three clusters.

Table 5.7: Distribution of each group in clusters.

	Cluster 1 (%)	Cluster 2 (%)	Cluster 3 (%)
Not overridden	11	29	60
Strategy 1	10	19	71
Strategy 2	12	26	62

5.3 New strategy

All strategies (i.e., strategies 1 and 2) get triggered in certain circumstances. For example, strategy 1 gets triggered by accelerating to a certain threshold. The criteria to activate the new strategy is based on the findings of the investigations done in this thesis. The investigation shows that an excellent indicator to override is a quick depress on the acceleration pedal (slope). However, there are cases the driver presses the accelerator pedal accidentally. To overcome this issue, a period is taken into account in which the driver's interaction with the acceleration pedal will have no impact. The mentioned period is equal to the average time needed for a driver to take action after assessing a situation.

Assuming that the new suggested strategy was implemented on the cars, the total number of CMbB interventions overridden by this strategy would be 379 events, Out of which 59 and 109 events could also be overridden using strategies 1 and 2, respectively.

One can argue that half of the overrides triggered by the new strategy could also be triggered with strategies 1 and 2. Although the argument is valid, the new strategy allows the driver to override the undesired CMbB faster than the other two strategies. Moreover, the new strategy covers some events where the driver could not override the CMbB intervention.

To evaluate the performance of the new strategy, the events in each group (i.e., no overriding drivers, overriding with strategy 1, and overriding with strategy 2) have been analyzed considering the reduction of needed time to override the CMbB intervention. Table 5.8 provides an overview of how the new strategy can enhance the current strategies considering the time it takes to override the intervention.

Table 5.8: The number of events could be overridden earlier by the new strategy in different groups.

	Number of events	Average reduced time (seconds)	Maximum reduced time (seconds)
Not overridden	211	0.532	2.4
Strategy 1	59	0.484	2.8
Strategy 2	109	0.628	2.6

Table 5.8 shows that if the new strategy existed, 211 of the non-overridden events in which the driver attempted to override, could be overridden. Furthermore, 59 events that are overridden using strategy 1 and 109 that are overridden using strategy 2 could be overridden earlier using the new strategy. The table also provides how quicker the new strategy can override the intervention on average. The last column of the table shows the maximum reduction in overriding time that could be found among all the events in each group.

6 Discussion & conclusion

This chapter interprets and explains the key findings of this master thesis in the same order as described in chapter 5, *Results*. The *Discussion* section of this chapter is divided based on the methodology of the report. Furthermore, the answers to the research questions are provided, followed by potential future work.

6.1 Descriptive statistics

At the beginning of this report, it was mentioned that the related researches on the driver behavior suggest that the behavior can be grouped into three main categories: (1) acceleration/deceleration, (2) steering, and (3) braking (Zfnebi et al. 2017). These categories were used in order to access the behavioral patterns of drivers.

In addition to these three categories, as the humans are interacting with the autonomous functions in the car, it is vital to consider the human reaction time. The studies mentioned in chapter 2, such as the research conducted by Green (2000) have concluded an approximate driver reaction time. Although these numbers are based on many factors which makes it hard to report a single number, Green (2000) states that the average reaction time in attentive drivers are 0.7 to 0.75 seconds. In this thesis, two investigation were conducted on the reaction time. The first is considering the effect of the ACC system on the reaction times of all the drivers (see figures 5.10 and 5.9). The second is considering the overriding drivers and how fast they press the accelerator pedal after the CMbB intervention (see figure 5.11).

The average reaction times reported in this thesis (1.27 and 1.56 seconds depending on type of the CMbB deceleration request) are higher than the numbers reported in studies such as Green (2000). This can be explained by considering that the measurements in this report are calculated based on different criteria than the addressed studies. In those studies, the reaction time is measured based on how fast the driver detects and responds (by braking) to an incoming object on the road. In this thesis, it was measured how fast the driver depresses the acceleration pedal after the intervention. The latency in the signal recorder can also be considered in our measurements. It is worth mentioning that, all these investigations are measuring the time it takes for the drivers to interact with the vehicle's pedals.

Furthermore, it was shown that the CMbB length of intervention is an important factor in giving the driver the possibility to override. Considering the driver reaction time, the length of intervention should be long enough to be felt by the drivers, and give them a chance to react to it.

Moreover, by looking at the acceleration behavior of all the drivers, it was observed that the drivers who override the intervention tend to have a higher acceleration *slope*. The term slope (see section 4.1.8) refers to the difference of the acceleration pedal ratio in two sequential samples.

6.2 Unsupervised machine learning

Two unsupervised machine learning models have been used in this project: (1) K-means clustering for the Summary data and (2) time series K-means on the Sensor datasets.

6.2.1 K-means clustering

K-means was used on the summary dataset using PCA as a feature reduction method. The Stadion stability trade-off introduced by Mourer et al. (2020) was used for determining the number of clusters. Three clusters were presented by the model. As mentioned at the beginning of chapter 4, the data has been split into three groups: (1) No overriding, (2) Overriding with strategy 1, and (3) Overriding with strategy 2. These three groups were used to analyze the result of each cluster. The analysis showed that 99.23 % of the drivers overriding the intervention with strategy 1 are located in one cluster and distinct from the other two groups (see table 5.3) .

As the summary dataset has many features, PCA was used to reduce the data dimensionality. As a result, seven principle components have been generated to represent approximately 86% of the data. Although 86% of the original data is covered in the principal components, using PCA comes with the cost of having less interpretable result, as Björklund (2019) states.

6.2.2 Time series K-means clustering

The time series K-means clustering was implemented using DTW as the similarity measure. The default similarity measure used in time-series clustering is the Euclidean distance. By replacing the Euclidean distance with the DTW, it was possible to capture the similarity between the sequences even if they were not following the same timeline, thus improving the clustering results. K-means with DTW were used on four different signals. The choice of these signals is based on the studies conducted on driver behavior addressed earlier in this paper at section 2.2. (i.e., acceleration/deceleration, braking, steering) variables based on different driver behaviors (Zfnebi et al. 2017).

1. **Acceleration pedal ratio:** The time series K-means clustering on this variable shows a quite distinct acceleration behavior between the drivers who overrode the CMbB intervention and those who did not. The findings show that changes in acceleration behavior are the best indicator for the overriding intention (see figure 5.14).

2. **Acceleration slope:** The result of the time series K-means clustering on this variable indicates that the overriding drivers have a higher acceleration slope during the intervention, than the non-overriding drivers (see figure 5.15).

3. **Steering angle speed** & **driver deceleration request:** Unlike the previous variables, the time series clustering was not able to identify distinct clusters with interpretable differences between these two variables. The different groups in the drivers (i.e., non-overriding, overriding with strategy 1, and overriding with strategy 2) have the same distribution in the distinct clusters as shown in table 5.6 and table 5.7.

6.3 The new strategy

The new strategy is not a replacement for the current strategies at VCC but complementary to achieve a more efficient overriding function. Although it has overlaying margins with the current strategies (i.e., strategies 1 and 2), it allows 22.5% of the overriding drivers who used strategy 1 to override faster with an average of 0.484 seconds. In addition, it allows 1.9% of drivers who used strategy 2 to override earlier with an average of 0.628 seconds. This strategy can also let 2% of the non-overriding drivers (who attempted to override but failed) override the CMbB intervention. A faster driver override will remove the brakes earlier and allow the driver to carry higher momentum as the initial velocity of the vehicle has not been significantly reduced.

6.3.1 Research questions

Question 1: *What is the typical driver reaction to an activated AEB intervention?*

All the drivers who experience the AEB activation are getting an FCW. It was concluded that based on the type of data used in this master thesis, this warning does not make a difference in the reaction time of the drivers, as it comes very close to the event. Furthermore, the drivers who tend to override the intervention (among the studied variables) are mostly reacting by pressing the accelerator pedal on an average of 1.27 (when CMbB is requesting a full-brake) to 1.56 seconds (when CMbB is pre-braking before full-braking) after the intervention. The answer to this question is provided based on the main behavioral categories addressed in this thesis (i.e., acceleration/deceleration, steering, and braking):

The time series clustering on the Sensor datasets shows that the acceleration is significantly harsher in drivers who tend to override. Moreover, the drivers who override show a relatively more stable acceleration behavior prior to the intervention.

Time-series clustering on the steering behavior shows that all the drivers are steering on a somewhat stable angle speed between -0.1 to 0.1 Rad/s after the intervention. No difference between overriding and non-overriding drivers was captured in this matter.

Time-series clustering on the braking behavior indicates that all the drivers start to brake approximately 0.5 seconds after the intervention. The drivers are grouped into three clusters based on how harshly they press the brake pedal. The first group, second group, and the third group are braking on an average of 5, 3.5, and 1.5 m/s^2, 0.5 seconds after the event, respectively. The model could not make any clusters perfectly presenting the driver groups (i.e., non-overriding, overriding with strategies 1 and 2).

Question 2: *Can the existing override strategies at VCC be improved?*

As there is no ground truth (i.e., labels) in the data indicating the intention to override for the drivers, it was not possible to perfectly analyze the current strategies at VCC. However, this thesis suggests a new strategy that can improve the already existing strategies at VCC. The improvement is regarding the time it takes to override the CMbB intervention. The new strategy uses the finding of the first research question of this thesis to suggest a new trigger to override the static threshold currently used at VCC. Furthermore, as this suggested strategy has a new way to get triggered, it could detect the drivers who attempted to override and could not override using the current strategies.

6.3.2 Future work

The data used in this project came from an older version of the VCC's systems. The data only consist of values from signals and vehicle statistics. Therefore, there is no ground truth (i.e., labels) about the driver's status or intention. Not having a ground truth, such as images taken from the driver or the vehicle's surroundings, makes the evaluation process challenging for the analysis of current strategies and the proposed new strategy. The methods and analysis used in this project could have been more informative if implemented on data with ground truth.
The finding on the FCW function in this report are from a brief investigation as the main focus of this project was the CMbB function. The results show that the FCW function could be investigated in detail for a more efficient FCW strategy.

The new strategy proposed in this report could be investigated further with the detailed data mentioned above. Since the new strategy triggers the driver override earlier, it will remove the brakes earlier. This allows the driver to carry higher momentum as the initial velocity of the vehicle has not been significantly reduced. However, the amount of energy preserved depends on the type of engine. Therefore, this statement can be further investigated and calculated to benchmark how much kinetic energy is preserved.

Furthermore, the verification of the new strategy can be done in two ways: (1) A study can be conducted using VCC's test fleets, where the drivers and how they interact with the system are studied. (2) This strategy can be implemented on the cars but not activated; Whenever this new strategy could get triggered, a new event log can be saved. The event logs can then be further analyzed by VCC to confirm the efficiency of the new strategy. These logs can also be used to find a suitable acceleration slope's threshold for the activation of the new strategy.

Finally, having labeled data in which the labels are ground truth for the driver's intention to override, a supervised machine learning model can be used to make predictions about driver overrides.

A
Summary dataset features

1. VehicleIdentity
2. VehicleSpeedAtCMbBStart
3. RoadSpeedLimit
4. RelativeSpeedAtCMbBStart (Relative speed to the target vehicle)
5. TotalVehicleSpeedReduction
6. VehilceSpeedReductionByCMbB
7. LengthOfIntervention
8. PrebrakeComesFirst (If the intervention starts with a pre-break)
9. FullBrakeLength
10. Classification (True Positive, False Positive or Nuisance)
11. MaximumDecelerationRequestbyCMbB
12. DriverBrakingAtCMbBStart
13. MaximumDriverDecelerationRequest
14. MinimumAcceleration
15. TimeBrakingBeforeIntervention
16. MaximumSteeringAngle
17. SteeringAngleAtCMbBStart
18. SteeringAngleSpeedAtCMbBStart
19. TimeBetweenCMbBEndAndDriverAcceleration
20. CMbBStartIndex
21. CMbBEndtIndex
22. OverrideStatus
23. SeverityOfScenario
24. TimeBetweenCMbBStartAndMaximumDriverDecelRequest
25. DriverBehaviour (Annotated)
26. MaximumPedalRatioDuringCMbB
27. MaximumSlopeOfAccelerationPedal
28. TimeFromCMbBStartToDriverBrake

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