Modelling Drivers’ Braking Behaviour and Comfort Under Normal Driving

by

Stavroula Panagiota Deligianni

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Abstract

The increasing growth of population and a rising number of vehicles, connected to an individual, demand new solutions to reduce traffic delays and enhance road safety. Autonomous Vehicles (AVs) have been considered as an optimal solution to overcome those problems. Despite the remarkable research and development progress in the area of (semi) AVs over the last decades, there is still concern that occupants may not feel *safe* and *comfortable* due to the robot-like driving behaviour of the current technology. In order to facilitate their rapid uptake and market penetration, ride comfort in AVs must be ensured.

Braking behaviour has been identified to be a crucial factor in ride comfort. There is a dearth of research on which factors affect the braking behaviour and the comfort level while braking and which braking profiles make the occupants feel safe and comfortable. Therefore, the primary aim of this thesis is to model the deceleration events of drivers under normal driving conditions to guide comfortable braking design. The aim was achieved by exploiting naturalistic driving data from three projects: (1) the Pan-European TeleFOT (Field Operational Tests of Aftermarket and Nomadic Devices in Vehicles) project, (2) the Field Operational Test (FOT) conducted by Loughborough University and Original Equipment Manufacturer (OEM), and (3) the UDRIVE Naturalistic Driving Study.

A total of about 35 million observations were examined from 86 different drivers and 644 different trips resulting in almost 10,000 deceleration events for the braking features analysis and 21,600 deceleration events for the comfort level analysis. Since deceleration events are nested within trips and trips within drivers, multilevel mixed-effects linear models were employed to develop relationships between deceleration value and duration and the factors influencing them. The examined factors were kinematics, situational, driver and trip characteristics with the first two categories to affect the most the deceleration features. More specifically, the initial speed and the reason for braking play a significant role, whereas the driver’s characteristics, i.e. the age and gender do not affect the deceleration features, except for driver’s experience which significantly affects the deceleration duration.

An algorithm was developed to calculate the braking profiles, indicating that the most used profile follows smooth braking at the beginning followed by a harder one. Moreover, comfort levels of drivers were analysed using the Mixed Multinomial Logit models to identify the effect of the explanatory factors on the comfort category of braking events. Kinematic factors and especially TTC and time headway (THW) were found to affect the most the comfort level. Particularly, when TTC or THW are increased by 1 second, the odds of the event to be “very comfortable” are respectively 1.03 and 4.5 times higher than being “very uncomfortable”. Moreover, the driver’s characteristic, i.e. age and gender affect significantly the comfort level of the deceleration event. Findings from this thesis can support vehicle manufacturers to ensure comfortable and safe braking operations of AVs.

Dedication

I would like to dedicate my thesis to the memory of my father,

Evangelos Deligiannis

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List of Acronyms

AASHTO	American Association of State Highway and Transportation Officials
ACC	Adaptive Cruise Control
ADAS	Advanced Driving Assistance Systems
AIC	Akaike Information Criterion
AISS	Arnett Inventory of Sensation seeking
AVs	Autonomous Vehicles
BIC	Bayesian Information Criterion
CAN	Controller Area Network
DBQ	Driver behaviour Questionnaire
FESTA	Field opErational teSt supporT Action
FOT	Field Operational Tests
GEV	Generalized extreme value
GPS	Global Positioning System
ICC	Intraclass Correlation Coefficients
LDWS	Lane Departure Warning System
LR	Likelihood Ratio
MMNL	Mixed Multinomial Logit
MNL	Multinomial Logit
MNP	Multinomial Probit
NDS	Naturalistic Driving Study
NHTSA	National Highway Traffic Safety Administration
NL	Nested Logit
OEM	Original Equipment Manufacturer
PTW	Powered Two-Wheeler
SALSA	Smart Application for Large Scale Analysis
SHRP	Strategic Highway Research Program
THW	Time Headway
TTC	Time to Collision
UDRIVE	eUropean naturalistic Driving and Riding for Infrastructure and Vehicle safety and Environment
VPC	Variance Partition Coefficients

1 Introduction

1.1 General background

The invention of the car in the late 19th century revolutionised transport systems. Vehicles have become an essential part of everyday life and the most popular mean of transport around the world, with their total number estimated to be 1.2 billion globally in 2014 (Voelcker, 2014). This number has grown rapidly, as in 2011 the estimated number of cars was 1 billion (Sousanis, 2011). Unfortunately, along with the increase in the number of cars, there has been an increase in road collisions. According to an estimate by the World Health Organization, 1.3 million people are killed and up to 50 million people incur non-fatal injuries in road collisions every year (World Health Organization, 2015). Moreover, road traffic injuries are the leading cause of deaths among young people, i.e. 15-29 years old. A total of 1793 people were killed in reported traffic collisions in Great Britain in 2017, 0% change since 2016 and there were 24,831 seriously injured and 170,993 casualties of all severity in reported road traffic accidents (Department for Transport, 2018). Another consequence of road collision is the costs to individuals, property and society. According to the 2017 Annual Report of International Transport Forum, the total cost of all reported and unreported road collisions accumulated to around GBP 35.5 billion a year (the unreported injuries were included for the first time in the total cost and it was around GBP 20 billion a year).

Previous studies identified human error as the dominant contributory factor to these collisions (Petridou and Moustaki, 2000; Lu et al., 2005; Elbanhawi et al., 2015). More specifically, the complex interactions between the driver, the vehicle and the environment are held responsible (Ungoren and Peng, 2005). According to the National Highway Traffic Safety Administration (NHTSA), human error is a contributing factor to 94% of the traffic collisions (Singh, 2015). Human errors are grouped by Umemura (2004) into three categories: cognitive errors (i.e. errors caused by oversights), judgment errors (e.g. misjudge the other’s vehicle speed or acceleration) and operation errors (e.g. failing to apply the brakes strongly enough in an emergency). There are also other factors that can lead to a driver error and cause a collision such as distraction, fatigue, risk-taking attitudes, an overestimation of capabilities, as well as alcohol and drugs (Petridou, 2000).

Vehicle automation aims to take the driver out of the driving task to eliminate human error. The basic objectives of this new disruptive technology are a reduction in traffic collisions, an increase in safety, a smoother traffic flow and an increase in driver comfort (Lay and Saxton, 2000). In fact, the road towards full automation has been opened for quite some time by technology such as anti-lock braking system (ABS) and electronic stability. The absolute goal is the development of fully AVs. To date, different systems from the fields of computer science and robotics have been applied to passenger cars, which have formulated the Advanced Driving Assistance Systems (ADAS). ADAS applications (e.g. emergency braking, lane-keeping assistance, adaptive cruise control) help to avoid collisions by assisting the driver in their driving task continuously either by warning the driver or taking control of the car. Apart from the increase of safety, ADAS also aims to improve the comfort and the efficiency of the cars (Lu et al., 2005). Nevertheless, there are still significant challenges in reaching the necessary safety integrity at an affordable cost.

Autonomously driving cars (also known as robotic, autopilot, driverless or self-driving cars) have been the purpose of many robotics researchers (Petrovskaya and Thrun, 2009). An autonomous car is an AV capable of fulfilling the transportation capabilities of a traditional car. It is fundamentally defined as a passenger vehicle that drives by itself (Forrest et al., 2007). Some of the possible advantages and limitations from the use of AVs can be summarised as follows.

The possible benefits of AVs include the improvement of traffic safety by reducing collisions, more efficient traffic flow by reducing congestion and setting higher speed limits, increased highway capacity and reduction of the total number of cars through car sharing (Lay and Saxton, 2000; Forrest et al., 2007; Petrovskaya and Thrun, 2009; Stevens and Newman, 2013). Moreover, there are environmental and financial benefits since they will reduce vehicle emissions and fuel consumption and optimise fuel usage. Furthermore, they will provide extended mobility for elderly and disabled people and contribute to time-saving.

On the other hand, there are still many challenges regarding AVs use (Figure 1.1) (Stevens and Newman, 2013; Catapult Transport Systems, 2016; Barabás et al., 2017; BSI and Catapult Transport Systems, 2017). Particularly, concerns about the liability for accidents with AVs and possible damage to them, the loss of driving-related jobs and the absence of adequate policy (Elbanhawi et al., 2015). There is a lack of international standards and common policy frameworks (Catapult Transport Systems, 2016). Another challenge is the reliability of the software, the systems and the sensors used in AVs and their integration, as well as cybersecurity (Parasuraman et al., 2000; Stevens and Newman, 2013; Catapult Transport Systems, 2016). The high cost of manufacturing AVs, the integration of AVs with the existing transport systems and changing adequately the current road infrastructure are more limitations (Forrest et al., 2007). Moreover, modelling AVs and particularly in mixed traffic conditions could prove the impacts and the potential advantages of AVs, although there is a lack of data on system and human performance (Stevens and Newman, 2013). It might also create ethical problems, for example, when an AV cannot avoid a collision, which criteria should it take into consideration to plan its action (NHTSA, 2016). Finally, the user's acceptance is one of the major challenges and it is connected to human factors (Stevens and Newman, 2013; BSI and Catapult Transport Systems, 2017). Those challenges are related to different stakeholders, i.e. cars manufacturers, researchers, legislators, regulators, insurers and drivers (Catapult Transport Systems, 2016).

This research, on the one hand, approaches different challenges by investigating braking behaviour, such as human factors, standards, and system design. On the other hand, it also mitigates among different stakeholders, such as researchers, drivers, and car manufacturers.

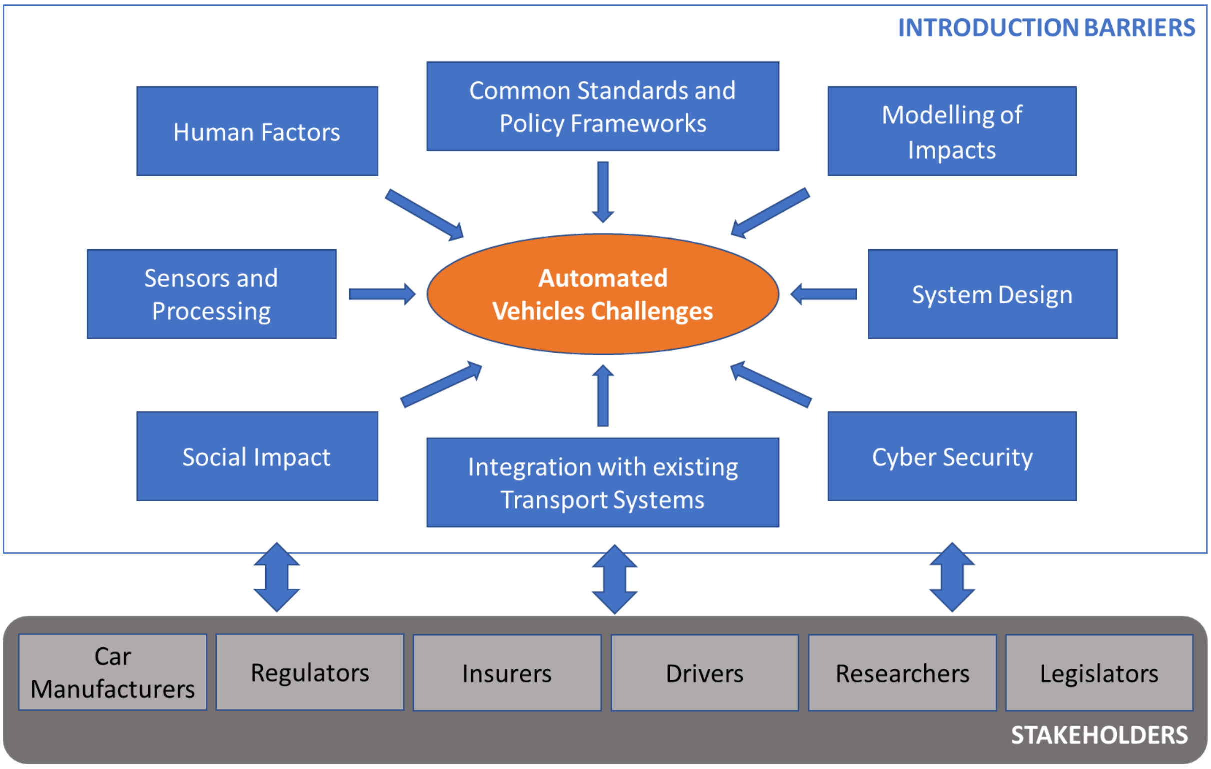


Figure 1.1: Challenges that arise with autonomous vehicle use

The challenges concerning human factors in relation to AVs must be overcome to ensure rapid market penetration. Winning the trust of people to allow a computer to drive a vehicle for them is one of the major challenges (Stevens and Newman, 2013) and it is closely connected with people feeling safe and comfortable inside AVs (Elbanhawi et al., 2015) (Figure 1.1). In general, if people believe that an automated system is untrustworthy, they may not accept it or use it even though it is actually reliable and safe (Parasuraman and Riley, 1997). People are reluctant to trust an autonomous system, for fear that it will go wrong, and they will be blamed for it (Parasuraman and Riley, 1997; Lee and See, 2004). By establishing common policy and international standards, that will clarify the legal liability, the trust of people on the new technology could increase. Previous research on human challenges has been conducted in the aviation field, showing that not only the lack of trust but also the overreliance on the system may cause problems, like the failure of monitoring (Majumdar et al., 2004; Young et al., 2007). Trust is closely connected with the user's acceptance. However, while trust may be increased with greater familiarity, acceptance does not (Somers and Weeratunga, 2015).

In order for the wide acceptance of AVs and their market penetration to happen, it should be ensured that the passengers feel safe and comfortable inside them (Kraus et al., 2010). Research has shown that different levels of automation in vehicles lead to different human factors problems, such as loss of the driving skill, loss of situational awareness of the driver, high or too-low workload and insecurity as far as the responsibility of the vehicle is concerned (Toffetti et al., 2009). Particularly, semi-AVs seem to be more challenging in relation to human factors, since a safe and fast transition between autonomous and human function is necessary for their safe operation (Stevens and Newman, 2013). Furthermore, it is important to develop an appropriate Human Machine Interface (HMI) to inform passengers about AV's actions (Reuschenbach et al., 2010). Finally, it is necessary to develop suitable human factor research tools i.e. the appropriate evaluation tools (e.g. simulators, vehicles) to evaluate the driver, the system and their interaction and to conduct research to overcome the abovementioned problems (Somers and Weeratunga, 2015).

1.2 Problem statement

Research on (semi-) AVs has attracted significant interest from the research community worldwide in recent years (Urmson et al., 2008; Silberg and Wallace, 2012; Wei et al., 2013; Le Vine and Polak, 2014; Lefèvre, Carvalho, and Borrelli, 2015). Fundamentally, vehicle automation aims to eliminate or decrease human involvements from the routine tasks of driving (Chiang et al., 2006). Some of the most challenging research issues in vehicle automation involve the need to understand human interactions with automation technologies, human needs and expectations to gain trust and acceptance (Lay and Saxton, 2000).

Despite the remarkable research and development progress in the area of (semi-) AVs over the last decades, there is still concern that occupants may not feel comfortable due to: a) the unnatural driving performance of the current technology (Elbanhawi et al., 2015; Kuderer et al., 2015; Lefèvre, et al., 2015a; Scherer et al., 2015) and b) the feeling of uncertainty people have about whether the AV recognizes and evaluates the traffic situation correctly or whether a critical manoeuvre has to be performed (Kraus et al., 2010). Specifically, the problem is based on the fact that the kinematics of (semi-) AVs are likely to differ from human-driven vehicles and ignore diverse driving styles due to the differences in perception, information processing, decision-making and actuation capabilities of humans and machines (Le Vine et al., 2015a). Therefore, there would be a mismatch between preferred driving style and the AV's driving style effectively causing physical and mental discomfort. Hence, to ensure ride comfort for different users, it is essential to ensure that (semi-) AVs adopt a human-like driving performance, i.e. a driving style according to user preferences (Kraus et al., 2010; Scherer et al., 2015).

Ride comfort is a subjective concept, which has been studied since early 1970, mostly concerning public transport (Gebhard, 1970; Hoberock, 1976; Constantin et al., 2014; Elbanhawi et al., 2015; Le Vine et al., 2015a). Ride comfort is a crucial factor since the acceptance of any transportation system is affected by the ride quality to which passengers are exposed. Accordingly, ride comfort is a major challenge for the development and acceptance of (semi-) AVs (Kraus et al., 2010; Kuderer et al., 2015; Lefèvre, et al., 2015a) and in general for the analysis of vehicle dynamics (Wu et al., 2013). While under-designing a system with respect to ride comfort may make it unacceptable to the public, overdesigning can be extremely expensive (Smith et al., 1978). Driver comfort is understood as a state which is achieved by the removal or absence of uneasiness and distress. For passengers not conducting any obligatory tasks, the ride discomfort can relate to general annoyance, inability to fall asleep, and difficulties for reading and writing (Marjanen, 2010).

Moreover, the perception of comfort may vary considerably among drivers, which makes studying ride comfort more challenging (Kuderer et al., 2015). Research has proven that human drivers prefer different driving styles based on their personality, the age, the gender, the motivations and the emotions (Yusof and Karjanto, 2015). In general, driver behaviour is complicated due to heterogeneity among drivers (Elbanhawi et al., 2015): While some drivers might prefer a more aggressive driving style with high accelerations and decelerations, others might prefer a safer one (Kuderer et al., 2015). Therefore, individual driving style, which is the dynamic behaviour of a driver on the road (Murphey et al., 2009), may significantly affect the idea of comfort.

Even though the concept of comfort is not perfectly clear, researchers have traditionally investigated ergonomic factors such as seat vibrations. Although, the development of AVs would lead to the examination of other factors beyond in-car ergonomics such as vehicle control, motion sickness and safe distance keeping (Elbanhawi et al., 2015). Specifically, some factors that clearly affect the comfort inside a vehicle are temperature, vibration, acoustic sound, space headway, time headway (THW), time gap, TTC, longitudinal and lateral acceleration /deceleration, jerk (the first derivative of acceleration), seating type, the perceived personal security etc. (Els, 2005; Chiang et al., 2006; Wu et al., 2009; Elbanhawi et al., 2015; Kuderer et al., 2015; Le Vine et al., 2015b). The literature has revealed that the most important factors for ride comfort are longitudinal acceleration and deceleration as well as the jerk (the derivative of acceleration). Occupants are subjected to accelerations in different directions because of vehicle vibration and road roughness, which makes them feel uncomfortable (Wu et al., 2013). Human reaction to vibration-braking depends on three factors (Marjanen, 2010): 1) characteristics of the vibration, 2) characteristics of the human and 3) characteristics of the environment.

Specifically, braking makes people feel ‘uncomfortable’ and ‘scared’ since sharp deceleration is an accident surrogate (Bagdadi, 2013). Therefore, a (semi-) AV should decelerate in a manner avoiding mental discomfort to both, people inside and outside the vehicle. Regarding the braking performance, stress and nervousness are apparent (Kazumoto et al., 2006):

- if the timing at which the vehicle automatically brakes differs from the driver’s own judgment,
- whether the level of deceleration is greater than the driver’s expectation or
- if the deceleration profile does not follow the one that the driver is used to.

It is, therefore, considered important to fully understand drivers’ braking behaviour and the factors affecting it in different scenarios with respect to the level of braking (e.g. harsh/sharp, normal, conservative), the duration of braking as well as the level of comfort while braking. Despite valuable contributions in the literature so far about the kinematic, driver, and situational factors affecting deceleration, it is not entirely clear how all those factors, when cooccurring, influence the deceleration behaviour. The question is: Could the resulting relationships be used to ensure comfort in braking systems by personalising it and choosing the appropriate deceleration threshold for each driving scenario?

In the context of (semi-) AVs and generally braking systems, it is also considered important to identify the deceleration profiles (e.g. how the deceleration values change over time since the start of braking) in the context of normal driving. Up to date literature has focused on modelling the deceleration against speed. Can deceleration profiles that were developed from normal driving be used to reduce discomfort during braking?

It should, however, be noted that safety always comes first, and hard deceleration is sometimes necessary in the case of an emergency situation in order to avoid a conflict or a collision. As a result, passenger tolerance to longitudinal deceleration will affect the design of the vehicle's braking system (Hoberock, 1976). An efficient approach in designing (semi-) AVs would be to monitor and identify how human drivers perform the driving tasks and then analyse and characterise such behaviours with the aim of developing various thresholds to implement them into the system (Goodrich et al., 1999). Vehicle automation with respect to braking is then possible to be designed emulating human behaviour.

This research aims to thoroughly explore the deceleration behaviour of drivers using naturalistic driving data from two Field Operational Tests (FOT) and one Naturalistic Driving Study (NDS)[1]. Consequently, the braking events observed within normal driving will be analysed. The definition of normal driving is 'subjective' and there is no generic definition in the literature. Moreover, perceptions of normal driving differ from country to country. In this work, normal driving means that the drivers execute the driving tasks under 'normal' driving conditions i.e. the absence of any safety-critical events such as 'near misses' or 'collisions'. In addition, this PhD research focuses on identifying acceptable thresholds and developing a statistical relationship between braking and related factors. The examined factors are human factors (i.e. age, gender

[1] A Field Operational Test is a large-scale testing experiment in real traffic conditions, whereas a Naturalistic Driving Study is undertaking using unconstructive observation when driving in a natural setting and without experimental control.

and driving miles per year), traffic factors (e.g. traffic density) and road network conditions. In addition, the deceleration profiles will be calculated. Furthermore, the comfort level of the deceleration events is decided using an adequate threshold and the factors affecting the comfort level are examined. Concluding, the last goal is to inform vehicle manufacturers about the results and suggest a way to implement those results into the design of an autonomous car to ensure that passenger presumes the braking operation as safe and comfortable.

1.3 Research importance

Vehicle automation research, including ADAS and AVs, is undertaken extensively nowadays as it seems promising and carries various possible benefits. However, a fundamental challenge is how to make these vehicles safe and trustworthy and persuade people to accept them. Feeling safe and comfortable inside a (semi-) AV is one crucial factor in addressing this challenge. Along with safety and efficiency, the increase in driver comfort is considered one of the main motivations for purchase (Hartwich et al., 2018). In these higher levels of automation, the driver is becoming a passenger, which is termed the loss of controllability (Elbanhawi et al., 2015; Hartwich et al., 2018). Therefore, when the passenger has little or no control of the car movements the autonomous system must generate movements that are perceived as pleasant (Erikson et al. 2015). This could be achieved by estimating the deceleration profiles that are generating from manual driving and then program the control mechanisms of AVs to follow those profiles.

The comfort experience when being a passenger in a human-driven car is affected by the driver’s driving style. Similarly, the same applies to a (semi-) AV (Bellem et al., 2016). Improving the implemented driving style is the key to influence experienced driving comfort inside a semi- or fully AV (Bellem et al., 2018). Generating different deceleration thresholds for different scenarios and different driving characteristics could aid the improvement of the implemented driving style. From a technologic perspective, the automated driving style is possible to mimic average human driving styles or to be constructed as an artificial one. In both cases researchers tried to discover the underlying factors determining a comfortable automated driving style, resulting in the majority in longitudinal and lateral acceleration and deceleration. This

PhD research is meaningful because it provides an in-depth analysis of the deceleration events. More specifically, it provides an estimation of deceleration profiles for different scenarios, qualitative results on the relationship of several contributory factors with deceleration values and with the level of comfort during a deceleration event. Braking is one of the most important factors related to discomfort. Without understanding deceleration and contributing influential factors and their cooccurrence, it is at least questionable whether (semi-) AVs will be able to perform braking that causes comparable feelings of comfort as manual braking while driving. Without feeling safe and comfortable inside an AV, humans will not trust and accept a computer to drive for them and this might make the transaction of manual vehicles to (semi-) AVs a more challenging task.

1.4 Aim and Objectives

The aim of this PhD research is to model the deceleration events of drivers under normal driving conditions to guide comfortable braking design.

The aim will be accomplished through the following objectives:

1. To identify factors affecting deceleration behaviour and ride comfort,
2. To describe and validate data collection approaches for analysing deceleration behaviour,
3. To investigate and refine the data to improve the analysis quality,
4. To develop the deceleration profiles,
5. To extract the underlying relationship between influencing factors and both, braking behaviour and comfort level,
6. To recommend for comfortable braking design.

1.5 Thesis outline

This section provides an outline of each chapter of the thesis. The whole thesis consists of eight chapters:

- In Chapter 2, an in-depth critical literature review in deceleration behaviour and ride comfort is conducted in order to understand why people may feel uncomfortable during the driving tasks and which factors affect the deceleration behaviour and the comfort of vehicle’s passengers.

- Chapter 3 begins with the literature review on the different data collection approaches used in driver behaviour analysis. Also, the data that have been used are illustrated thoroughly in this Chapter. They are demonstrated along with descriptive statistics for a better understanding of the samples

- In Chapter 4 the methodology is presented. The chapter starts with the description of the algorithm that detects the deceleration events and estimates the braking profiles. Following are the statistical models that are employed, i.e. the multilevel model and the mixed logit discrete model as well as the classification and clustering methods.

- Chapter 5 presents and explains the results of the estimated braking profiles, the clustering, and the statistical models revealing the relationship of the deceleration variables with their influencing factors.

- The results of the ride comfort evaluation and modelling are displayed and interpreted in Chapter 6.

- Chapter 7 discusses the results of this research and provides recommendations for applying them in braking design.

- Finally, Chapter 8 summarises the research project, lays out the contribution to knowledge as well as its limitations. Following are suggestions for future research directions.

The outline of the thesis is shown below:

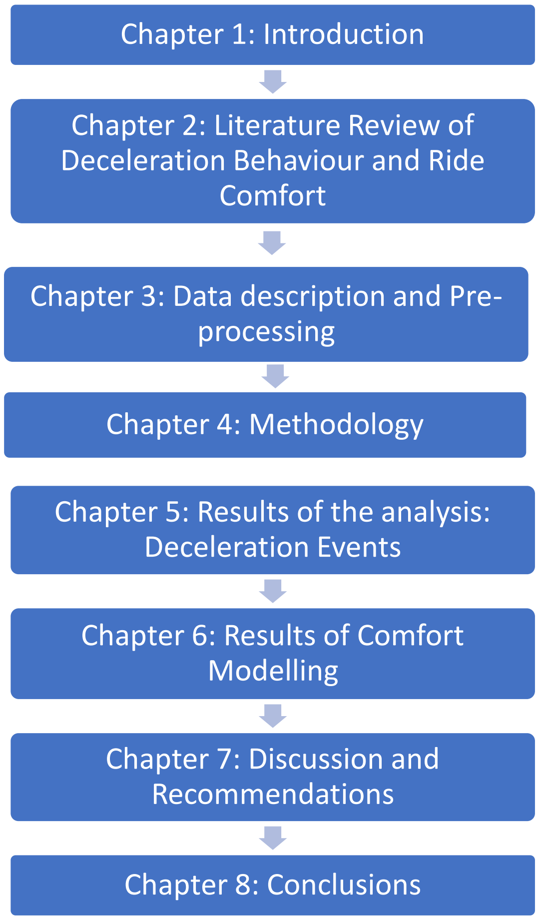


Figure 1.2: Outline of the thesis

2 Literature Review of Deceleration Behaviour and Ride Comfort

The idea behind the conducted research is to increase the naturality of (semi-) AVs and existing braking systems while braking and raise the level of comfort for the passengers. Therefore, the literature review begins with the human factor challenges regarding automation. Narrowing human factors down, the ride comfort problem is revised. Numerous factors contribute to braking behaviour and ride comfort. To fully comprehend the research problem, in-depth knowledge and an understanding of these factors are required. Starting from a more generic perspective to set the conducted research into context, driving behaviour is reviewed, before the braking behaviour is studied.

Purposefully, the literature review consists of three main sections. The aim of each section is briefly presented below:

1. Human factors: This section summarises the human factors regarding automation and specifically AVs along with the challenges that different levels of automation cause.
2. Ride comfort: The second section is dealing with the ride comfort inside a vehicle, which is strongly connected with some challenges related to human factors i.e. acceptance and trust. The term is explained, and the influencing factors are displayed in detail.
3. Driving behaviour: The third section of the literature review defines the driving behaviour and presents different studies that have dealt with the recognition and the implementation of various driving behaviour into AVs. Last but not least, the braking behaviour is described and specifically the appropriate thresholds and the braking behaviour's influencing factors are presented.
4. Research Gap: The last section describes the research gap, originating from a comprehensive understanding of the research environment.

2.1 Human Factors regarding vehicle automation

Much of the literature on automation generally and AVs particularly pays attention to the concept of human factors, making it crucial to study and understand them.

An AV is defined as a passenger car that is capable of driving by itself (Arora et al., 2013; Kaur and Rampersad, 2018). Autonomous means having the power for self-government and involves decision making. On the other hand, automation is the process of following predefined instructions (Elbanhawi et al., 2015). An AV is a vehicle capable of fulfilling the main transportation capabilities of a traditional car, specifically, sense its environment and navigate through a transport network without human input (Campbell et al., 2010; Arora et al., 2013). It is necessary here to clarify exactly what is meant by human factors: This is a scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the discipline that applies theory, principles, data and methods to design a system in a way that optimizes human well-being and overall system performance (Wogalter et al., 2012).

One of the main goals in studying human factors is to prevent human errors in order to ensure safety since human error is the main reason for collisions in transportation (Shappell and Wiegmann, 2000). Two approaches to the problem of human fallibility exist, i.e. the person and the system. The person approach focuses on the unsafe acts-errors of individuals, (e.g. inattention, carelessness etc.), whereas the system approach concentrates on the conditions under which individuals work and tries to build defences to avert errors or mitigate their effects (Reason, 2000). A similar approach is followed by the Reason latent failure model of human error where the incident can be caused by both ‘active failures’ (caused by system operators) and ‘latent failures’ (result from organization practices) (Majumdar et al., 2004).

There are many human factors (e.g. user’s acceptance, overreliance on the system, HMI) affecting the use of automation. These factors need to be taken into consideration while designing and developing an automation system (Saffarian et al., 2012). Muir and Moray (1996) dealt with the trust in automation resulting in more trust in an automated system that leads to more use but less monitoring. Analysing the effect of trust in automation, Parasuraman and Riley (1997) presented some studies referring to the problems of use, misuse, disuse and abuse automation. In their study, the term ‘use’ meant the voluntary activation or disengagement of automation by a human. They defined ‘misuse’ as overreliance on automation (e.g. use it when they should not fail to monitor it effectively) and ‘disuse’ as the opposite i.e. as underutilisation of automation (e.g. ignoring or turning off automated alarms or safety systems). Finally, they described ‘abuse’ as the inappropriate application of automation by designers or managers and they proposed strategies to overcome those problems. Moreover, the out of the loop problem in automation was highlighted by Endsley and Kiris (1995), leading to loss of manual skills and loss of awareness about the state and the processes of the automated system.

Many studies through the literature support that the research conducted considering human factors in aviation will be a great lesson for exploring the human factors challenges regarding autonomous driving (Lee and See, 2004; Majumdar et al., 2004; Merat and Lee, 2012; Young et al., 2007; Parasuraman and Wickens, 2008; Weyer et al., 2015). To begin with, Lee and See (2004) and Parasuraman and Wickens (2008) focused on the trust in automation, taking examples from aviation, where pilots failed to intervene and take the control when it was crucial (misuse). Lee and See (2004) supported that people are not always willing to trust automation (disuse) and that those behaviours result from the user’s feelings and attitudes, like trust. Whereas Parasuraman and Wickens (2008) analysed trust focusing on reliance and compliance. To guide the design of automated vehicles, Merat and Lee (2012) combined different research regarding driver interaction with automated vehicles acknowledging that the understanding of this interaction is largely based on the findings from aviation and process control research. Weyer et al. (2015) conducted an in-depth analysis of the loss of control phenomenon in smart cars using hypotheses based on the findings from aviation research. Moreover, the design philosophies of hard and soft automation, extracted from the aviation field, are discussed in terms of suitability for road vehicles in the work of Young et al. (2007). Hard automation employs the technology to prevent error (automation can override the user) while soft automation just aids the user in different functions. Last but not least, Majumdar et al. (2004) investigate the causation of the airspace incidents by using the Reason model for human errors (active failures, local factors relating to the task and organisational factors) showing that there are more things than the individual user to be taken into consideration in accident prevention.

In Table 2.1, the most important human factors challenges derived from the literature are displayed, along with their definitions and studies that have dealt with them.

Table 2.1: Human factor challenges regarding Autonomous driving

Human factor challenge	**Definition**	**Associated studies**
Acceptance	A wide concept that can be related to the utility and usefulness of the system from the driver's point of view, the reliability of the system, and the trust by the driver.	(Martens et al., 2007; Somers and Weeratunga, 2015)
Comfort	A state which is achieved by the removal or absence of uneasiness and distress.	(Martens et al., 2007; Kuderer et al., 2015; Lefèvre, et al., 2015a)
Overreliance (Complacency, Overtrust, Misuse)	The situation where the driver trusts the automation too much, without questioning its performance or monitoring its status and hence fail to detect possible failures.	(Parasuraman and Riley, 1997; Parasuraman et al., 2000; Lee and See, 2004; Parasuraman and Wickens, 2008; Saffarian et al., 2012)
Behaviour adaptation	The unintended changes in the driver's behaviour due to automation use. For example, the driver's perceived risk might change resulting in higher speed or shorter headways.	(Farida Saad, 2006; Martens et al., 2007; Saffarian et al., 2012)
Mental workload	Even if the aim of the automation is to decrease the driving workload, there is evidence that in unexpected situations the automation can increase the mental workload.	(Parasuraman et al., 2000; Martens et al., 2007; Young et al., 2007; Merat et al., 2012; Saffarian et al., 2012)
Skill degradation (Loss of skills)	Automation can result in degradation of the driving skills since the driver will use these skills to a minimum time.	(Parasuraman et al., 2000; Martens et al., 2007; Saffarian et al., 2012)
Situational awareness	Situational awareness is referred to as the state of being aware, realizing and understanding the modus of the vehicle,	(Parasuraman et al., 2000; Martens et al., 2007; Young et al., 2007; Merat et al., 2012; Saffarian et al., 2012)

	the driving environment and the dangerous events.	
Trust	Trust is a social phycological concept that influences the actual, behavioural dependence on automation. It can be defined as one's willingness to place himself/herself in a vulnerable position, regarding a technology.	(Muir and Moray, 1996; Lee and See, 2004; Parasuraman and Wickens, 2008; Kaur and Rampersad, 2018)
Underutilisation (Disuse)	When the driver does not trust the automation even if it is reliable and it does not use it (when for example the driver ignores or turns off the safety alarms).	(Parasuraman and Riley, 1997; Lee and See, 2004; Parasuraman and Wickens, 2008)
Abuse	The inappropriate application of automation by designers or managers.	(Parasuraman and Riley, 1997)
Loss-of-control (Out of the loop)	High level of automation may raise the complexity and intransparency of vehicles leading to loss-of-control for the drivers.	(Endsley and Kiris, 1995; Parasuraman et al., 2000; Weyer et al., 2015)
Carsickness	Carsickness is the motion sickness that is the result of the conflict between the visual sensory system and the movement of the human body.	(Diels, 2014; Elbanhawi et al., 2015; Diels and Bos, 2016)

Narrowing it down, there has also been intense research on human factors regarding AVs. The transition from the conventional to the fully autonomous cars will not happen at once but gradually passing through different levels of automation. The US National Highway Transportation Safety Agency (NHTSA, 2016) has defined four levels of automation, 0 through 4 as depicted in Figure 2.1:

No-Automation (Level 0): The driver controls the vehicle's operations at all times: brake, steering, throttle, and motive power.

Function-specific Automation (Level 1): Automation at this level involves one or more specific control functions. The vehicle automation assists the driver in some vehicle controls, such as braking in order to enable the driver to gain control or stop faster.

Combined Function Automation (Level 2): This level involves automation of at least two primary control functions designed to work in unison to relieve the driver of control of those functions. A combination of ACC (controls the brake and the throttle) and lane centering (controls the steering) is an example of level two automation.

Limited Self-Driving Automation (Level 3): At this level of automation the vehicle has the full control of all safety-critical functions under certain traffic or environmental conditions and monitor all the time for changes in those conditions which may require transition back to driver control. So, the driver should be ready to take control when is needed, but with sufficiently comfortable transition time. An example of level 3 automation is the Google car.

Full Self-Driving Automation (Level 4): In the last level of automation the vehicle is designed to perform all safety-critical driving functions and monitor roadway conditions for an entire trip. The passenger (not the driver anymore) needs to provide destination or navigation input, but he is not expected to be available to take over the control of the car at any time during the trip.

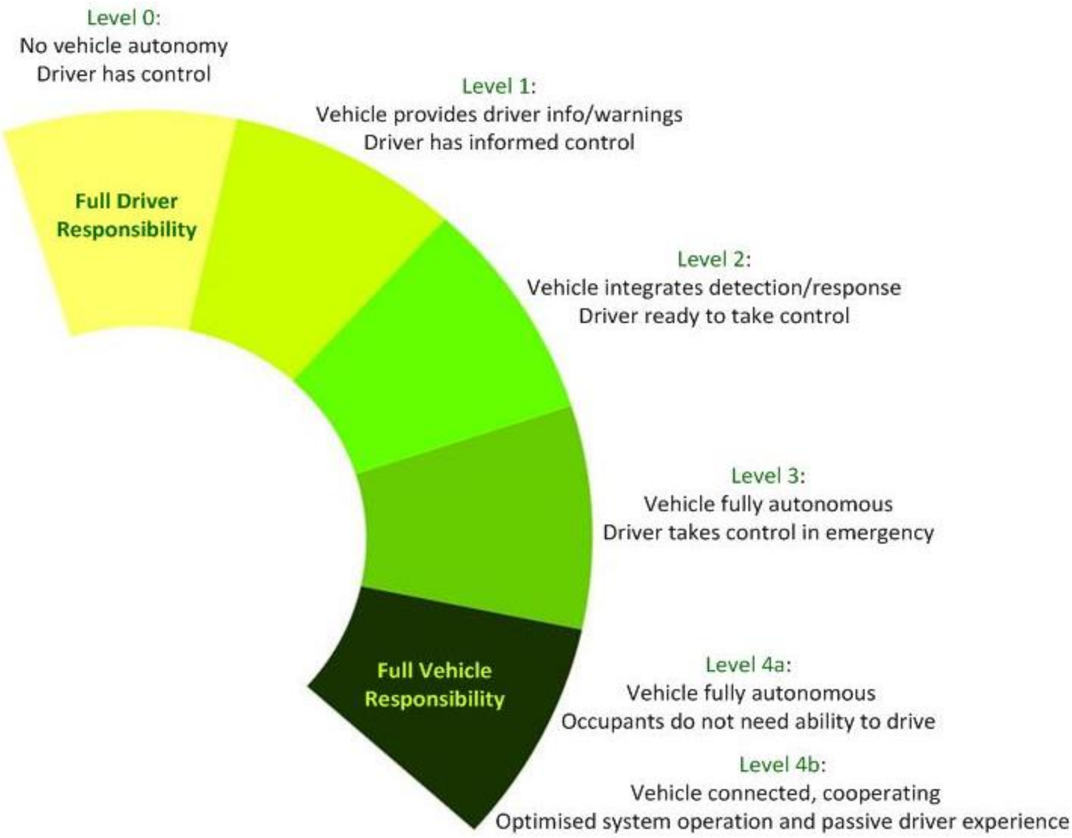


Figure 2.1: The levels of Vehicle Automation (NHTSA, 2013)

To date, different autonomous operations have been applied to conventional cars, allowing them to perform some functions (Level 1 and Level 2 of automation). Many challenges are related to human factors in every automation level and require a better understanding to ensure the development and the wide acceptance of AVs. Many studies focus on topics of transfer of control, loss of control, HMI design, trust, situational awareness, carsickness and user acceptance (Table 2.1). In the report of Martens et al. (2007), a number of human factors issues are underlined: behavioural adaptation, distraction, skill loss, driver's acceptance, risk compensation, awareness of technology capabilities and limitations. Saffarian et al. (2012) also highlighted the problems of overreliance, behavioural adaption, skill degradation, reduced situation awareness, transition and driver-vehicle communication and suggested possible solutions, for example, shared control, new training methods, adaptive automation. Through the historical analysis undertaken by Kyriakidis et al. (2015) regarding railway accident caused by human error, it was found that distraction, familiarity, safety culture and workload contributed the most in those accidents. Through the literature, it has been widely supported that partial automation is more challenging than full automation since people have to interact intensively with the semi-AV and give and take control of the car when it is needed and at a specific transition time (Norman, 2014). However, the biggest problem is winning the trust of people to allow a computer to drive a vehicle for them in every level of AVs (Forrest et al., 2007). Inappropriate level of trust might lead to disuse (not enough trust in the automated system) or misuse (more trust in the system than appropriate) (Banks and Stanton, 2016).

Trust is closely connected to the acceptability of new technology. Acceptability is defined as a person's evaluation of technology without any prior interaction with it (Hartwich et al., 2018). According to Elbanhawi et al. (2015), this shift of the role from driver to passenger produces new-comfort-relevant issues, i.e. motion sickness, the effect of disturbances, naturalness of driving manoeuvres and apparent safety.

One of the main problems in the acceptance of AVs is the loss of control, the transition from being a driver to being a passenger (Elbanhawi et al., 2015; Le Vine et al., 2015a; Bellem et al., 2016; Hartwich et al., 2018). The loss of control problem (i.e. if semi-automation raises the complexity of driving was examined with self-reported statements by Weyer et al. (2015) who concluded that the satisfaction of the drivers was high and they did not experience any severe problem. The problem that was underlined by Banks & Stanton, (2016) is that humans are not good at monitoring a task for a long period and then suddenly taking effective control. This also results in reduced situational awareness. According to Parasuraman et al. (2000), humans tend to be less aware of the driving environment, the state of the system and dangerous situations when another agent (in this case the automated system) is in charge. Parasuraman et al. (2000) proposed a guide to design automation that is based on human-automation interaction and takes into consideration the most important of the human factors' challenges, i.e. skill degradation, complacency, mental workload and situational awareness. In addition, Merat et al. (2012) concluded that vehicle automation had a negative effect on the driver's situational awareness because of overreliance on the system, lack of knowledge about the system's capabilities and reduced monitoring.

Several studies have been conducted to deal with the problem of interaction between the driver and the AV in different automation levels. Beggiato et al., (2015) conducted a study to investigate driver's information needs at different levels of automation which suggested that partial automation was more exhausting and more difficult for the drivers. In two other studies, Merat and Jamson, (2008) and Merat et al., (2012) compared the effect on the driver's performance in manual and highly automated driving. Their results showed that driver's response to all critical events was slower in the automated driving condition than in manual driving, which may be due to the reduction of the driver's situational awareness or to overreliance on the system. All these studies suggested that partial automation is more challenging and demands full attention from the drivers almost as much as in normal driving.

2.2 Ride comfort

As mentioned in the previous section, comfort is one crucial human challenge for vehicle automation. To achieve high user-acceptance and market penetration in the domain of autonomous driving, the design of automated driving functions is crucial and should offer flexibility and adaptability (Griesche et al., 2016). The importance of driving comfort is highlighted by The European Road Transport Advisory Council (2017) next to safety and efficiency (Hartwich et al., 2018). However, there is still a lack of knowledge about how the driver wants to be driven and which manoeuvres are perceived as uncomfortable (Scherer et al., 2015).

Ride comfort is a major challenge in the development and acceptance of AVs (Kraus et al., 2010; Kuderer et al., 2015; Lefèvre, et al., 2015a). Ride comfort is a subjective concept understood as a state achieved by the removal or absence of uneasiness and distress. It is a subjective, pleasant state of relaxation given by confident and apparently safe vehicle operation (Constantin et al., 2014). A global definition including psychological aspects describes comfort as 'a pleasant state of physiological, psychological and physical harmony between a human being and the environment' (Hartwich et al., 2018). Although, when considering driver comfort, we must not omit safety precautions. Safety is far more important than comfort under any circumstance (Wu et al., 2009).

Comfort may vary considerably among drivers since human drivers adopt different driving styles based on their personality, age, gender, etc. (Kuderer et al., 2015; Powell and Palacín, 2015). Nevertheless, there have been many attempts in the literature to evaluate it and discover which factors affect it. Some of these factors are noise, temperature, air quality, car seat and motion, i.e. vibrations (Martin and Litwhiler, 2008; Constantin et al., 2014; Elbanhawi et al., 2015). Those form the traditional ergonomics factors (Figure 2.2). Vibration has been widely studied as a comfort measurement. Vibrations can be transmitted through the seat surface, backrest and through the floor and can occur in all 3 axes (longitudinal, lateral and vertical) (Park and Subramaniyam, 2013). There are 4 different standards throughout the world today designed to evaluate ride comfort with respect to human response to vibration. Those standards are the ISO 2631 standard, which is used mainly in Europe, the British Standard BS 6841 used in the United Kingdom, VDI 2057 used in Germany and Austria and the Average Absorbed Power mainly used in the United States of America and their overall purpose is to evaluate the trip as a whole in respect to ride comfort (Els, 2005). In the work of Constantin et al. (2014), most of the traditional ergonomics factor were analysed and the seat, the space inside the car, climate and noise were found to be the most important ergonomic factors affecting the comfort.

Traditional ergonomic factors have been investigated a lot, although, with the development of AVs, factors beyond ergonomics such as naturality, disturbances, apparent safety and motion sickness will affect the comfort level (Figure 2.2). Naturality is connected to executing familiar to the passenger maneuverers by mimicking the human driving style. Apparent safety does not refer to the vehicle behaving in a safe manner but to the feeling of the passengers that it actually does. Regarding disturbances, they can result from vertical forces (road disturbances) or horizontal forces (load disturbances). Last but not least, motion sickness is apparent when what the passenger sees and expects does not agree with what the vehicle does (Elbanhawi et al., 2015). Therefore, a single subjective evaluation of ride comfort and investigation of traditional ergonomics factors are no longer considered an acceptable and competitive way to assess the passenger experience (Elbanhawi et al., 2015).

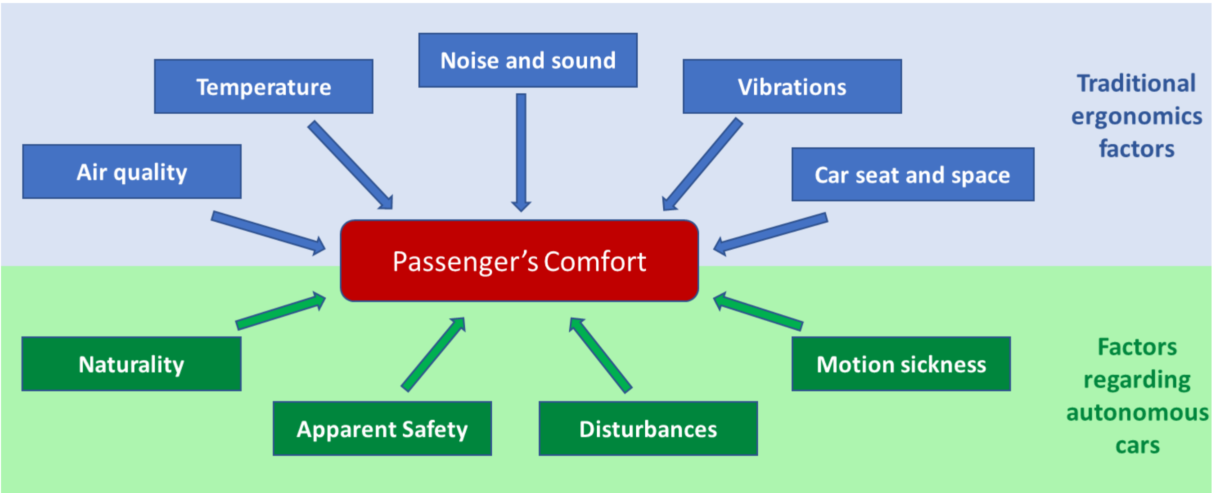


Figure 2.2: Factors influencing ride comfort in autonomous cars

Another approach to addressing comfort is to focus on manoeuvre-based analysis, instead of trip-based, which is the most common. If the AV executes manoeuvres familiar to the passenger, it would undoubtedly contribute to the passengers' comfort enhancement, since they will not have the feeling of being driven by a robotic operator (Elbanhawi et al., 2015; Bellem et al., 2016, 2017, 2018). This would improve the factor naturality. The most common analysed manoeuvres are deceleration, acceleration and lane changing. As far as the apparent safety is concerned, it can be improved by suitable development of the driver-machine interface, to inform the driver early about the next movements and to reassure the driver that it detects a possible danger.

Moreover, executing the manoeuvers in a familiar way, especially the timing of the braking can help to raise apparent safety. Car sickness relates to the longitudinal and lateral acceleration, i.e. when driving at a constant speed, the possibility of experiencing car sickness is dropping. To prevent carsickness, the ability of the driver to anticipate the future motion plan should be maximized (Diels, 2014).

Moreover, the types of disturbances that passengers are exposed to and play an important role in their comfort can be categorised into road and load disturbances. Driver’s control of braking, acceleration, and turning results in serious disturbances and belong to load disturbances whereas road disturbances mostly include vertical vibrations (Elbanhawi et al., 2015). It can be concluded that a manoeuvre-based analysis focused on the deceleration, acceleration and steering can help to solve some of the problems regarding comfort that have been arising due to autonomous driving.

There are many studies that focus on the comfort inside of Autonomous vehicles, which factors affect it and how can be achieved. One of the studies dealing with comfort in AVs was conducted by Yusof and Karjanto (2015). Its purpose was to make autonomous driving style comfortable for the passengers by discovering the relationship between two human driving styles (assertive and defensive) that were identified by questionnaires and three autonomous driving styles (light rail transit, assertive and defensive), which were tested in a field experiment in three different locations: junction, speed hump and roundabout. The comfort of the passengers is the main goal in the study of Dovgan et al. (2012) as well. They measured the comfort as the change of acceleration, i.e. the jerk and they developed a two-level multi-objective algorithm to optimise the control action with three objectives, i.e. travelling time, fuel consumption and comfort. They tested the algorithm on a real-world route. Comparing the results from the algorithm they developed with the ones from an algorithm which does not optimise the comfort, it was found that significant improvement on comfort can be made in control actions with low-fuel consumptions, but not with short travelling time.

Having the same general aim, Scherer et al. (2015) presented two studies related to how to model driving styles in highly automated vehicles. The first one was a simulator study with the additional use of questionnaires and its goal was to detect which driving parameters are essential for passengers to feel comfortable inside an autonomous car. It was revealed that the most frequently mentioned comfort parameters were the longitudinal safety margin, braking, velocity and acceleration proving that parameters of longitudinal control were affecting comfort the most. Therefore, those parameters, specifically braking and acceleration were examined in the second study which used real driving data.

One of the most important and critical factors of perceived safety and comfort inside vehicles is braking. This is because sharp deceleration is closely connected to collisions. It should be noted that deceleration is only one dimension of passengers' ride experience while braking; others include vibration and jerk (Le Vine et al., 2015b; Bellem et al., 2016). It is strongly supported through the literature that vehicle acceleration/deceleration and the time rate of change of acceleration, i.e. the jerk can have a significant impact on passenger's comfort and safety (Martin and Litwhiler, 2008; Wu et al., 2009; Jensen et al., 2011; Powell and Palacín, 2015). Those factors could result in excessive external forces applied to the passengers, which affect passenger's stability and discomfort (Powell and Palacín, 2015). Table 2.2 presents the most common features that have been used through the literature to identify comfort during manoeuvre-based analyses.

Table 2.2: Kinematic factors connecting to the disturbances

Kinematic factors affecting the comfort	**Explanation**	**Factorial Literature Review Evidence**
Acceleration and deceleration	Describe the longitudinal control and are expressed as the change of speed.	(Diels, 2014; Scherer et al., 2015; Bellem et al., 2016, 2017)
Jerk	The rate of deceleration/ acceleration.	(Dovgan et al., 2012; Bellem et al., 2016, 2017, 2018)
TTC, Headway distance, TTMD (time to minimum distance)	Factors connecting to following a car situation.	(Bellem et al., 2016, 2017)

Martin & Litwhiler (2008) support that accurate control of the braking profile can result in significant improvements in the safety and comfort of the passengers. In their work, Powell & Palacín (2015) found that there is considerable variation between the perceptions and stability of different individuals and therefore there are no precise limits for comfort longitudinal acceleration. This is further supported by the review of

Hoberock (1976) and Gebhard (1970a) on ground transportation vehicles, where they found that there is wide variability in passenger acceptance of any specific acceleration-jerk profile (Gebhard, 1970; Hoberock, 1976). However, it was concluded that the range 0.11g to 0.15g is considered comfortable deceleration for more studies and regarding the jerk, the value should not exceed 0.3g/s to be perceived as acceptable. For electric rapid transit cars in the U.S. normal braking is set from 0.12 g to 0.14 g and emergency braking from 0.14 g to 0.30 g (Hoberock, 1976).

Le Vine et al. (2015a) used different scenarios in simulation to identify how AVs will influence the intersection capacity and level-of-service if they travel according to the maximum acceleration/deceleration rates of rail transport. Maximum typical rates of acceleration and deceleration during revenue service for light rail speed rail: 1.34 m/s^2 (Le Vine et al., 2015a). In another paper, the purpose is to identify metrics that enable the parameterisation of a safe, functional and comfort automated driving style (Bellem et al., 2016). They split the trip into manoeuvres and into highways or urban/rural scenarios, underlying the importance of a manoeuvre-based analysis. Bellem et al. (2016) concluded that acceleration, jerk, quickness and headway distance are the essential components to build a comfortable highly automated driving style. Trying to investigate how highly automated vehicles should drive to ensure driving comfort for the now passive drivers, Bellem et al. (2018) rated and analysed different variations of three central manoeuvres, i.e. lane change, acceleration and deceleration. The variations were configured by manipulating the longitudinal and lateral jerk in simulators studies. Also, personality traits, as well as the driver's age and gender, resulted in having no effect on manoeuvres preferences.

In automated or semi-automated vehicle networks, fast starts and stops will be necessary in order to merge vehicles into high-speed traffic at close headways. Passenger tolerances to longitudinal acceleration and jerk loads will thus affect not only the design of the vehicle propulsion and braking system, but also the central headway, speed, and scheduling controls for the entire network (Hoberock, 1976). The values for the comfort deceleration limits suggested for public transportation are smaller in absolute value than those found in motor cars in different studies. For instance, Shen et al. (2000) set the minimum acceleration at which a passenger feels discomfort at 0.25g and the acceleration at which a passenger cannot stand at 0.5g.

Moreover, it was reported by Abernethy et al. (1977) that 95% of the passengers were able to remain securely in their seats when the deceleration was less than 4.12 m/s^2 (=0.42g) (Abernethy et al., 1977). Also, they set the limit of emergency deceleration on 1.96 m/s^2 (=0.2g). On the contrary, Wu et al. (2009) set that limit (2m/s^2=0.204g) as a critical value for a comfortable longitudinal deceleration (Wu et al., 2009). Bogdanović and Ruškić (2013) defined normal vehicle acceleration as acceleration values from 0 to 3.5 m/s^2. In two important projects, the EuroFOT and the 100-Car NDS, the limit of 4 m/s^2 was used for the identification of “hard” braking, which is assumed to be perceived as uncomfortable. Comfortable decelerations on surface streets vary from 1.47 m/s^2 to 4.12 m/s^2 (0.15g to 0.4g) whereas on freeways where speeds are higher, decelerations from 0.98 m/s^2 to 1.96 m/s^2 (0.1g to 0.2g) can be considered high (McLaughlin et al., 2009). Nevertheless, in some naturalistic driving studies, braking at 5.88 m/s^2 (=0.6g) or higher was common, based on the driver and the driving situation.

Through the literature, there are different descriptors used to characterise deceleration and ride comfort. One example is: insensible, just sensible, noticeable, slightly uncomfortable, very uncomfortable. Interestingly, in a study by Urabe and Nomura, three correlated measures, i.e. perception, comfort and acceptability were used to address ride comfort during a deceleration event (Gebhard, 1970; Hoberock, 1976).

2.3 Driving Behaviour

In the last decades, the number of transport modes has increased dramatically and despite their improvement in the performance, they have worsened traffic congestion, especially in major cities (Constantinescu et al., 2010). This affects the city driver’s behaviour which has become aggressive and careless, reducing, therefore, traffic safety. To deal with that problem, it would be helpful to study and categorise the driving style. That categorisation could be done based on the driver’s behaviour, which can be described by means of various driving parameters (Sagberg et al., 2015).

As stated in the introduction (Chapter 1- see page 4), AVs should not only be safe and reliable, they should also provide a comfortable user experience. However, an individual may perceive comfort differently (Kuderer et al., 2015). Comfort can be influenced by various factors including driving style, age, driven experience. A (semi-) AV should adapt its driving behaviour according to user preferences in addition to maintaining safety, in order to be comfortable for different users. Different driving styles for an automated vehicle can be achieved by varying the model parameters of its motion planning algorithm and the parameters of the functions of its control system.

It remains crucial to understand how driving behaviour and driving style are defined. Studying the literature review revealed different definitions of driving style. The definition by Murphey et al. (2009) differs considerably from most other definitions, in being almost equivalent to driving behaviour. According to their study, driving style is a dynamic behaviour of a driver on the road. Another definition of driving style can be found in the study of Saad (2004), where the driving style represents the choice of the driver about the driving way and so it is a relatively stable characteristic of the driver. Kuderer et al. (2015) characterised the driving style as a habit, i.e. the natural way a driver drives without forcing it.

It is really important to clarify the distinction between driving style and driving behaviour in general. Meiring et al. (2015) define driving behaviour as a comprehensive term used to represent different concepts related to a driver's actions and driving mannerisms. In addition, Sagberg et al. (2015) mention that the concept of driving behaviour includes all the actions a driver performs during driving and that driving behaviour varies systematically across different road, traffic, and driving conditions, such as traffic density, road geometry, weather, light conditions etc. in contrast with the driving style which is more consistent.

There is also a large volume of published studies dealing with the recognition and classification of driving styles. A lot of attention has been paid to aggressive driving, so a common classification is aggressive versus normal driving (Dula and Geller, 2003; Hamdar et al., 2008; American Automobile Association, 2009; Kaysi and Al-naghi, 2011). Identifying aggressive driving is important from a safety point of view because aggressiveness has been shown to be a major cause of traffic collisions. Murphey et al. (2009) classify the driving style into calm, normal, aggressive and no speed by analysing the jerk profile i.e. how fast a driver accelerates and decelerates. Simons-Morton et al. (2011) and Guo & Fang (2013) dealt with risky driving behaviour.

There are also some more detailed classifications. One of them includes four types of driving styles namely, aggressive driving style, inattentive driving style, drunk driving style and “normal” or safe driving style (Meiring and Myburgh, 2015). Furthermore, Jeon (2015) referred to five driving styles, which are: angry driving, anxious driving, dissociative driving, distress-reduction driving and careful driving.

Table 2.3: Information about Driving Behaviour

Measures from the car identifying the driving behaviour	Factors that influence driving behaviour	Data collection methods for studying driving behaviour
•Speed •Acceleration and deceleration (longitudinal and lateral) •Time and space headway •Tailgaiting •Steering angle •Violation of traffic signs and speed limits •Lane change •Time to collision •Checking at mirrors	•Roadways (Motorway, A-class road, B-class road, minor road) •Road configuration (e.g. roundabouts, junctions) •Vehicle type •Geo-graphical profile (the origin- destination profile) •Socio demographics (e.g. age, gender, driving experience) •Trip distance •Traffic density	•Simulator studies •Naturalistic driving studies (NDS) •Field operational tests (FOT) •Surveys/ Questionnaires/ Interviews •Traffic data

In the literature, different kinematic factors have been used to identify the driver’s behaviour and style, for example, the speed, the acceleration and deceleration as well as the activity of the driver on the acceleration pedal (Table 2.3) (Scherer et al., 2015). In their study, Kuderer et al. (2015) concluded that the human’s driving style affects different features such as speed, acceleration, jerk and distance to other vehicles. Similarly, to create a model to represent car-following behaviour, speed, space headway, acceleration and the speed difference between the leading vehicle and the following vehicle were taken into consideration (Ma and Andréasson, 2008). To evaluate the driver risk, Miyajima et al., (2011) used the deceleration acceleration and steering measures. The features that were hypothesised to be indicative of driving behaviour in Quek & Ng (2013)’s study are the acceleration/ deceleration profile, speed and mileage. Furthermore, the risky drivers were identified by g-force events, specifically by hard braking, rapid starts and hard turns (Simons-Morton et al., 2011). To provide real-time behaviour detection, Carmona et al. (2015) took into account several parameters, i.e. velocity, steering wheel angle, brake frequency, throttle, acceleration. Finally, Murphey et al. (2009) classified the driver's driving style into calm, normal aggressive and no speed by analysing the jerk profiles. Moreover, Wang et al. (2010) tried to classify the longitudinal driving behaviour by identifying measurable parameters and by using real-world car-following data. The parameters that were used are the THW, the inverse of TTC (TTCi), and the switch time from accelerator release to brake activation.

Considering the aggressive driving style, many researchers study it in more detail. Characteristics that found to be affecting the aggressiveness at signalised intersections are the performance measures (the surrounding moving traffic and pedestrians), the intersection geometry (the intersection design features), and the impedance (the red timing and the presence of law enforcement figure) (Hamdar et al., 2008). In another study conducted by Paleti et al., (2010), a number of factors affecting driving aggressiveness were presented, i.e. driver characteristics (gender, age, seat belt usage, etc.), environmental and situational factors (time of day, weather, and company in the car), vehicle characteristics (type of vehicle), and roadway characteristics (speed limit). Finally, by formulating a model that predicts an aggressive manoeuvre at unsignalized junctions, Kaysi and Abbany (2007) concluded that age, car performance and speed were the main indicators of aggressive behaviour.

The most used methods in order to collect data among the research on driving styles are self-report methods and observations of actual driving (Sagberg et al., 2015) (Table 2.3). Moreover, in some studies, a combination of those methods has been used. French et al. (1993) used a Driving Style Questionnaire (DSQ) in order to assess driving style to the 711 drivers who took part in the survey and then they conducted a multiple regression analysis trying to explain why some people have more accidents than others. In another study conducted by Taubman-Ben-Ari et al. (2004) questionnaires were used and the analysis revealed eight main factors (i.e. dissociative, anxious, risky, angry, high-velocity, distress reduction, patient, and careful), each one representing a specific driving style. Both studies concluded that there is a significant association between driving behaviour, on the one hand, and human factors, like gender, age, driving experience, personality anxiety and neuroticism on the other (as presented in Table 2.3). Furthermore, the study of Ulleberg and Rundmo (2003) was based on a self-completion questionnaire, which included measures of risk perception, attitudes towards traffic safety and self-reported risk-taking in traffic and they concluded that only the risk-taking attitude and the altruism have a direct effect on risk-taking behaviour.

In addition, Simons-Morton et al. (2011) and Guo and Fang (2013) used naturalistic data to determine the factors which affect the driving risk. Specifically, Simons-Morton et al. (2011) wanted to compare rates of risky driving among novice adolescent and adult drivers and the results revealed that novice adolescent drivers maintain a risky style of driving. In the investigation of the factors which affect the driver risk, Guo and Fang (2013) used data from the 100- NDS and concluded that age, personality and critical incident rate are the most significant factors.

Taking into consideration the different driving behaviour, it can be useful for the design of (semi-) AVs. Designers can use different approaches and strategies for user experience, depending on different driving styles and driving scenarios. For example, when they must deal with anxious drivers, they can design the interface so that drivers can feel more controllability and vehicle systems serve as driver assistance. Also, the developers can program its function to mimic the different driving styles, in order for the passengers to feel totally comfortable and relaxed (Jeon et al., 2015). But it is really challenging to mathematically express the different behaviours and to find a way to introduce them into the AVs.

Several attempts have been made to implement the different driving behaviours into the AV. Lefèvre et al. (2015b) used a combination of real data and simulation to evaluate the learning-based driver model that they developed and can represent human driving control strategies on the highway. They tested it in two applications, i.e. a Lane Keeping Assistance and an ACC, and the results showed that it was more effective and safer than the standard systems. In another study, Lefèvre, et al., (2015a) described a learning-based method for the longitudinal control of an AV on the highway, using learning-by-demonstration approach and predictive control method. The results indicated that the driver model could generate accelerations which replicate the behaviour of a human driver. Based on those accelerations and some safety constraints, the controller selected the appropriate acceleration. Using a learning-based approach, Kuderer et al. (2015) also tried to include different driving styles to AVs. This approach allows the user to demonstrate the desired style by driving the car manually. Then the desired style was modelled in terms of a cost function by calculating some feature and applying it to the autonomous mode of the vehicle.

2.3.1 Braking / Deceleration behaviour

The analysis of the braking behaviour has gained some attention in the literature over the past decades. A braking event is normally described using the deceleration value, the speed at the beginning and at the end of the event, the perception/reaction time and the duration (Akçelik and Besley, 2002). The aim of this section is to synthesise existing studies on drivers' braking behaviour and identify factors affecting the braking behaviour and thresholds related to comfortable braking performance.

Braking behaviour was studied during the design and implementation of ACC. It is perhaps the most studied feature of advanced vehicle systems (Goodrich et al., 1999a; Goodrich et al., 1999b; Chiang et al., 2006). In both studies (Goodrich et al., 1999a; Goodrich et al.,1999b), the authors tried to identify the braking behaviour and apply the results to the design of ACC. In both, a driving simulator and a controlled test track were used. The braking behaviour was characterised by the perceptual trajectory using time-to-collision (TTC) versus THW. In their first study Goodrich et al. (1999a) conducted a series of experiments from which they concluded that in order to produce a comfortable performance, ACC designers need to develop controllers that emulate a trajectory, which does not violate the smooth counter-clockwise characteristics of the human-generated one. In the second study it was further postulated by Goodrich et al. (1999b) that in order to achieve a human interaction with the ACC system which results in safe and comfortable vehicle dynamics, the automated braking behaviour should match that of a skilled human operator. Consequently, the design and programming of the advanced vehicle system can benefit from a careful analysis of the human actions and the interaction between human and automation.

On a more theoretical base, a categorisation of the factors that influence braking behaviour includes driver factors such as awareness, expected/ unexpected need of action and experience; vehicle factors and situational factors such as external environment (i.e. other road users, weather and traffic conditions) (Young and Stanton, 2007). Another classification relates to initiating and mediating factors (Xiong and Boyle, 2012). Initiating factors have an immediate effect on the driver's comfort and are based on the driver's direct interaction with the system, the environmental cues and the actual risk. On the other hand, mediating factors are more subjective, but they may have a greater influence on how the driver feels when the brake is applied. These factors emerge from exposure to a system in conjunction with perceived risks, motivational factors (e.g. willingness to use automation), attitudes/biases (e.g. driving styles, trust in automation, and overall system use) and experiences.

Some studies have dealt with the factors which affect the braking behaviour (Haas et al. 2004; Kazumoto et al., 2006; El-Shawarby et al., 2007; Loeb et al., 2015). For instance, El-Shawarby et al. (2007) conducted a study to analyse field data and to characterise driver deceleration rates at the onset of a yellow-phase transition on high-speed signalised intersection approaches. The study concluded that deceleration rates are sensitive to the roadway grade, the age and the gender of the driver. In contrast to El-Shawarby et al. (2007), who examined braking behaviour during normal driving, the study of Loeb et al. (2015) was conducted in a simulator and analysed the differences in emergency braking performance between novice teen drivers and experienced adult drivers. Their results showed significant differences both in performance and quality of braking between novice teens and experienced adults, with novice teens decelerating on average 50% less than experienced adults on the same scenarios, indicating a poor response.

The purpose of the study conducted by Haas et al. (2004) was to evaluate driver deceleration and acceleration behaviour at stop sign-controlled intersections on rural highways in southern Michigan. Their results seemed to indicate that drivers showed wide variability in rates of acceleration and deceleration and that the initial speed had a strong and statistically significant dependence on the deceleration rate while the other examined factors (e.g. driver demographics and time-of-day) had not. Finally, Kazumoto et al. (2006) conducted a discriminant analysis on factors which influence the braking behaviour of drivers. The factors were: the speed of the following vehicle, the distance between the two examining vehicles, the relative velocity, the TTC and the rate of change of visual angle. They found that the rate of change of visual angle, which is the inverse of TTC, is the most closely related factor to a driver's judgment about when to apply the brakes.

There are some studies focussing on modelling deceleration behaviours. For example, in the study by Bennett and Dunn (1995) the driver deceleration behaviour at the exit ramp on a motorway (freeway) in New Zealand was monitored. The deceleration rate was discovered to be proportional to the initial speed such that higher speed drivers decelerate harder over a short period of time. Therefore, they developed equations for predicting the deceleration behaviour of vehicles as a function of approach speed and cumulative time. In addition, Maurya and Bokare (2012) have studied the deceleration behaviour of different types of vehicles and proposed different models for each type. They concluded that the vehicle type plays a significant role in deceleration behaviour, that higher maximum initial speed results in higher deceleration duration, higher deceleration values and higher deceleration distance and that during a deceleration event the jerk initially increases until it reaches its maximum value and then it decreases. Moreover, Chiang et al. (2006) presented a complete Longitudinal Automation System that accelerates and decelerates based on the recognized target distance from the detected leading vehicle. In their study, Wu et al. (2009) examined occupants' comfort during longitudinal deceleration events. They generated a brake comfortable car-following model for longitudinal acceleration considering the friction coefficient between the car and the road surface. In 2012, Reschka et al. (2012) proposed that the longitudinal controller for acceleration and deceleration of the vehicle needs to perceive and calculate road and weather conditions in order to achieve safety and comfort. Hence, they developed a longitudinal control based on that.

As mentioned above, one approach to the design of automated systems is to formulate human behaviour and then train the autonomous system to adopt it. For example, in two separate studies, Wada et al. (Wada et al., 2008, 2010) formulated mathematical models that closely mimic the deceleration patterns of an expert driver, as a proxy for comfortable braking patterns; the difference was that the second study specifically examined the last-second braking. Adopting a similar approach to Wada et al. (Wada et al., 2008, 2010), Lefèvre, et al., (2015a) developed a learning-based model for the longitudinal control of an AV which goes a step further by reproducing different driving styles from different drivers.

Table 2.4 summarizes the factors affecting the deceleration which were revealed from the literature review.

Table 2.4: Factors affecting deceleration behaviour

Category	Factor	Studies
Driver factors	Driver's age	(El-Shawarby et al., 2007; Loeb et al., 2015)
	Driver's gender	(El-Shawarby et al., 2007)
External environment factors	Traffic conditions	(Young and Stanton, 2007)
	Weather conditions	(Young and Stanton, 2007; Reschka et al., 2012)
	Road conditions	(El-Shawarby et al., 2007; Reschka et al., 2012)
	Friction coefficient	(Z. Wu et al., 2009)
Trip factors	Type of vehicle	(Maurya and Bokare, 2012)
Kinematic factors	Initial speed	(Bennett and Dunn, 1995; Haas et al., 2004; Maurya and Bokare, 2012)
	TTC	(Goodrich et al., 1999a; Goodrich et al.,1999b; Kazumoto et al., 2006)
	THW	(Goodrich et al., 1999a; Goodrich et al.,1999b)
	Headway	(Chiang et al., 2006; Kazumoto et al., 2006)

2.4 Research Gap

The research to date on AVs has tended **to focus on the safety aspect rather than the comfort of the passengers**. It is obvious that safety is the most important element and should always come first, however in order to facilitate their rapid uptake and deployment, AVs should ensure that occupants feel both safe and comfortable. As it was discussed previously, the comfort is a subjective term and is influenced by different factors. One of the most important factors is the deceleration behaviour. It is, however, unclear how deceleration profiles, values and durations affect the level of occupants' comfort.

Through an in-depth literature review, the key points of the research gap were extracted:

- Lack of examining situational factors and the co-occurrence of different affecting factors

Previous studies of deceleration behaviour and comfort during braking have examined factors that are related either to the driver (Loeb et al., 2015), i.e. age, gender and experience; or to the vehicle, i.e. kinematic factors such as the initial speed (Haas et al., 2004; Kazumoto et al., 2006). There is a lack of research in studying situational factors such as the reason for braking, and the traffic density at the moment of braking which still could play an important role in the driver's decisions (apply and release the brake harder or softer; apply the brake for a longer or shorter period of time). In addition, no research has taken into consideration all those factors at once, which demands multilevel analysis. So far, this method has only been applied to social, education and medical sectors. Therefore, it is not clear yet the impact of all these factors (driver, kinematics, situational) on the deceleration behaviour and specifically on the deceleration profiles, values and durations and how they relate to different roadway infrastructure and traffic operational conditions.

- Dearth in research on detecting deceleration events

Moreover, through the literature, there have been different thresholds to evaluate passenger's comfort during the driving task and to detect especially the braking events (Naito et al., 2009; Wu et al., 2009). So, an overall method and thresholds are needed to be established in order to detect and analyse deceleration events.

Also, the need to apply thresholds that have been tested to passengers' comfort and create the appropriate comfort levels is apparent. Establishing the passengers' preferences is an important item for the future research agenda (Le Vine et al., 2015a). Moreover, it is important to examine which factors affect those comfort levels and increase the likelihood of an event to become very uncomfortable which might lead to dissatisfaction or even motion sickness for the passenger of the AV.

- Use of naturalistic driving data to study deceleration behaviour

So far the methods that have been used the most in studying deceleration and general driver behaviour in order to obtain the necessary data are self-reported methods (French et al., 1993; Ulleberg and Rundmo, 2003; Taubman-Ben-Ari et al., 2004) and simulators (Goodrich et al., 1999b; Lefèvre, et al., 2015b; Yusof and Karjanto, 2015). Both of those methods can provide useful data but not so trustworthy since it is not certain to what degree people will be honest when completing a questionnaire or if they will behave exactly as they do in the real road environment when being in a simulator. On the contrary, studies on drivers' braking behaviour observed in normal driving by using naturalistic data that can overcome the aforementioned disadvantages, are limited.

Last but not least, a considerable amount of literature has been published on implementing the driving behaviour into AVs (Kuderer et al., 2015; Lefèvre, et al., 2015b). Nevertheless, they did not suggest any general recommendation to the autonomous cars' designers since these studies used mostly learning-based methods (learning from demonstration) for a specific driver or a specific situation.

This study aims to fill in these knowledge gaps by analysing drivers' braking behaviour from normal driving using naturalistic data in different scenarios (i.e. different road infrastructure and different road conditions). It will focus on discovering the relationship between the braking behaviour and its influencing factors by taking into consideration as many factors as possible, such as human factors, trip factors, situational and kinematics ones. In addition, the situational, kinematic and driver factors that may affect the comfort of the deceleration event will be examined and suggestions will be made to avoid the situations that increase the discomfort of the event.

3 Data Description and Pre-processing

This work is a data-driven PhD project in which the availability of high-quality data is vital for ensuring both the validity and clarity of the study. Moreover, data quality is important in studying driver behaviour, especially in normal real-world driving conditions. The data should describe the situation while drivers are driving naturally without taking into consideration that they are monitored in order to be completely representative of normal driving. Therefore, this research uses naturalistic driving data.

This chapter begins with a review of the data collection approaches used to analyse driving behaviour. Then, it describes the features of the datasets which were employed in the analysis. The three projects, from which the data were obtained, are described. Moreover, a part of the chapter is dedicated to the examination of the data.

3.1 Review of Data Collection Approaches

To date, various methods have been developed and introduced in order to collect the necessary data for studies in the fields of traffic automation and driving behaviour. In section 2.3 of the Literature review chapter different collection methods have been mentioned (e.g. simulator studies, questionnaires, naturalistic driving studies), however in this section those methods are presented in detail.

To start with, a number of studies have obtained data from simulators (Goodrich et al., 1999b; Lefèvre, et al., 2015b; Yusof and Karjanto, 2015). Simulator studies have several advantages for research of this nature. First, they can be used to test situations which would not be able to be tested in field studies, such as life-threatening situations, collisions etc. In addition, they can be used in really controlled experimental studies and ensure that only the effects of the variables of interest are taken into consideration. Finally, a lot of different scenarios can be easily examined in order to collect data (Stanton and Young, 1998). On the other hand, there are some important challenges, such as to what degree the simulated environment looks and behaves like the real environment. Moreover, there is a concern that people do not behave in the simulator as they do in reality, because they are influenced by the fact that they are monitored.

Another method which has been extensively used to collect data for studies on driving behaviour is a self-report method such as questionnaires (French et al., 1993; Ulleberg and Rundmo, 2003; Taubman-Ben-Ari et al., 2004). Apart from the conservative methods for collecting data some other more innovative methods have been also applied. For example, Paefgen et al. (2012) and Eren et al. (2012) utilize smartphone sensors, in order to design a car-independent system which does not need vehicle-mounted sensors and to minimize the cost. On the other hand, Carmona et al. (2015) and Ly et al. (2013) collected the required data from the vehicle's inertial sensors from the controller area network (CAN bus).

However, a large and growing body of literature has investigated driving behaviour using naturalistic data, i.e. data that were obtained while drivers conduct the driving task normally in a car (Guo et al., 2010; Simons-Morton et al., 2011; Guo and Fang, 2013). It seems that naturalistic data collection fills the gap in current data collection methods. There are two common methods to gather naturalistic driving data, namely NDS and FOTs and they will be described in the following sections.

3.1.1 Naturalistic Driving Study

Naturalistic driving, also known as naturalistic observations, is a traffic research method, pioneered by the Virginia Tech Transportation Institute (VTTI), in the United States (Regan et al., 2012). Specifically, the 100-Car NDS, conducted by the VTTI and sponsored by the National Highway Traffic Safety Admin (NHTSA), was a ground-breaking work since it was the first instrumented vehicle study aiming to gather a large volume of naturalistic driving data from many drivers over a long period of time (Dingus et al., 2006). An NDS can be defined as "A study undertaken to provide insight into driver behaviour during everyday trips by recording details of the driver, the vehicle and the surroundings through unobtrusive data gathering equipment and without experimental control" (Eenink et al., 2014). Existing methods for collecting data on driver performance and behaviours such as questionnaires and controlled experiments are inferior to NDS because, in naturalistic driving studies, the data are a mixture of normal and safety-critical situations and are gathered in uncontrolled, thus natural, conditions (Regan et al., 2012). More research attention has focused on studying not only safety-critical but also normal conditions (Baldanzini et al., 2010), making NDS a really valuable research method for data gathering.

Typically, in a naturalistic observation study, passenger cars are equipped with devices, various data-logging instruments (e.g. radars, lidars, sensors, GPS, cameras, and accelerometers) that continuously monitor various aspects of driving behaviour including information about:

- vehicle movements (acceleration, deceleration, speed)
- the driver (eye, head and hand movements)
- and the direct environment (traffic densities, THW, road and weather conditions)

What gives NDS an advantage against other methods is that its purpose is to observe (individual) road user behaviour in the driver's everyday driving life (Research., 2012). Specifically, the drivers are not affected at all from the study since they are not given any special instructions, no experimenter is present, and the data collection instrumentation is unobtrusive (Neale et al., 2005). Studies in the United States show that Naturalistic Driving provides very interesting information about the relationship between drivers, road, vehicle, and weather and traffic conditions. It is important to display other conventional methods of data collection and their advantage and disadvantage (Figure 3.1) in order to gain a deeper understanding of the benefits of the naturalistic driving data (Baldanzini et al., 2010; Regan et al., 2012; Research., 2012).

Specifically, controlled experiments, i.e. simulator studies and test tracks have the advantage to obtain large control on the examined variables and the traffic environment (SWOV Institute for Road Safety Research, Leidschendam, 2012) (Figure 3.1). For example, with these methods, researchers can focus on the variable of interest by changing it, conducting multiple experiments and comparing the results. On the other hand, there is concern that with these methods the drivers do not always drive as they do in real-world and simulators and test tracks cannot mimic exactly the combination of complex driving environments and driver behaviours (Regan et al., 2012). By using questionnaires, information that is difficult accessible can be obtained, especially for the driver's personality and attitude, although the degree of truth is questionable (Baldanzini et al., 2010; SWOV Institute for Road Safety Research, Leidschendam, 2012) (Figure 3.1). Regarding the epidemiological research into crashes, it can provide a large amount of information about crashes which although doesn't give sufficient insight and detail to reveal the factors affecting the crash (SWOV Institute for Road Safety Research, Leidschendam, 2012).

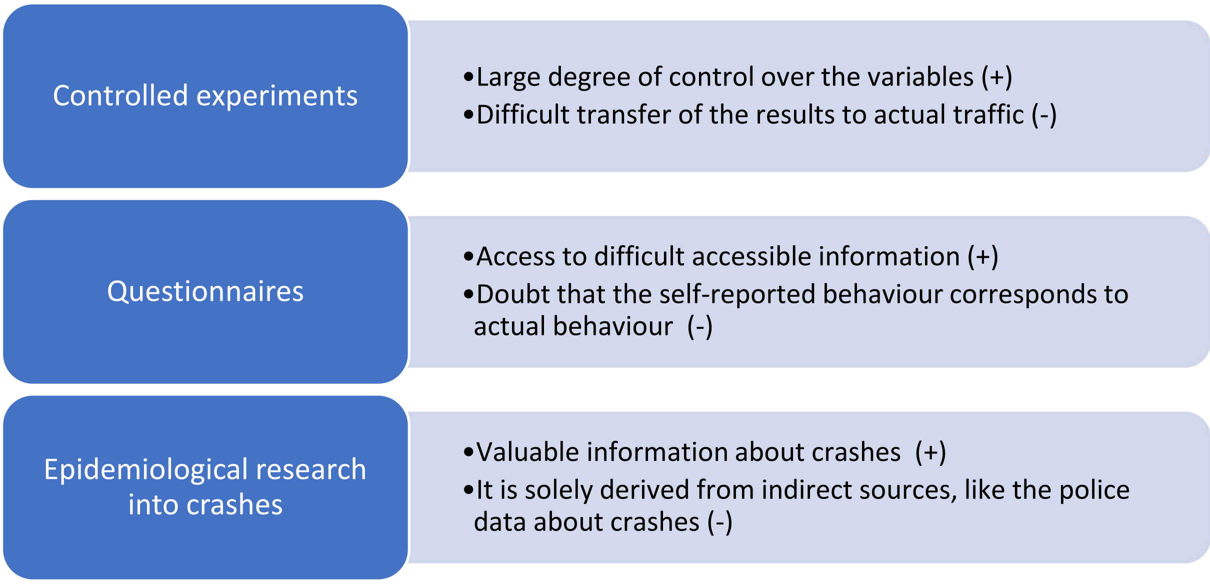


Figure 3.1: Conventional methods for data collection in studying driving

In summary, these data collection methods are limited with respect to the depth and quality of information they provide - especially information about human factors (Regan et al., 2012). The NDS method overcomes a range of those problems associated with traditional approaches to data collection as it provides information about normal behaviour and about all types of crashes and near-crashes, which were unreported with the other data collection methods (Regan et al., 2012; SWOV Institute for Road Safety Research, Leidschendam, 2012). Moreover, it allows for direct observation of driver behaviours and of the factors that result in different events, e.g. deceleration, acceleration, turning etc.

However, there are also some challenges associated with the NDS method. First, it is very resource-demanding in terms of sample recruitment, data gathering, data storage and data analysis. Also, the same problem as in simulators may appear but in a smaller degree, i.e. the behaviour of the driver may be influenced by having in mind that there are cameras and other sensors monitoring every action. Furthermore, due to the fact that crashes are rare events, a very large sample size of traffic data is needed to obtain a sufficient number of crash-events (Regan et al., 2012).

Some Naturalistic driving studies and their objectives are:

- ✓ *100-Car NDS* in the United States. A primary goal of this study was to provide vital exposure and pre-crash data in order to understand the causes of crashes, refine the crash avoidance countermeasures and use them to reduce crashes and their consequences. The most important outcome of this study was that in almost 80 per cent of all the crashes observed in this study, distraction or inattention played a role (Neale et al., 2005).
- ✓ *Strategic Highway Research Program 2 (SHRP2)*. SHRP 2 was created to find solutions to four strategic focus areas: the role of human behaviour in highway safety; rapid renewal of ageing highway infrastructure; congestion reduction through improved travel time reliability; and transportation planning that better integrates community, economic, and environmental considerations into new highway capacity.
- ✓ *INTERACTION project*. Its main objective was to understand driver interactions with in-vehicle technologies. It studies why, how and when drivers use intelligent technologies in their vehicle and their effect on driving behaviour. The technologies that are studied are: cruise control, mobile phone, navigation systems and speed limiters.
- ✓ *PROLOGUE* (PROmoting real Life Observations for Gaining Understanding of road user behaviour in Europe). PROLOGUE aims to assess the feasibility and usefulness of a large-scale European NDS and to create a market for this type of research. Benefits and feasibility are partly determined by five field studies focusing on various aspects of road safety, such as the everyday driving behaviour of novice drivers, cyclists and pedestrians (Research., 2012).
- ✓ *DaCoTA*. It is intended to provide policymakers and other stakeholders in Europe regarding road safety and methods for data collection and processing.
- ✓ *2-BE-SAFE project*. The aim of the 2-BE-SAFE project was to design and implement a broad-ranging research program that produces fundamental knowledge on Powered Two-Wheeler (PTW) riding behaviour, performance, and safety, when being alone and when interacting with other road users. Also,

it aims in the development of a broad and integrated package of public policies for improving the safety of PTW riders in Europe.

- ✓ *UDRIVE* (European naturalistic Driving and Riding for Infrastructure and Vehicle safety and Environment). UDRIVE is the first large-scale European NDS on cars, trucks and PTWs. The UDRIVE project builds further on the experience of the PROLOGUE feasibility study and various FOTs and follows the Field opErational teSt supporT Action (FESTA)-V methodology. This 57 months project is funded under the 7th EU Framework Programme and the project partners are the SWOV (coordinator), BASt, CDV, CEESAR, CIDAUT, DLR, ERTICO, FIA, IBDIM, IFSTTAR, KFV, LAB, Or Yarok, Loughborough University, SAFER, TNO, TU Chemnitz, University of Leeds and VOLVO. It aims to increase the understanding of road user behaviour in different European regions and in regular as well as (near-) crashes conditions. Moreover, it focuses on making road traffic safer and more sustainable by reducing fuel consumption and harmful emissions. The description and modelling of road user behaviour and specifically the effects of driving style, road network characteristics and traffic conditions is another objective of UDRIVE project. Last but not least, the UDRIVE project intents to provide data access to researchers from all over the world to assist with subsequent analyses regarding road safety (Eenink et al., 2014b; Barnard et al., 2016).

3.1.2 Field Operational Tests

Another method which is commonly used for data collection is FOTs. An FOT is a relatively new method, especially in Europe, for studying the impacts of functions on transport. FOTs are large-scale testing studies, which are used to collect naturalistic data and aim to examine the efficiency, quality, robustness and acceptance of the new technology solutions, such as navigation and ADAS, used for smarter, safer and more comfortable transport (FOT-Net, 2010). FOT, as defined by the EU project FESTA, (2008) is “A study undertaken to evaluate a function, or functions, under normal operating conditions in environments typically encountered by the host vehicle(s)”.

Up to date, several FOTs have been conducted all over Europe, the United States and Asia. Some important European FOTs are (FOT-Net WIKI):

- *euroFOT*: Its main goal is the improvement of the quality of European road traffic by identifying and coordinating in-the-field testing of new Intelligent Vehicle Systems. This permitted assessing their effectiveness on actual roads while determining how they perform towards the intended objectives.
- *Dutch AOS FOT*; It is a large-scale FOT to test accident prevention systems for Lorries. Five systems were tested: ACC, Lane Departure Warning, Forward Collision Warning, Directional Control and BlackBox Feed Back.
- *TeleFOT*: It is the largest pan-European FOT that has been conducted to date and consists of functions provided by in-vehicle aftermarket and nomadic devices. It aims to assess the impacts of functions provided by these devices on several transport domains, including safety, efficiency, environment and mobility.

However, conducting an FOT is not an easy task. The FESTA V, which is displayed in Figure 3.2 (FESTA Consortium, 2008), depicts the FOT Chain that covers the steps that need to be carried out during an FOT. The large arrows that form the “V” indicate the timeline. The FOT Implementation Plan takes up all the steps and integrates them into one big table which can be used as a reference when carrying out an FOT. The first steps include setting up the aim of the study and selecting a suitable research team. On the other hand, the last steps include an overall analysis of the systems and functions tested and the socio-economic impact assessment. Both the first and the last steps deal with the more general aspects of an FOT and with the aggregation of the results. Then further down on FOT Chain V-Shape the steps are located, the more they focus on aspects with a high level of detail, like which Performance Indicators to choose, or how to store the data in a database. The ethical and legal issues have the strongest impact on those high-level aspects, where the actual contact with the participants and the data handling takes place (FESTA Consortium, 2008).

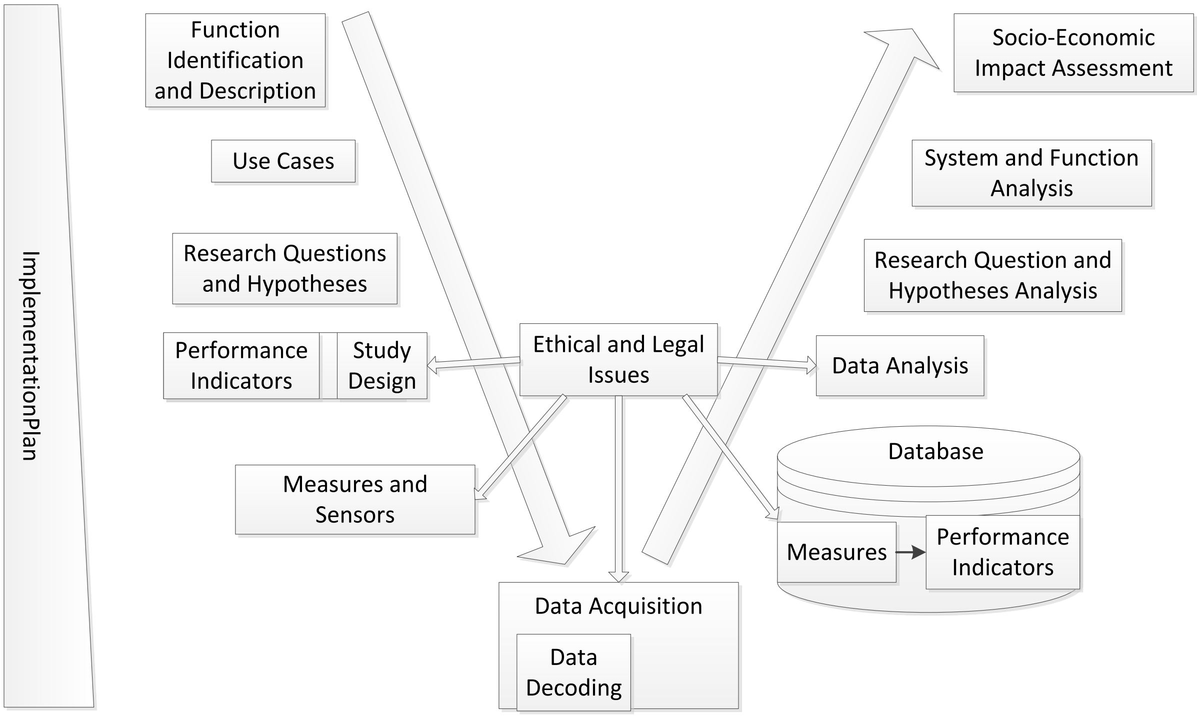


Figure 3.2: The necessary steps to conduct an FOT (FESTA Consortium, 2008)

To be confident in the robustness of the results from the analysis of the data which were obtained from an FOT study, one must follow some strategic rules in the process of data analysis. There are five operations linked together in terms of data treatments: a data quality control, a data processing and mining operation, a performance indicator calculation, a testing of hypothesis and a global assessment (Figure 3.3) (Lassarre et al., 2008). As can be noted from Figure 3.3 each process takes as input the outputs of the previous operation.

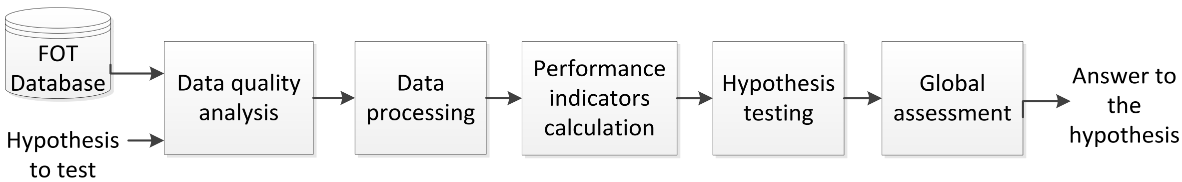


Figure 3.3: Block diagram for the data analysis (Lassarre et al., 2008)

3.1.3 Comparison

Since both methods (NDSs and FOTs) can be used to obtain naturalistic data, it is useful to point out their similarities and their differences. These two types of studies use similar approaches to measure and record driver and vehicle behaviour in real-time since in both instrumented vehicles with the same equipment, such as GPS, accelerometer, cameras etc. are used to obtain the data. Moreover, they are both conducted in a natural driving environment and gather data in normal and safety-critical driving conditions. However, they are slightly different in scope that:

- NDSs observe the natural behaviour of a driver while interacting with the surrounding environment during driving tasks, and collect observational and performance data, while;
- FOTs evaluate one or more functions (e.g., advanced driver assistance systems) under normal operating conditions in environments typically encountered by the vehicle. They seek to quantify the impact of functions on driver performance and safety and driver's acceptance of them (Baldanzini et al., 2010).

Several studies through the literature have used naturalistic driving data, obtained from NDS or FOT. There are two ways to do so: 1) Conduct a new NDS or FOT, which is a difficult and time-consuming task but offers data absolutely suitable for the study's purpose, or 2) obtain the necessary data from an existing NDS/FOT (Guo et al., 2010; Simons-Morton et al., 2011; Xiong and Boyle, 2012; Loeb et al., 2015).

3.2 General data characteristics across projects

Prior to the characterisation of the data that were used in this research, a short description of the ideal dataset will be presented. First, the naturalistic driving data is ideal for describing the driving behaviour, thus the deceleration behaviour too. A big naturalistic driving study with many participants conducting a lot of trips in different driving environments (i.e. motorway, rural, urban) would benefit the objectives of this research since it will provide enough information and variability to extract the influencing factors and their impact on deceleration behaviour. Moreover, the ideal dataset includes many variables regarding the braking events and those variables are easily accessible. Specifically, it should include trip characteristics, driver characteristics, kinematic variables, weather variables, information about the deceleration event i.e. the reason for braking, the traffic conditions and the surroundings. Finally, the dataset should not contain a lot of outliers or missing values.

The data that was used in this research was obtained from three projects: (1) the TeleFOT project, (2) a collaborative project of OEM and Loughborough University and (3) the UDRIVE project (Hrzic, 2017). All these three projects provide naturalistic driving data. The first two projects used the FOT approach and the UDRIVE project was an NDS. In these projects, the driving behaviour was monitored the whole time, using different in-vehicle sensors such as GPS, accelerometer, radar and cameras. The variables of our interest were obtained by extracting them directly from the time series data available for each trip, by calculating them via an algorithm developed in Matlab aided by manually viewing the recorded videos.

The data from all the three projects share some common characteristics that aided in the selection of the applied methods and the performed analysis. The most important is that they follow a hierarchical structure (Figure 3.4). It is obvious that the deceleration events are nested into the trips since in every trip many deceleration events occur, and the trips are nested into the driver level because each driver executes multiple trips. Moreover, the variables that need to be taken into consideration can be categorised into these levels-categories: driver factors, factors related to the trip and factors related to the deceleration events and Table 3.1 displays some examples of this categorisation. The multilevel model that will be described in the Methodology chapter is suitable for the analyses of those data, since it takes into consideration the hierarchical structure of the data, explaining the dependencies between and across the drivers and the trips. The data should be formulated in a way that displays the nested structure in order to apply the multilevel modelling as shown in Table 3.2 (the rest of the explanatory variables are added on the right part of the table).

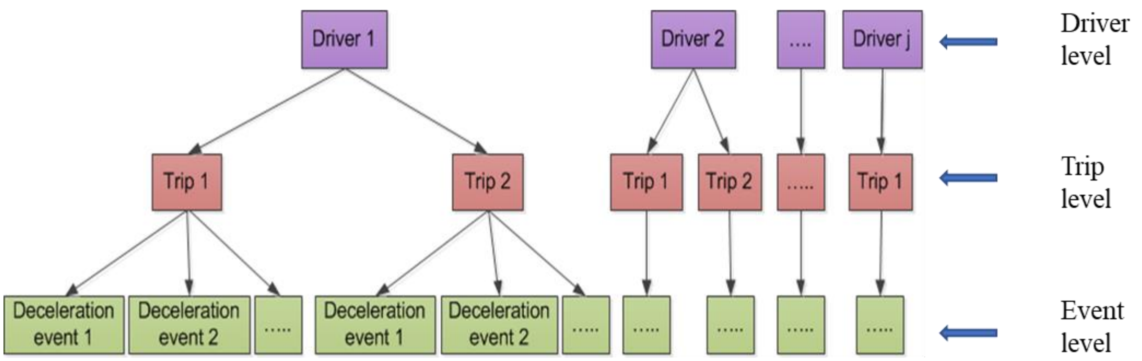


Figure 3.4: The hierarchical structure of the traffic data for the deceleration events

Table 3.1: Examples of the categories of the variables

Hierarchical level	Example of Hierarchical Level	Example Variables
Level-3	Driver Level	Gender
		Age
		Experience
Level-2	Trip Level	Trip duration
		Trip distance
Level-1	Event Level (Braking)	Initial speed
		Initial TTC
		Cause of braking
		Traffic density

Table 3.2: Data structure for three-level linear models

Classifications or levels			Response	Explanatory variables	
Driver ID	Trip ID	Event ID	Deceleration	Speed at the beginning of the event	Best fit function
1	1	1	-2.26	11.31	2
1	1	2	-2.03	7.25	2
1	1	3	-2.35	7.91	3
1	2	4	-2.64	14.19	2
1	2	5	-2.43	11.64	1
1	2	6	-2.03	12.84	1
1	2	7	-2.35	5.64	2
1	2	8	-2.66	12.07	1
1	2	9	-2.93	4.60	1
1	2	10	-2.61	8.24	1
1	2	11	-2.01	4.44	2
2	1	1	-2.30	10.86	2
2	1	2	-2.05	12.80	2
2	1	3	-2.16	5.83	2
2	1	4	-3.29	6.83	1
2	2	5	-2.11	19.71	2
2	2	6	-2.07	8.48	2
2	2	7	-2.33	15.71	2

2	2	8	-2.19	14.73	2
2	2	9	-2.09	12.52	2

In the remaining chapter, the three projects are described in detail, and some descriptive statistics of the data are displayed to better understand them.

3.3 TeleFOT project

The first data set used in this PhD project was obtained from the TeleFOT project which is a large-scale collaborative European FOT funded under the seventh European Commission framework research programme. The objectives of the TeleFOT project were related to safety and mobility as well as economic/fuel-efficient driving and user-acceptance aspects of aftermarket and nomadic devices (e.g. SatNav, Speed Alert etc.) that can be introduced into the vehicle once it has ‘left the showroom’.

As part of the experimental work in TeleFOT, the participants were asked to drive along a specific 16.5 km long route in the Leicestershire area of England, as depicted in Figure 3.5a, after driving for a couple of hours to familiarize with the instrumented car and their behaviour was captured, monitored and analysed using a software programme developed by Race Technology Ltd. The route was carefully chosen to have a good mixture of different road elements such as roundabouts, T-junction, cross-junction, traffic light, mid-block crossings and the existence of dynamic obstacles (e.g. other vehicles, pedestrians, cyclists). This was to capture braking behaviours that significantly vary due to the road element. There were 44 trips conducted by 25 drivers in which data-logging occurred, as 19 of the drivers performed multiple trips.

An instrumented vehicle capable of recording driver behaviour, vehicle kinematics and driving environment (e.g. traffic density, road elements) was employed. Since a single vehicle was used in the experiment, the influence of vehicle-related factors (e.g. engine size, vehicle power and braking performance) need not be considered. The vehicle was equipped with four video cameras (forward road view, driver face, backward road view, driver reaction from the passenger seat), GPS, speedometer and accelerometer (see Figure 3.5b). The sampling frequency was 100 Hz for the duration of the entire trip with an average driving time of 30 minutes per trip. This resulted in a total of 10.8 million observations. The data was processed by software (with a built-in noise filter) developed by Race Technology (Figure 3.5) (Fruttaldo, 2011).

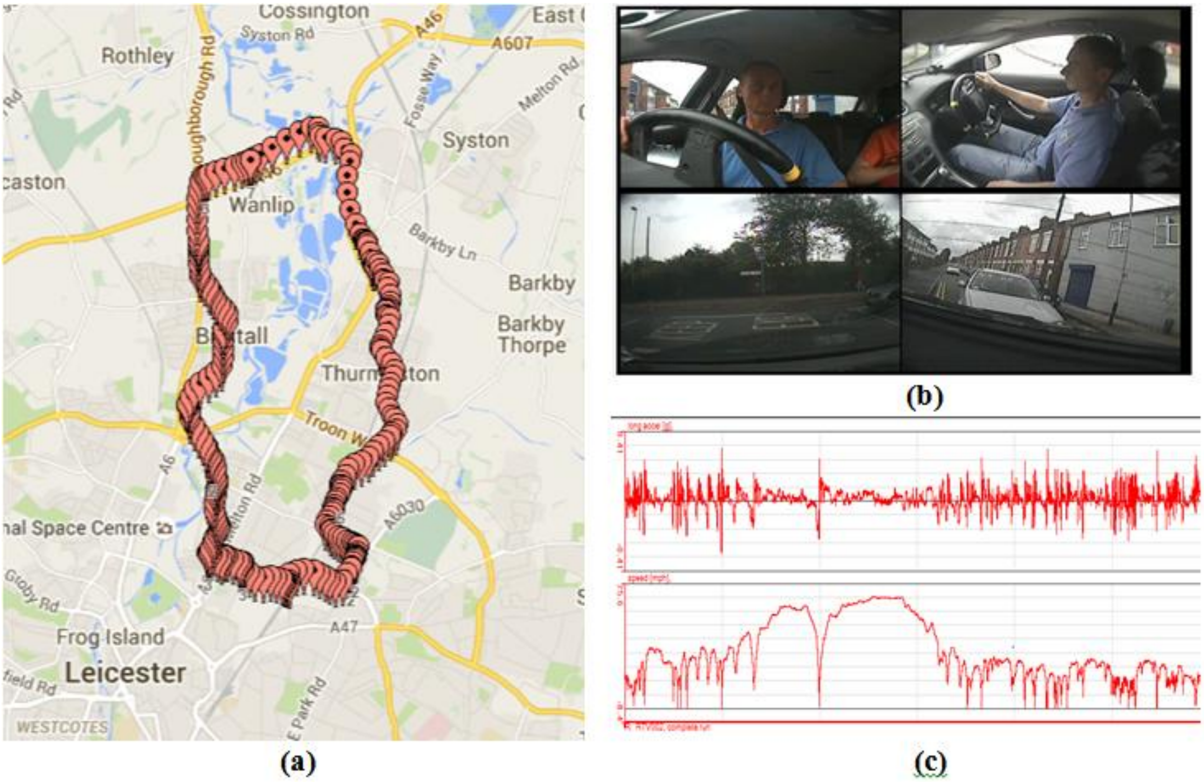


Figure 3.5: The route of the field test (a), the view from the 4 cameras (b) and the acceleration-time and speed-time diagram for the whole trip from the Race Technology programme (c).

In order to extract the data of interest from this project, the Race Technology V8.5 software was used. For each of the trips, available time-variant variables were: time, longitudinal acceleration, speed of the car, travelling distance, the video frame and the GPS coordinates. Traffic characteristics data for the study area were not available from the traffic management centre. However, traffic density is an important variable that might affect driving behaviour along with other variables that were not included in the available time-series, such as the reason for braking, the existence of congestion etc.

To obtain these variables that might play a significant role in the braking behaviour, the videos were watched, and the desired variables were extracted qualitatively. The procedure was as follows: first, the detection algorithm extracted all the deceleration events of the dataset and saved in a different file the video frame number that corresponds to the beginning of each deceleration event. Then, the video of each trip was initiated and by tracking the video frame number of each event, the necessary variables were obtained.

Specifically, the traffic density was measured by counting the number of vehicles and taking into account the length of the visible roads. Since it was calculated qualitatively, it was included in the models as a categorical variable (i.e. low, medium or high traffic density). Moreover, the situational factors (i.e. the reason for braking) were also determined qualitatively by viewing the videos related to the deceleration events (Table 3.3 and Table 3.4). The situational factors that were examined were: the presence of a traffic light, whether the car stops in car blocks, which indicates the existence of congestion and the cause for braking (i.e. if the car decelerates because it approaches a roundabout, a cross or T-junction, a pedestrian crossing or because of an obstacle like pedestrian, bicycle or road jump). In detail, by watching multiple times the video frame starting 5 seconds before the beginning of the deceleration event it was possible to recognise the most challenging variable, the reason for braking.

Table 3.3: Percentage of deceleration events by reason for braking

Reason for braking	Deceleration event Percentage (%)
Roundabout	16.86
T junction	30.07
Cross junction	8.37
Pedestrian Crossing	5.20
Dynamic Obstacle	39.50
Existence of traffic light	15.33

Table 3.4: Percentage of deceleration events by traffic density

Traffic Density	Deceleration event Percentage (%)
Low	65.64
Medium	27.85
High	6.51

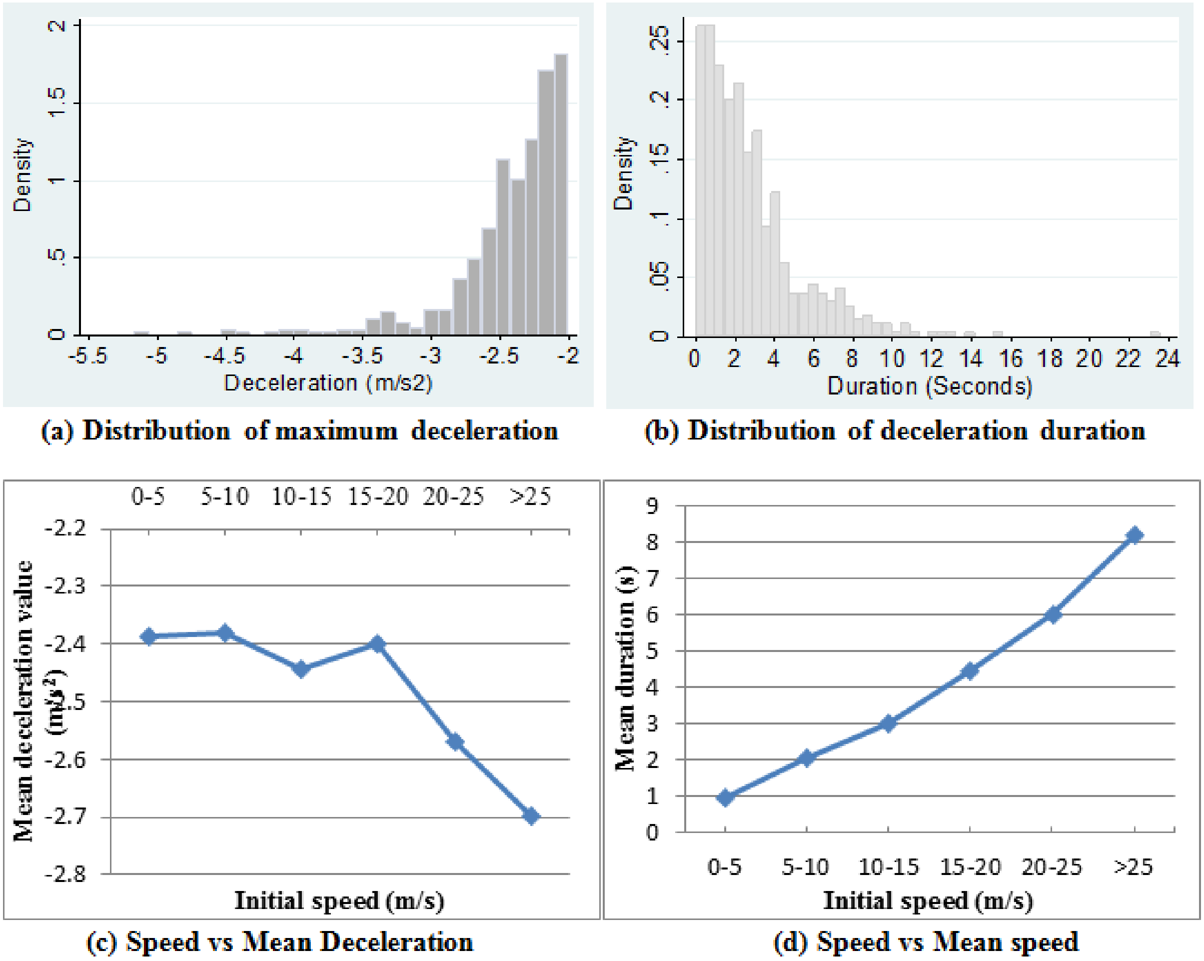
The rest of the data that are important for the analysis were obtained by developing a data extraction algorithm which was implemented in Matlab. Specifically, the trip duration, the maximum and the mean deceleration of the car during the event, the mean and the initial speed of the car during the event, the duration of the event and the travel distance during the event were calculated. Furthermore, the sample was composed of 25 drivers (14 males and 11 females) with an average age of 40 years, varying from 23 to 59 years old. Information on the driver (subject number, age, gender, driven miles per year) was reported in the summary sheet of the file.

Table 3.5: Descriptive statistics of the variables during deceleration events

Variable	Mean	SD	Minimum	Maximum
Max deceleration (m/s^2)	-2.38	0.4	-4.885	-2.00
Duration (sec)	4.26	1.98	0.74	14.95
Mean deceleration (m/s^2)	-1.32	0.34	-3.46	-0.50
Final speed (km/h)	13.57	11.84	0.00	78.49
Initial speed (km/h)	34.66	14.99	4.10	107.51
Mean speed (km/h)	24.71	12.75	1.88	88.2
Distance covered (m)	2.31	2.27	0.8	18.52
Trip duration (min)	33.02	4.70	22.58	43.05

Given the range of data types captured by the instrumented vehicle, it was possible to analyse the deceleration events (i.e. the deceleration value and the duration) based on different influencing factors related to the driver (e.g. age, gender and experience), vehicle kinematics (e.g. the initial speed before the event), traffic (e.g. *low*, *medium* and *high* traffic density) and road infrastructure. Various descriptive statistics were generated to understand these factors (Table 3.5). The average max deceleration value was found to be -2.38 m/s^2 and its absolute maximum value was -4.85 m/s^2, while the average duration was 4.26 sec, with a maximum value of 14.95 sec.

Most of the deceleration rates observed in this study are relatively low as can be seen in Figure 3.6(a) and this may be due to the nature of the FOT which reflects the driver's normal braking and does not include any safety-critical events. Therefore, the threshold was set at 2m/s^2 for this study, which is the lowest value found in the literature to detect deceleration events (Wu et al., 2009), as it was explained in the methodology section.



(a) Distribution of maximum deceleration (b) Distribution of deceleration duration

(c) Speed vs Mean Deceleration (d) Speed vs Mean speed

Figure 3.6: Characteristics of extracted deceleration events.

The beginning and the end of the deceleration event are defined according to the threshold that was described in the Methodology chapter. The algorithm, that was developed in the Matlab software package R2016a to detect the deceleration events resulted in a total of 937 events. That algorithm also computes some essential parameters i.e. the duration (sec) of the deceleration event (see Figure 3.6b), the maximum and the mean deceleration rate (m/s^2), the speed at the beginning and at the end of the event, the video frame of the start of the event in order to detect it in the videos and receive more information and the travelled distance (m) of each event. Moreover, the algorithm splits each event into two parts and calculates the best fitted braking function for each event, which is added as an explanatory variable.

It should be noted that after detecting the deceleration event, a dataset that includes the dependent variables, i.e. the deceleration value and the deceleration duration, and all the explanatory factors that were obtained directly from the Race Technology V8.5

software, from the algorithm and from the videos was formatted as depicted in Table 3.2. The next step was the detection and the deletion of any possible outliers, that might have resulted from the computational procedure or the data gathering procedure. Since, the deceleration events are of interest, univariate detection of outliers considering the duration of the event was performed. Specifically, the percentiles of the duration were calculated in SPSS and the upper and lower threshold were computed by these equations:

Inter Quartile Range (IQR) = Q3 – Q1

Upper Threshold (UT) = Q3 + 2.2 IQR

Lower Threshold (LT) = Q1- 2.2 IQR

Moreover, since the values of the duration were small, the lower threshold came out to be negative but a deceleration event with really small duration, for example, 0.3sec should not be taken into consideration since it is really short to be analysed and modelled, a lower limit of 0.5sec was set for the duration. The same procedure was following for the adjusted R^2 of the fitted functions that were calculated. Therefore, the observations whose values are outside the limits were excluded from the database, resulting in 869 deceleration events.

One more thing that should be taken into consideration in the pre-processing is the possibility of any two explanatory variables to be correlated. If there are two or more correlated variables, only one should be included in the statistical analysis. Therefore, the correlation table was computed using the SPSS software and if the Pearson-correlation value was more than 0.8 indicating a high correlation between the variables, then only one of them was included in the model. For the TeleFOT data only the event_id, the trip_id and the driver_id were highly correlated.

For the deceleration events, the average initial speed was 40 km/h (25 mph), with 80% of the events starting at speeds between 5 m/s (11 mph) and 15m/s (33 mph). The mean duration and mean deceleration value for different initial speeds are presented in Figure 3.6 and Table 3.6 and it can be concluded that the higher the initial speed the longer and harder the deceleration event.

Table 3.6: Average deceleration statistics based on different factors

	Mean values	
	Maximum deceleration value (m/s^2)	Duration (sec)
Gender:		
male	-2.447	2.64
female	-2.423	2.83
Initial speed:		
0-5	-2.385	0.94
5-10	-2.379	2.08
11-15	-2.442	3.04
16-20	-2.399	4.48
21-25	-2.570	6.01
>25	-2.697	8.23
Traffic density:		
low	-2.426	2.70
medium	-2.422	3.17
high	-2.379	2.82
Age:		
20 - 30	-2.490	2.48
30 - 40	-2.486	2.39
40 - 50	-2.374	2.91
50+	-2.388	2.80
Traffic light:		
Signalised	-2.480	3.44
Unsignalised	-2.380	2.57
Reason of braking:		
Roundabout	-2.375	3.94
T-junction	-2.407	3.34
Cross- junction	-2.355	2.54
Mid-block crossing	-2.500	1.53
Dynamic-obstacle	-2.406	1.91

As far as the traffic density is concerned, most of the deceleration events (66%) occurred in low traffic density conditions, 29% in medium traffic conditions and only 5% in high-density conditions. The mean of the maximum deceleration values for different traffic densities (-2.43 m/s^2 for low traffic density, -2.42 m/s^2 for medium traffic density and -2.38 m/s^2 for high traffic density) did not indicate that a relationship exists between the observed rates and the traffic density (see Table 3.6). Moreover, it can be noted that gender does not affect the deceleration value but affects the duration as males seem to decelerate in a shorter time than females. However, as can be seen in

Figure 3.7 the male drivers have a bigger percentage of hard deceleration events (deceleration value<-3m/s^2) comparing to female drivers.

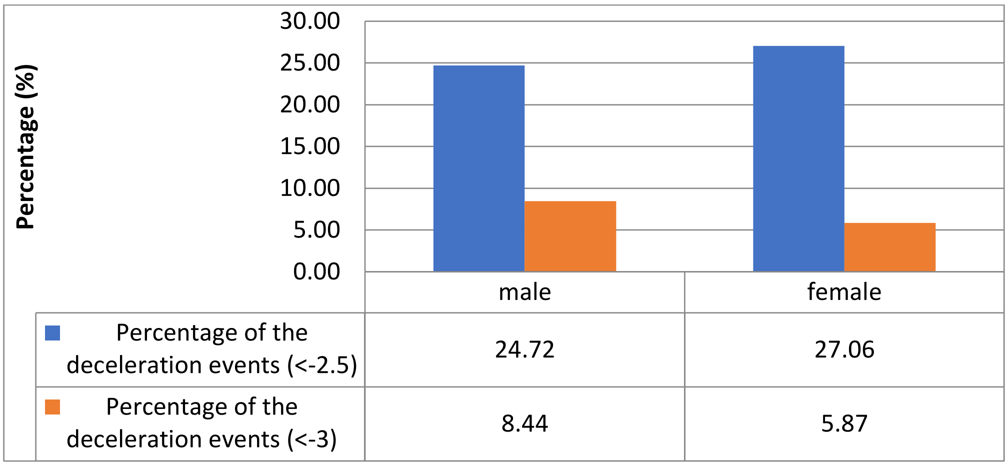


Figure 3.7: Percentage of different deceleration values based on the gender of the driver.

Also, younger drivers seem to decelerate in a harder way, both greater deceleration value and shorter duration. For example, drivers aged between 20-30 years old had a mean deceleration value of -2.49 m/s^2, which is 5% lower than the deceleration value of the 40-50-year-old drivers and the deceleration event lasts on average 15% less.

The deceleration events for each reason of braking are 143 in roundabouts, 255 in T-junctions, 71 in cross-junctions, 44 in mid-block crossing and 335 for obstacles (Table 3.6). As can be concluded from Table 3.6 the reason for braking affects slightly the deceleration value and more the duration of the event, with the durations for mid-block crossings and dynamic-obstacles being relatively shorter. Finally, some influence is noted between the deceleration event and the fact that a road element is signalised or not, which is that for signalised road elements the deceleration value is greater than for non-signalised (Figure 3.8). Moreover, the duration time of the deceleration event for the non-signalised elements is smaller indicating harder braking (see Table 3.6).

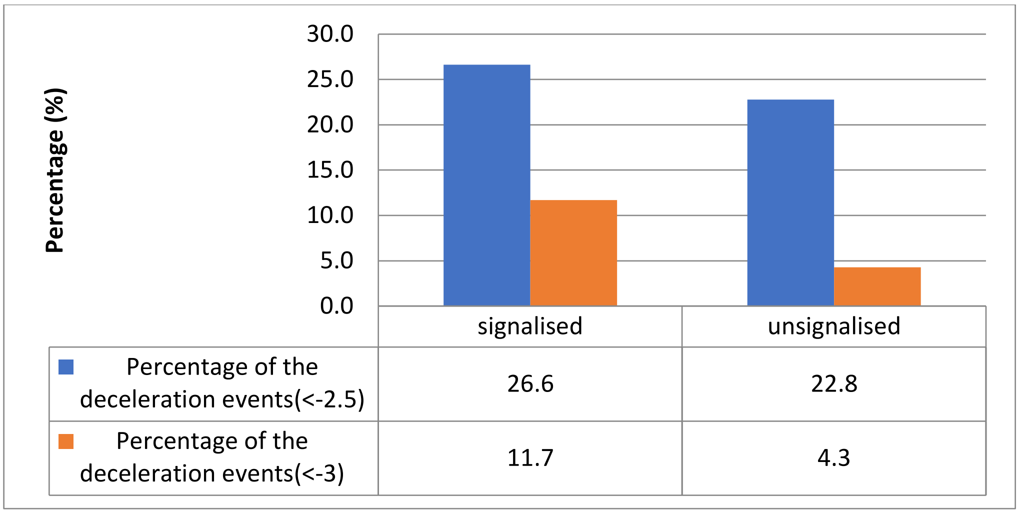


Figure 3.8: Percentage of different deceleration values based on signalised or non-signalised road elements

3.4 OEM project

The second project from which data for the analysis was taken is an FOT conducted by Loughborough University for an OEM company. The purpose of that study was to find more about visual behaviour in relation to the vehicle instrument cluster (e.g. speed, RPM, fuel-level and Heating, Ventilation and Air-Conditioning (HVAC) controls) during normal driving in different road environments.

In this PhD the data was used for a different purpose, i.e. to analyse the deceleration behaviour during normal driving in different scenarios (road environments) and therefore these data are adequate. The design of the study was different than the TeleFOT study. The sample consisted of 12 drivers (6 males and 6 females) from 23 to 65 years old. Information on the driver (subject number, age band, gender) was reported in the summary sheet of the project (see Table 3.7). Three different make/models of vehicle were used in this project. Therefore, the influence of the vehicle can be examined to some extent by including the model of the car in the analysis. All the cars were equipped with Race Technology Ltd equipment, which comprises a GPS and accelerometer package linked and synchronised to a four-channel video system (forward road view, driver face, backward road view, driver reaction from the passenger seat), and so they were capable of recording vehicle kinematics and driving environment features. The sampling frequency was 100 Hz and the data was processed by Race Technology V8.5 software.

The participants first spent a short period of dynamic familiarisation with all three cars; this step ensured that all drivers felt comfortable in what was likely to be an unfamiliar vehicle and then they were asked to drive along three specific routes in the Leicestershire county of England. Each route represented a different road type: motorway ("out and back" route using one junction of the M1), urban (Loughborough) and rural (around the forest area between Loughborough and Leicester) (see Figure 3.9). The routes were chosen carefully to include different scenarios, different road elements (e.g. high-speed roads, dual carriageways, roundabouts, cross-junction, traffic light, mid-block crossings) in order to be possible to analyse and compare the deceleration behaviour in all those different scenarios.

Table 3.7: Driver population by age and gender

Age Band	Male	Female	Total
17-30	1	1	2
31-40	1	1	2
41-50	1	3	4
51-60	2	1	3
60+	1	0	1
Total	6	6	12

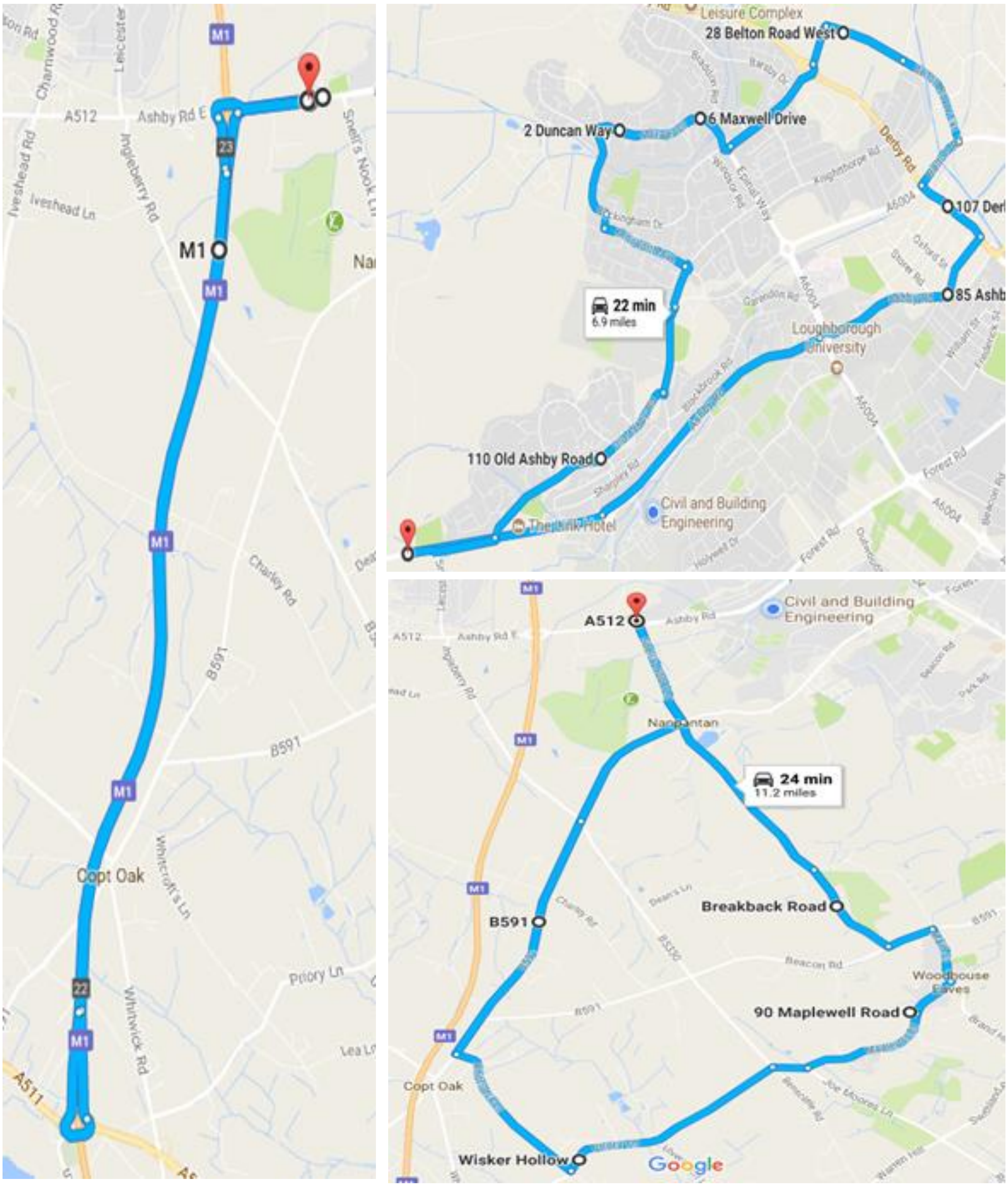


Figure 3.9: The three routes of the field test

Each participant completed all three driving scenarios; the total trial driving time was approximately one hour, split between motorway (10-15 minutes), rural (20-25 minutes) and urban (20-25 minutes). Each participant began from the same start point and ended at the same endpoint, however, to control for order/learning effects the order in which the segments are administered was randomized. It is also introduced an extra trip, a fourth one which occurred during the night. So, each participant drove 4 different scenarios (different car and day/night) each in three different road types, which lead to 130 trips in total (a few trips were missing, since 3 drivers withdraw after executing some trips and did not complete the tests). The sampling frequency was 100 Hz for the duration of all trips so this yield over 15.3 million observations.

Using the algorithm, described in the Methodology chapter, to detect the deceleration events, 1,785 events were identified. As in the TeleFOT project, the variables that were essential for the analysis were extracted from the Race Technology V8.5 software or calculated from the data extraction algorithm or determined qualitatively by viewing the videos related to the deceleration events. Moreover, as with the TeleFOT dataset, the outliers were detected and excluded resulting in 95 outliers and 1690 remaining deceleration events and the correlation between the explanatory variables was examined identifying correlation only between the Driver_id and the Trip_id.

From the histogram of the deceleration rates (Figure 3.10), it can be observed that the deceleration values are relatively low since the data represent normal driving and did not include any collisions. More specifically the average deceleration value was found to be -2.57 m/s^2 and the maximum value was -7.08 m/s^2, while the average duration was 6.2 sec and the maximum duration was 33.06 sec. Various descriptive statistics were generated for the different factors to obtain a general picture and understand how the deceleration change in relation to specific manoeuvres (Table 3.8).

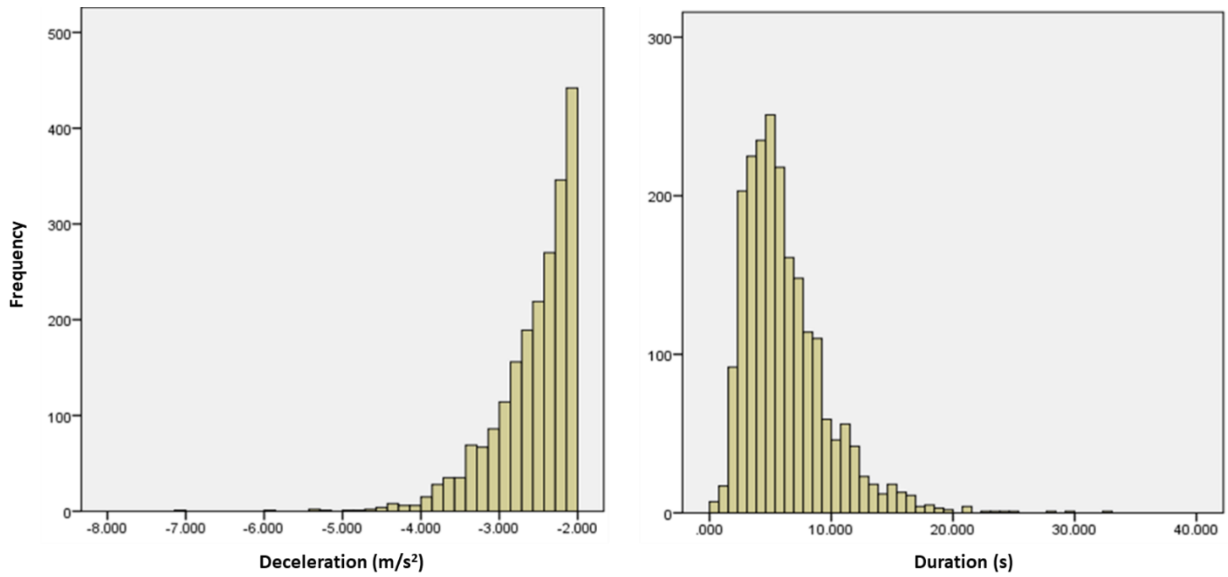


Figure 3.10: The distribution of the deceleration values (left) and of the duration(right) of the events

As far as the initial speed is concerned, its average value was 45 km/h (12.5m/s), with 60% of the events starting at speeds between 18 km/h (5 m/s) and 54 km/h (15 m/s). The mean duration and mean deceleration value for different initial speeds are presented in Figure 3.11 and it can be concluded that the higher the initial speed the longer and harder the deceleration event (see Table 3.8 too).

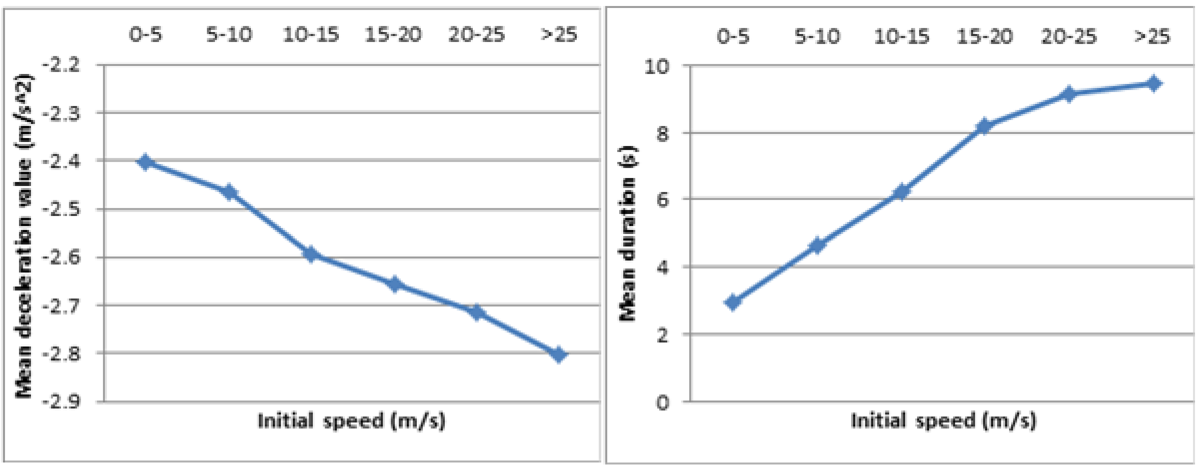


Figure 3.11: Diagram of the initial speed vs the mean deceleration (left) and the mean duration (right)

Table 3.8: Deceleration features' statistics based on different factors

		Mean values	
	Number of cases	Maximum deceleration value (m/s^2)	Duration (sec)
Gender:			
male	888	-2.59	6.26
female	1216	-2.56	6.2
Initial speed:			
0-5	169	-2.40	2.95
5-10	564	-2.46	4.62
11-15	743	-2.59	6.21
16-20	417	-2.65	8.22
21-25	166	-2.72	9.16
>25	47	-2.81	9.49
Traffic density:			
low	1175	-2.59	6.35
medium	395	-2.54	6.61
high	148	-2.53	6.17
Age:			
17-30	322	-2.58	6.54
31-40	349	-2.55	5.76
41-50	697	-2.62	6.41
51-60	580	-2.5	6.24
60+	156	-2.58	5.74
Traffic light:			
Signalised	277	-2.52	6.56
Unsignalised	1827	-2.58	6.17
Reason of braking:			
Roundabout	306	-2.54	7.31
T-junction	446	-2.52	6.12
Cross- junction	250	-2.58	7.65
Pedestrian crossing	40	-2.79	5.24
Mid-block crossing	51	-2.5	5.24
Dynamic-obstacle	918	-2.58	5.48
End of the trial	93	-2.68	7.25
Road Type:			
Motorway	275	-2.6	7.48
Rural	994	-2.63	6.6
Urban	835	-2.49	5.37
Car model:			
Vehicle A	573	-2.52	5.22
Vehicle B	845	-2.66	6.9
Vehicle C	686	-2.5	6.16

Most of the deceleration events (68.3%) occurred in low traffic density conditions, 23% in medium traffic conditions and only 8.7% in high-density conditions. The mean of the maximum deceleration values and of the duration for different traffic densities did not indicate that a relationship exists between the observed rates and the traffic density (see Table 3.8). Regarding the road type, it can be concluded from the Table 3.8 that the deceleration value is almost the same on motorways and rural roads but it is smaller at urban roads which indicate a softer deceleration and also a shorter one.

Moving onto the driver factors it can be noted that age affects neither the deceleration value nor the deceleration duration. The gender seems to have some influence in the deceleration value as males seem to decelerate harder than females, but the deceleration duration is really similar.

In addition, the deceleration value and duration seem to differ depending on the vehicle model. More specifically the biggest deceleration value and the longest duration was observed to happen when the participants were driving Vehicle B and the smallest and shortest when they were driving Vehicle C.

Last but not least, the situational factors will be discussed. The deceleration events for each reason of braking are 306 for roundabouts, 1446 for T-junctions, 25 for cross-junctions, 40 for pedestrian crossings, 51 for stopping at car blocks, 918 for obstacles and 98 to stop because the trial is over. As can be seen from Table 3.8 the reason for braking affects the deceleration behaviour: hard braking due to the pedestrian crossing, both big deceleration value and short duration, can be observed. Also, the braking behaviour is quite similar for the roundabouts, the cross and T-junctions. Finally, some influence is noted between the deceleration event and the fact that a road element is signalised or not, which is that for non-signalised road elements the braking is harder since the deceleration value is greater than for signalised roads and the duration is shorter.

3.5 Combining the OEM and TELEFOT project

To ensure that the results are not driven by the specific project that the data were obtained from and are widely valid, data from the two projects were then combined into one dataset. The summary of the participants' information for both projects is presented in Table 3.9:

Table 3.9: Driver's information for the combination dataset

age category	male	female	total
17-30	3	3	6
31-40	6	3	9
41-50	3	7	10
51-60	6	4	10
61+	2	0	2
total	20	17	37

As a result, a total of about 28 million observations (sampling frequency 100Hz) were examined and around 2,700 deceleration events (2635 after the exception of the outliers) from 37 different drivers and 174 different trips were identified and analysed. The histograms of the deceleration event factors, i.e. the max deceleration value and the duration are presented in Figure 3.12.

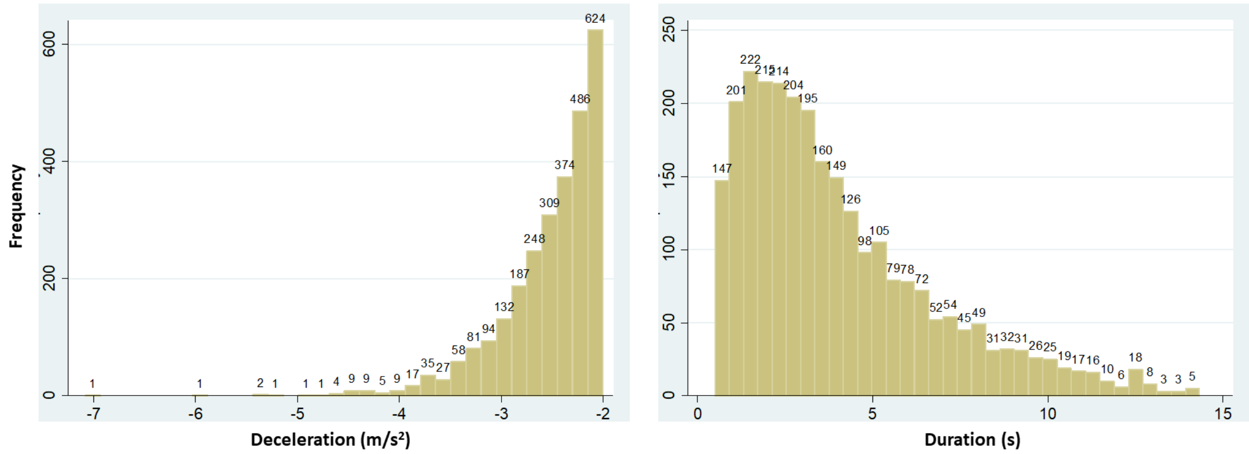


Figure 3.12: Histogram of the deceleration values and the duration for the combination dataset

3.6 UDRIVE Data

The third source of data for this work was obtained from UDRIVE ("European naturalistic Driving and Infrastructure & Vehicle safety and Environment") project. UDRIVE is the first large-scale European NDS on cars, trucks and PTW, organised all over Europe as a collaborative project. Naturalistic Driving meaning that the behaviour of road users during everyday trips is observed unobtrusively in a natural setting without experimental control by recording details of the driver, the vehicle and the surroundings (Eenink et al., 2014a; Bärgman, J. et al., 2017).

The main objective of UDRIVE data is to increase our understanding of road user behaviour. Its objective is two-fold: the first focuses on identifying well-founded measures to improve road safety up to Horizon 2020 and the second is to make road traffic more sustainable by reducing harmful emissions and fuel consumption. More specifically, it aims at describing and identifying road user behaviour in different European countries addressing 5 different scopes: (i) collision causation and risk, (ii) normal-everyday driving, (iii) distraction and inattention, (iv) interaction with vulnerable road users and (v) eco-driving. This will be achieved by providing recommendations for safety and sustainability measures linked with driver awareness, road design, regulation and driver training. The project started in 2012 and lasted for 4 years.

UDRIVE project roughly follows the steps of the FESTA-V methodology as presented below:

- Study design
- Data management
- Data collection
- Data analysis
- Impact

It has derived its subprojects (SP) according to FESTA V shape as it can be seen in Figure 3.13 (Lai et al., 2013; Barnard et al., 2016).

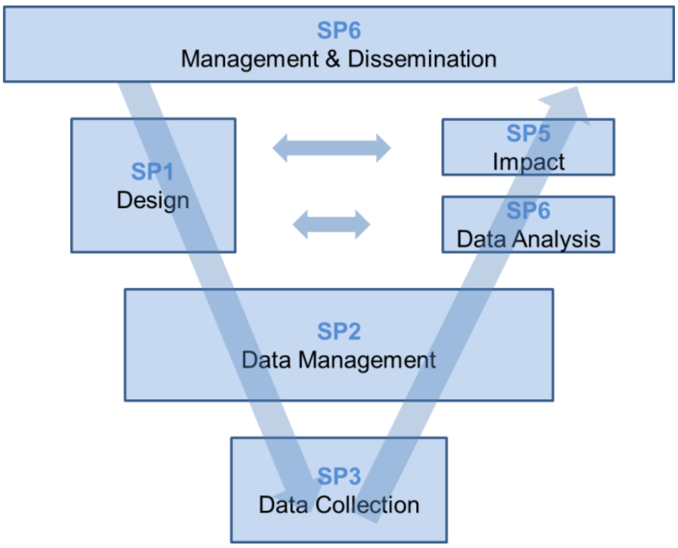


Figure 3.13: FESTA V-Shape steps followed by UDRIVE project

The UDRIVE project involves a large-scale field trial across seven countries and three types of vehicles (Table 3.10). The country of interest for this work is the United Kingdom since the aim is to compare the results from this analysis with the results of the analysis of the 2 other projects that took place in the UK. In order to investigate driver deceleration behaviour under different braking scenarios, as recorded for the UDRIVE participants, it was first necessary to select the trips that will be examined. All the drivers from the UK (i.e. 49 drivers, one driver had dropped out) were examined and 10 trips from each driver were selected almost randomly across the data. The only criterion for a trip to be selected is to have duration more than 1200sec (equals to 20 minutes) so as to contain many deceleration events, resulting in at 470 trips. All 10 Hz and 1 Hz data were analysed in order to obtain the necessary information for each deceleration event.

Table 3.10: Distribution of vehicles for the UDRIVE project

Type of vehicle	Country	Number of participants
Car	France	50
	Germany	50
	Poland	50
	UK	50
PTW	Austria	15
	Spain	25
Truck	Netherlands	75

The sample of drivers consists of 24 males and 26 females aged 19-65 years old (Table 3.11).

Table 3.11: Drivers' characteristics in UDRIVE project

Age	Male	Female	Total
20-29	3	4	7
30-49	10	13	23
50-65	11	9	20
Total	24	26	50

Three different types of cars were selected since this is the minimum required number to observe behavioural differences due to vehicle types. These cars are:

- Small car: Renault Clio 3
- Medium-sized family car: Renault Megane 3/ Scenic
- Premium car: Volvo S60/XC60/XC90

The data were stored in a dedicated tool developed in UDRIVE project, called SALSA (Smart Application for Large Scale Analysis). This tool is integrated within MATLAB and enabled researchers to develop their own algorithm for calculating derived measured, events etc. Therefore, for each driver, all logged records were processed in order to obtain as many variables as possible and were extracted by developing an algorithm in the MATLAB software. The extracted time series from the 10 Hz and the 1Hz datasets can be viewed in Table 3.12. Then the dataset was analysed using a variety of tools and specifically SPSS, R, MS Excel, and MATLAB.

Table 3.12: The extracted time series in UDRIVE dataset

Time series	**Frequency**
GPS latitude	1 Hz
GPS Longitude	1 Hz
Speed limit	1 Hz
One direction road	1 Hz
Direction	1 Hz
Number of lanes positive	1 Hz
Number of lanes negative	1 Hz
Speed	10 Hz
Acceleration	10 Hz
Time	10 Hz
Distance	10 Hz
Steering_angle	10 Hz
Jerk	10 Hz
TTC	10 Hz
THW	10 Hz
Headway	10 Hz
Lead vehicle speed	10 Hz
Traffic congestion	1 Hz
Pedestrian	1 Hz
Cyclist	1 Hz
Ptw	1 Hz
Following a car	1 Hz
Intersection	1 Hz
Arrive at traffic congestion	1 Hz

After obtaining these time series data, it was possible to detect and analyse the deceleration events based on different factors related to the driver, vehicle kinematics, road infrastructure and trip factors. The detection of the deceleration events was accomplished using the procedure described in the Methodology Chapter and resulted at 7163 deceleration events without any outliers (deceleration limit -2 m/s^2). The variables that will be used for the analysis and consist of the available variables for the drivers and the obtained variables for the trip and the event are presented in Table 3.13:

Table 3.13: The available explanatory factors in the UDRIVE dataset

Variable	Level	Variable name
driver	Driver	driver_id
gender	Driver	gender
age categories	Driver	age_1
		age_2
		age_3
Arnett Inventory of Sensation Seeking (AISS)	Driver	AISS_total
Driver behaviour Questionnaire (DBQ)	Driver	DBQ_total
		DBQ_aggressive_violations
trip	Trip	trip_id
Car model	Trip	car_model
Duration of the trip	Trip	trip_duration
Type of road	Trip	rural
GPS latitude	Event	GPS_lat
GPS longitude	Event	GPS_long
Speed limit	Event	speed_0_30
		speed_30_40
		speed_40_50
		speed_50_60
		Speed_60
Direction	Event	direction
Number of lanes positive	Event	1_nu_of_lanes_pos
Number of lanes negative	Event	1_nu_of_lanes_neg
One direction road	Event	one_direction_road
Speed	Event	min_speed
		max_speed
		mean_speed
Acceleration	Event	max_deceleration
		mean_deceleration
Time	Event	duration
Covered distance	Event	distance
Maximum steering angle	Event	max_steering_angle
Jerk	Event	max_jerk
		max_jerk_position
TTC	Event	min_ttc
		initial_ttc
THW	Event	min_thw
		initial_thw
Headway	Event	min_headway
		initial_headway
Lead vehicle speed	Event	max_lead_vehicle_speed
		min_lead_vehicle_speed
		mean_lead_vehicle_speed

Traffic congestion	Event	traffic_congestion
Pedestrian	Event	pedestrian
Cyclist	Event	cyclist
Ptw	Event	ptw
Following a car	Event	Following_a_ car
Intersection	Event	intersection
Arrive at traffic congestion	Event	Arrive_at_traffic_congestion

The correlation of these explanatory variables was explored, and it was concluded that some of the variables are highly correlated. Therefore, in the statistical analysis, only one of the correlated variables was included, testing different ones each time to gain the best results. In detail, the correlated variables were the min_THW with the initial_THW, the max_speed with the distance, the min_speed with the mean_lead_vehicle_speed, the mean_speed with the min_speed, the max_speed and the mean_lead_vehicle_speed and finally the mean_lead_vehicle_speed with the min and max_lead_vehicle_speed.

Two of the variables displayed in Table 3.13, i.e. the AISS and the DBQ indexes (DBQ_total and DBQ_agressive_violations), resulted from behaviour questionnaires that drivers filled to reveal their driving personality. A higher overall AISS score denotes a higher level of sensation seeking and a higher DBQ violation score indicates a greater propensity to commit violations. Moreover, the age categories that were given from the report were: 20-29, 30-39, 40-49 and 50-65 but after applying the statistical model, using different age categories, it was concluded that the best classification was young (20-29), middle-aged (30-49) and old (50-65) drivers. Furthermore, the variable speed limit was used in the analysis in two ways; as a categorical variable that shows the speed limit and as an indicator of the road type, i.e. motorway, rural or urban. Specifically, if the speed limit was 113km/h (70mph), it was labelled as motorway (even if this limit exists in motorways and dual carriageways). If the speed limit was more and equal to 80km/h (50mph) or equal to 97km/h (60mph), then it was labelled as rural (single carriageways). Finally, it was considered urban if the speed limit was less or equal than 48km/h (30mph).

Table 3.14: Descriptive statistics of important variables in UDRIVE dataset

Variable	Mean	Std. Deviation	Min.	Max.
Initial speed (km/h)	46.87	19.6	4.16	128.85
Max_deceleration (m/s^2)	-2.59	0.59	-11.3	-2.0
Duration (s)	7.58	4.1	0.1	28.4
Min speed (km/h)	14.06	17.03	0	119.9
Max_jerk (m/s^3)	-1.4	0.68	-9.63	-0.1
Min_TTC (s)	23.256	27.67	1.41	78.21
Min_THW (s)	2.157	1.54	0.29	13.16
Min_HW (m)	13.28	16.01	0.78	111.25

From the histogram of the deceleration rates (Figure 3.14), it can be observed that they are relatively low since the data represent normal driving. More specifically the average deceleration value was found to be -2.59 m/s^2 and the maximum value was -11.3 m/s^2, while the average duration was 7.58 sec and the maximum duration was 28.4 sec. Various descriptive statistics were generated for the different factors to get a general picture and are presented in Table 3.14.

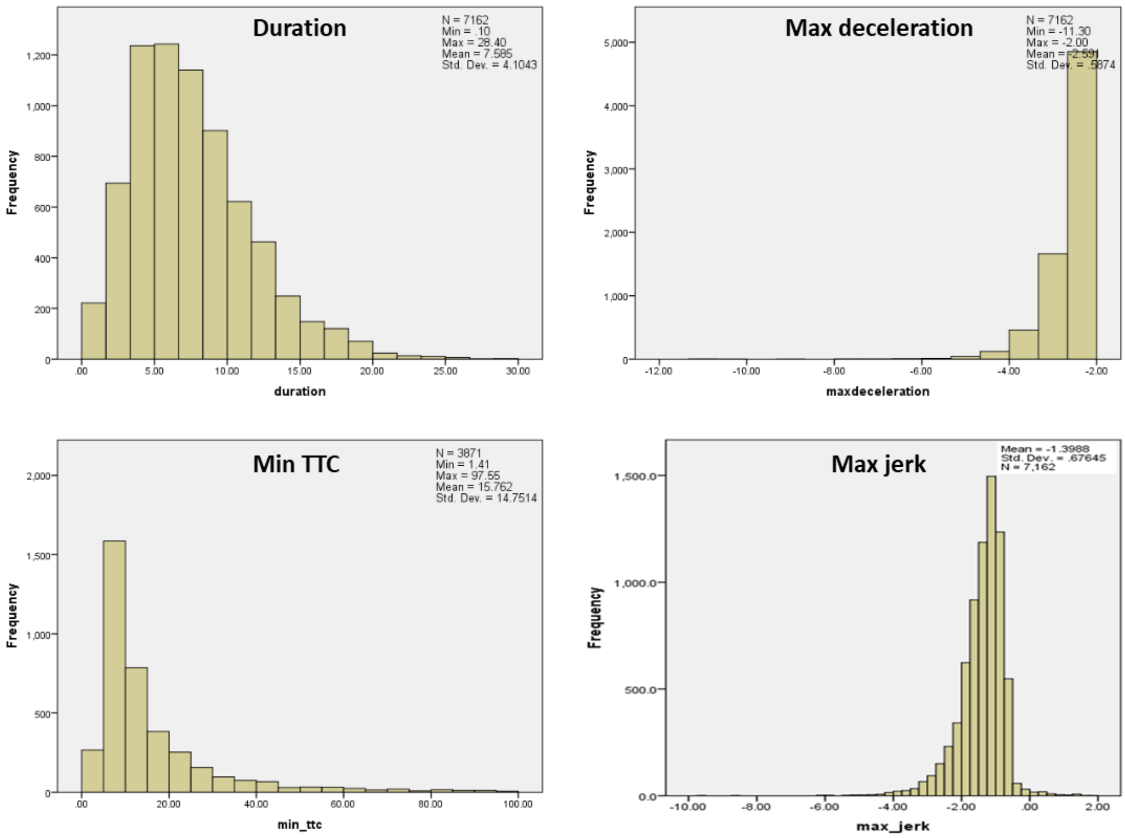


Figure 3.14: Histograms of different variables from the UDRIVE dataset

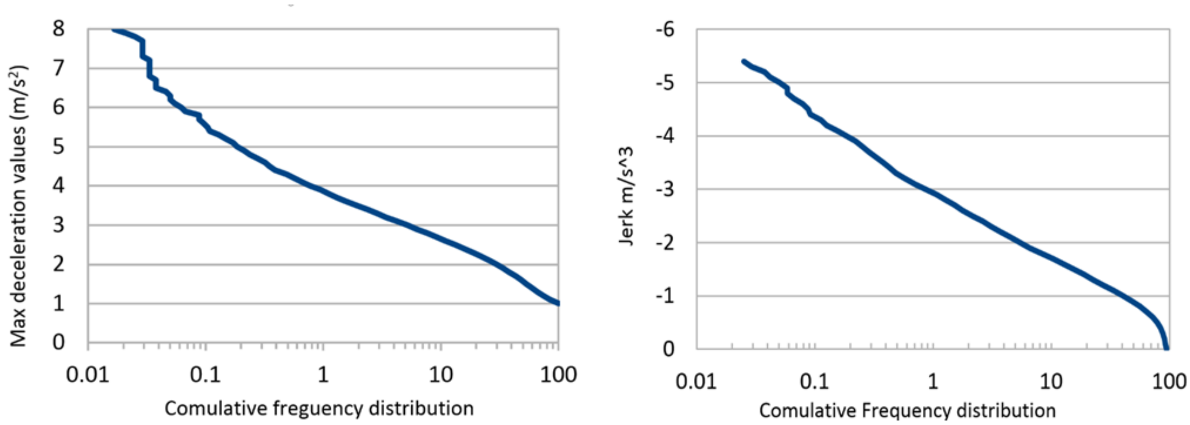


Figure 3.15: Cumulative frequency distribution for the max deceleration and the jerk

It is really interesting to observe the importance of the threshold of the deceleration event. In Figure 3.16 it is shown the frequency of deceleration events, detected with different thresholds for 10 random drivers. It can be observed that by changing the threshold, the order of the drivers conducting more deceleration events is changing too.

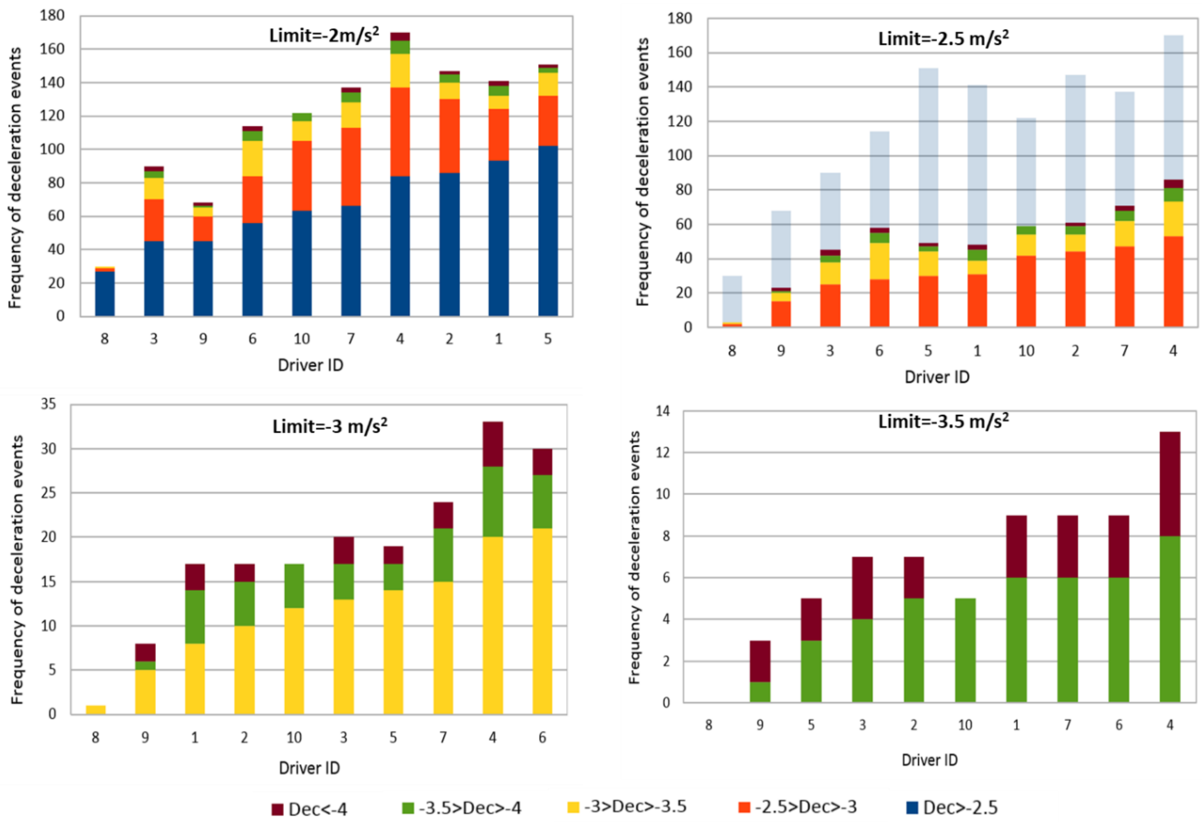


Figure 3.16: Frequency of the deceleration event per driver based on different thresholds

Another variable that was calculated indirectly, was the speed violation. Meaning that if the speed at the beginning of the deceleration event was larger than the speed limit, then it was marked as speed violation. The relationship between the frequency of speed violations and the frequency of harder acceleration was examined and it can be observed from Figure 3.17 that there is such relationship and that the more speed violations a driver has, the harder decelerations he makes.

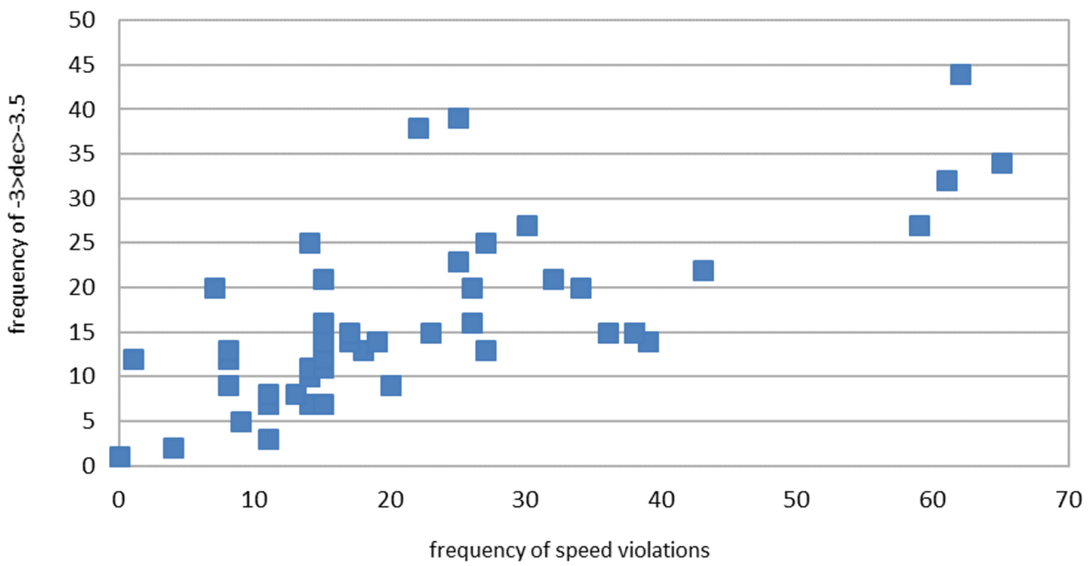
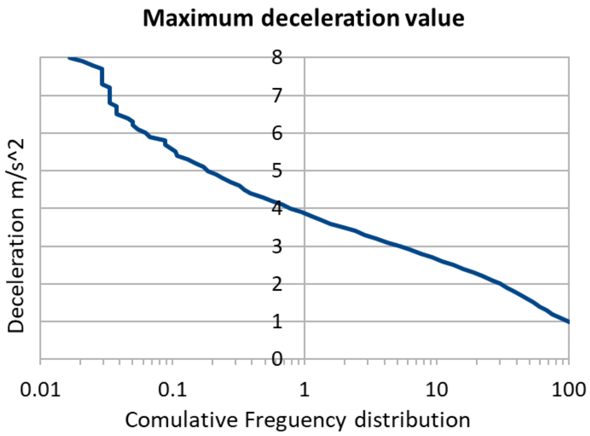


Figure 3.17: Plot of the frequency of driver's speed violations against the amount of the deceleration events

3.6.1 UDRIVE Comfort Modelling

As it was described in the Methodology Chapter, the UDRIVE dataset will be used for the comfort modelling analysis. First, following the described procedure for the detection of the deceleration events for the comfort analysis, 21,600 deceleration events (deceleration limit -1 m/s^2) were identified and will be used for the modelling. The cumulative frequency of both the deceleration value and the jerk, which are the variables that set the limits for the comfort categorisation are displayed in Figure 3.18. It can be observed that 99% of the deceleration events have maximum deceleration value smaller than 3.9m/s^2 in absolute value and jerk bigger than -3m/s^3.



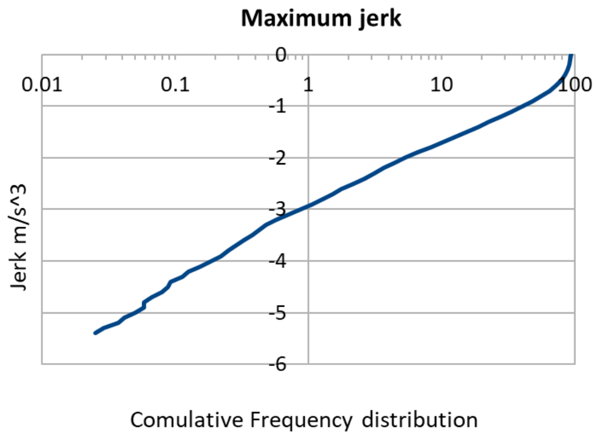


Figure 3.18: Cumulative Frequency of the deceleration value and the jerk

For the modelling, the dependent variable is the comfort level, which is a categorical variable. As it was described in Chapter 3, different classifications of the deceleration events regarding comfort level took place. The first classification had four categories, the second has three and the third has only two categories (i.e. binary). The frequency of the deceleration events that belong to each of the four comfort categories is presented in Table 3.15. It can be noticed that only 4.4% of the events were perceived as very uncomfortable whereas 45.2% of the events were slightly comfortable.

Table 3.15: Frequency of the deceleration events of classification A

	Frequency	Per cent	Cumulative Percent
Very comfortable	8094	33.8	33.8
Slightly comfortable	10813	45.2	79.0
Slightly uncomfortable	3966	16.6	95.6
Very uncomfortable	1060	4.4	100.0
Total	23933	100.0	

The frequency of the deceleration events to each category for Classification B and C are presented in Table 3.16 and Table 3.17 respectively.

Table 3.16: Frequency of the deceleration events of classification B

	Frequency	Per cent	Cumulative Percent
Comfortable	8094	33.8	33.8
Neutral	11882	49.6	83.4
Uncomfortable	3957	16.6	100.0
Total	23933	100.0	

Table 3.17: Frequency of the deceleration events of classification C

	Frequency	Per cent	Cumulative Percent
Comfortable	11908	49.8	49.8
Uncomfortable	12025	50.2	100.0
Total	23933	100.0	

Moreover, the explanatory variables that were examined are presented in Table 3.18. It can be observed that the variables can be categorised at the event level variables and the driver level ones.

Table 3.18: Explanatory variables used in the logit modelling

Code name	**Explanation**	**Variable type**
Initial speed	The speed that the vehicle has at the beginning of the deceleration event.	Continuous Variable
TTC	The time to collision (TTC) from the leading car at the beginning of the event.	Continuous Variable
THW	The THW at the moment that the deceleration event starts.	Continuous Variable
HW	The space headway at the moment that the deceleration event starts.	Continuous Variable
Traffic congestion	If there is traffic congestion when the deceleration event is taking place.	Categorical Variable (0-> no traffic congestion)
Motorway	If the event is happening in a motorway.	Categorical Variable (0-> the event is not happening in a motorway)
Rural (reference variable)	If the event is happening in a rural area (single carriageway roads or dual carriageways).	Categorical Variable (0-> the event is not happening in a rural area)
Urban	If the event is happening in an urban area.	Categorical Variable (0-> the event is not happening in an urban area)
Intersection	If the reason for braking is approaching an intersection.	Categorical Variable (0->there is no intersection)
Pedestrian	If the reason for braking is a pedestrian.	Categorical Variable (0->there is no pedestrian)
PTW	If there is braking because of a PTW.	Categorical Variable (0->there is no ptw)
Cyclist	If the reason for braking is a cyclist.	Categorical Variable (0->there is no cyclist)

One_lane	If the deceleration event is happening on a one-lane road.	Categorical Variable (1->one lane road)
Male	Driver’s gender	Categorical Variable (0->if the driver is a woman)
Age 18-30	Driver’s age	Categorical Variable (1->if the driver belongs to the specific age category)
Age 31-50		
Age >50 (Reference variable)		
AISS_total	Arnett Inventory of Sensation seeking	Continuous Variable
DBQ_all_violations	Driver behaviour Questionnaire	Continuous Variable

Some non-parametric tests were performed to depict if there are differences for the independent variables in each comfort category. In Figure 3.19, two examples of boxplots of two variables (initial TTC and initial THW) against comfort categories are presented. It can be seen that THW has some extreme values for every category. Also, for each comfort category, both TTC and THW seem to have different values and that might indicate that they have a significant effect on the comfort level of the deceleration event.

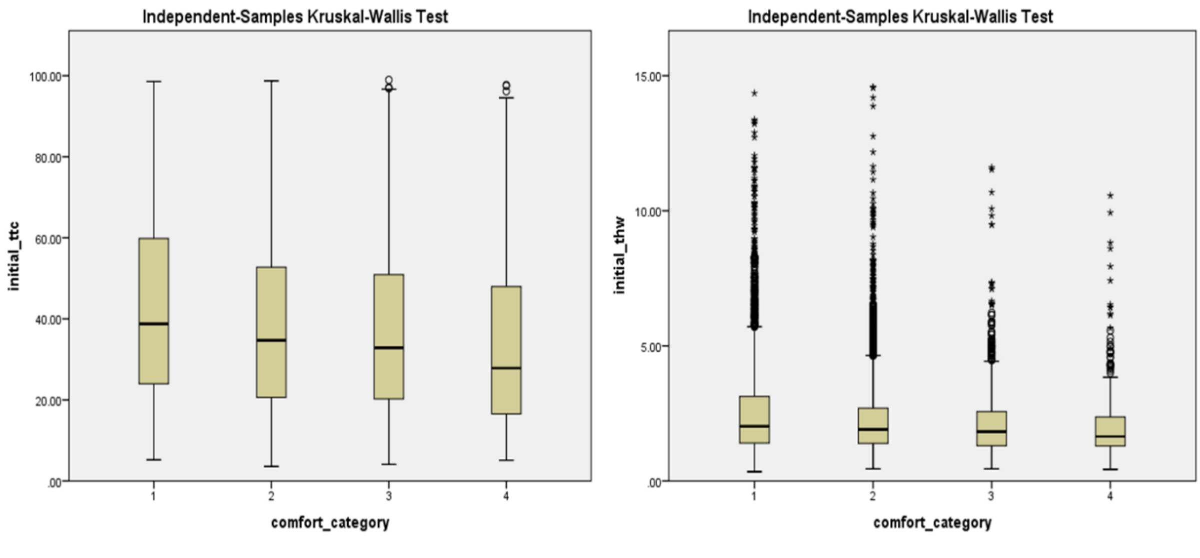


Figure 3.19: Boxplot of initial TTC and the initial THW for each comfort category

Last but not least, it should be noted that two statistical analyses will be undertaken; If all the variables are included, then fewer observations can be considered at the models since some explanatory variables are not available for all the observations (e.g. the TTC, THW and space headway are available only if there is a vehicle in front of the examined car when it is braking). Therefore, in the first one (Statistical Analysis

I), all the explanatory variables from Table 3.18 were included, leading to fewer observations. Specifically, from 23,933 deceleration events that were identified, 5,843 events were included in the model. Many events happened without the existence of a leading vehicle and so, the variables TTC, THW, headway do not exist. Also, not all drivers have completed the questionnaire. In the second analyses (Statistical Analysis II) all the observations were included by taking out the variables that were mentioned before.

3.7 Summary

This chapter started with a review of the data collection methods used in driving behaviour analysis. Moreover, it presented the datasets that will be employed to conduct statistical and cluster analysis. The purpose of this work required naturalistic driving data, so the data were obtained from two FOT and an NDS. The data that were employed represented normal driving, i.e. absence of emergency events and were representing different scenarios, considering the road type, the reason for braking, the traffic situation, the initial kinematics and the drivers. Comparing the ideal dataset described in Section 3.2 with the datasets that were used in this research and were described in detail in this Chapter, it is concluded that all the dataset are satisfactory. To begin with, they provide naturalistic driving data and are consist of many drivers having conducted many trips. Moreover, most of the kinematic, driver, trip, event variables are available except for weather and light conditions and some driver variables, such as education level, income, sentimental state. However, not all the variables were easily accessible since to obtain some of them, complicated calculation or time-consuming processes (i.e. the examination of the trip videos) were essential. Finally, outliers and missing values were included in the datasets, which were detected and excluded.

In more detail, the TeleFOT project consist of 25 drivers conducting 44 trips in different conditions, the OEM had 12 drivers undertaking 130 trips and finally, from the UDRIVE NDS, 49 UK drivers were selected conducting 470 trips (Table 3.20). The deceleration events detection algorithm for the analysis of the braking characteristics had as outcome almost 10000 deceleration events, 869 for the TeleFOT project, 1690 for the OEM project and 7162 for the UDRIVE. However, the detection algorithm for the ride comfort analysis resulted in 21600 deceleration events. The datasets that were developed for each project consists of as many observations as the deceleration events and includes the deceleration characteristics, the kinematic values at the beginning and during the event, the driver characteristics, the trip characteristics and the situational factors that were obtained from the videos and from the developed algorithm in MATLAB. Analytically, the variables that were extracted and imported in the models along with their availability for each dataset are presented in Table 3.19.

Table 3.19: The extracted variables for each dataset

Variable category	Variable	TeleFOT	OEM	UDRIVE
Driver level	driver ID	X	X	X
	gender	X	X	X
	age categories	X	X	X
	Arnett Inventory of Sensation Seeking (AISS)			X
	Driver behaviour Questionnaire (DBQ)			X
Trip level	Trip ID	X	X	X
	Trip duration (min)	X	X	X
	Trip distance (km)	X	X	X
	Car_model		X	X
Trip level	Road Type (rural, urban, motorway)	X	X	X
Event level	Initial speed	X	X	X
	GPS latitude	X	X	X
	GPS longitude	X	X	X
	Speed limit			X
	Traffic density	X	X	
	Traffic light	X	X	
	Time	X	X	X
	Covered distance	X	X	X
	Driver's reaction	X	X	
	Traffic congestion			X
	Arrive at traffic congestion/ stops at car block	X	X	X
	<u>Reason for braking:</u>			
	Roundabout	X	X	
	T-junction	X	X	
	Cross- junction	X	X	
	Intersection	X	X	X
	Pedestrian crossing	X	X	X

	Dynamic-obstacle	X	X	
	Other	X	X	X
	Cyclist			X
	Ptw			X
	Direction			X
	Number of lanes positive			X
	Number of lanes negative			X
	One direction road			X
	Maximum steering angle			X
	Jerk			X
	TTC			X
	THW			X
	Headway			X
	Lead vehicle speed			X
	Following a car			X

Finally, Table 3.20 summarizes the characteristics of the three datasets. Specifically, the number of drivers, trips and events is outlined for each dataset along with the drivers' characteristics. It can be concluded that the UDRIVE data gives a bigger number of different drivers and trips comparing to the other two datasets. Moreover, a balance regarding the gender of the drivers can be observed which doesn't happen in the age since the younger age group has only 8 drivers in comparison with 42 for the middle and 32 for the old age group. Moreover, the statistical values (average, standard deviation, minimum and maximum) of some important variables are displayed in Table 3.20 and some differences along the datasets can be observed. First, in the TeleFOT dataset, the deceleration value was smaller in absolute value than in the other datasets, indicating softer braking. The average duration, as well as the standard deviation of the duration, shows a significantly shorter duration of the braking events in the TeleFOT dataset. Finally, as far as the speed is concerned, higher initial and final speed (both average and maximum values) are observed in the OEM and UDRIVE datasets. The lower speed values of the TeleFOT dataset might be due to the low percentage of observations happening in a motorway (only 7.5%).

Regarding the frequency of the variables in the observation, it should be noticed that there is a satisfactory percentage for almost all the variables. The pedestrian and the motorway are the exceptions. Only in the UDRIVE dataset, there is a big percentage of observations happening in a motorway and braking occurring due to the presence of a pedestrian. Furthermore, only in 6.5% and 8.1% of the observations in the

TeleFOT and OEM datasets respectively there is high traffic density, which might undervalue the effect of high traffic density in the braking event. Accordingly, the results of the modelling might be influenced by the lack of observations in some variables.

Table 3.20: Comparison of the characteristics of the three datasets

	TeleFOT				**OEM**				**UDRIVE**			
Drivers	25				12				49			
Trips	44				130				470			
Events	869				1690				7163			
Age	*young*		*middle*	*old*	*young*		*middle*	*old*	*young*		*middle*	*old*
	4		13	8	2		6	4	7		23	20
Gender	*male*		*female*		*male*		*female*		*male*		*female*	
	14		11		6		6		24		26	
Variable	*Mean*	*SD*	*Minimum*	*Maximum*	*Mean*	*SD*	*Minimum*	*Maximum*	*Mean*	*SD*	*Minimum*	*Maximum*
Max deceleration (m/s^2)	-2.38	0.40	-4.89	-2.00	-2.62	0.52	-7.08	-2.00	-2.59	0.59	-11.30	-2.00
Duration (sec)	4.26	1.98	0.74	14.95	8.65	4.80	0.85	24.80	7.58	4.10	0.10	28.40
Final speed (km/h)	13.57	11.84	0.00	78.49	16.16	17.99	0.00	116.00	14.06	17.03	0.00	119.90
Initial speed (km/h)	34.66	14.99	4.10	107.51	49.25	19.72	2.60	142.03	46.87	19.60	4.16	128.85
	Frequency (Percentage)				Frequency (Percentage)				Frequency (Percentage)			
intersection	38.4				37.3				57.0			
Pedestrian	5.2				2.2				16.0			
arrive at traffic congestion	11.1				12.3				10.3			
road typo: urban	44.8				40.5				57.4			
rural	47.6				44.4				22.1			
motorway	7.5				15.1				20.5			
Traffic density: low	65.6				68.0							
medium	27.9				23.8							
high	6.5				8.1							

4 Methodology

According to the literature review, it is really important for the wide acceptance of (semi) AVs that passengers feel safe and comfortable inside them. Moreover, deceleration events are crucial for comfort and should be carried out in a way that resembles human behaviour. Therefore, this study focuses on the analysis of the deceleration events observed within normal driving with the aim of identifying acceptable thresholds and relationships with different factors associated with braking behaviour under different driving and operational conditions. The factors that will be tested are human factors (i.e. age, gender, driven miles per year and driver behaviour indices from questionnaire), traffic (e.g. traffic density), situational (e.g. reason for braking) and kinematic factors (i.e. speed, TTC, THW, headway at the beginning of the event) and road network conditions. The purpose of this analysis is to identify and explain the affecting factors at a deceleration event, i.e. the factors that influence the maximum deceleration and the duration of the event. Moreover, the comfort level of the deceleration events is analysed, using different thresholds, to determine which thresholds best explain the comfort level and to recognise the comfort influencing factors. All this information is useful for informing vehicle manufacturers about the deceleration behaviour observed during normal driving and suggesting how this could be transformed into (semi) AVs so as to ensure comfortable and safe braking operations.

4.1 Research Design

This PhD study was divided into six objectives as described in the Introduction chapter. Table 4.1 illustrates the objectives and the methods utilized to accomplish that aim.

Table 4.1: The research design of this PhD

Objective ID	Objectives	Methods	Chapter
1	To identify factors affecting deceleration behaviour and ride comfort.	Literature review	2
2	To describe and validate data collection approaches for analysing deceleration behaviour.	An in-depth critical review of literature	3

3	To investigate and refine the data to improve the analysis quality.	Utilization and analyses of naturalistic driving data from FOTs and NDS	3
4	To develop the deceleration profiles which are perceived natural and comfortable.	Algorithm development in Matlab	4, 5
5	To extract the underlying relationship between influencing factors and both, braking behaviour and comfort level.	Statistical analyses -> Multilevel regression models and Multinomial Logistic models	4, 5, 6
6	To recommend for comfortable braking design.	Outcomes from this work and comparison with the literature	7

Objective 1 has been discussed earlier in the Literature review section, whereas objective 2 and 3 will be explained in the Data chapter and objective 6 in the Discussion and Recommendations Chapter (Chapter 7). In the next section, the methods used to approach the rest of the objectives will be reviewed. Specifically, the methodology used to detect the deceleration events and estimate the most comfortable deceleration profiles (objective 4) is described in the subsection 4.2. The one part of the objective 5, i.e. to extract the underlying relationships between the influencing factors and the braking event will be achieved by the methods presenting in the subsections 4.3 and 4.4. To accomplish the other part of objective 5, i.e. to reveal the relationships between the affecting factors and the comfort level, the identification of the comfort level as well as multinomial logistic models will be used and are described in detail in the subsection 4.5.

Finally, the next figure presents a flowchart of the methodology that was followed in this PhD to achieve the abovementioned objectives.

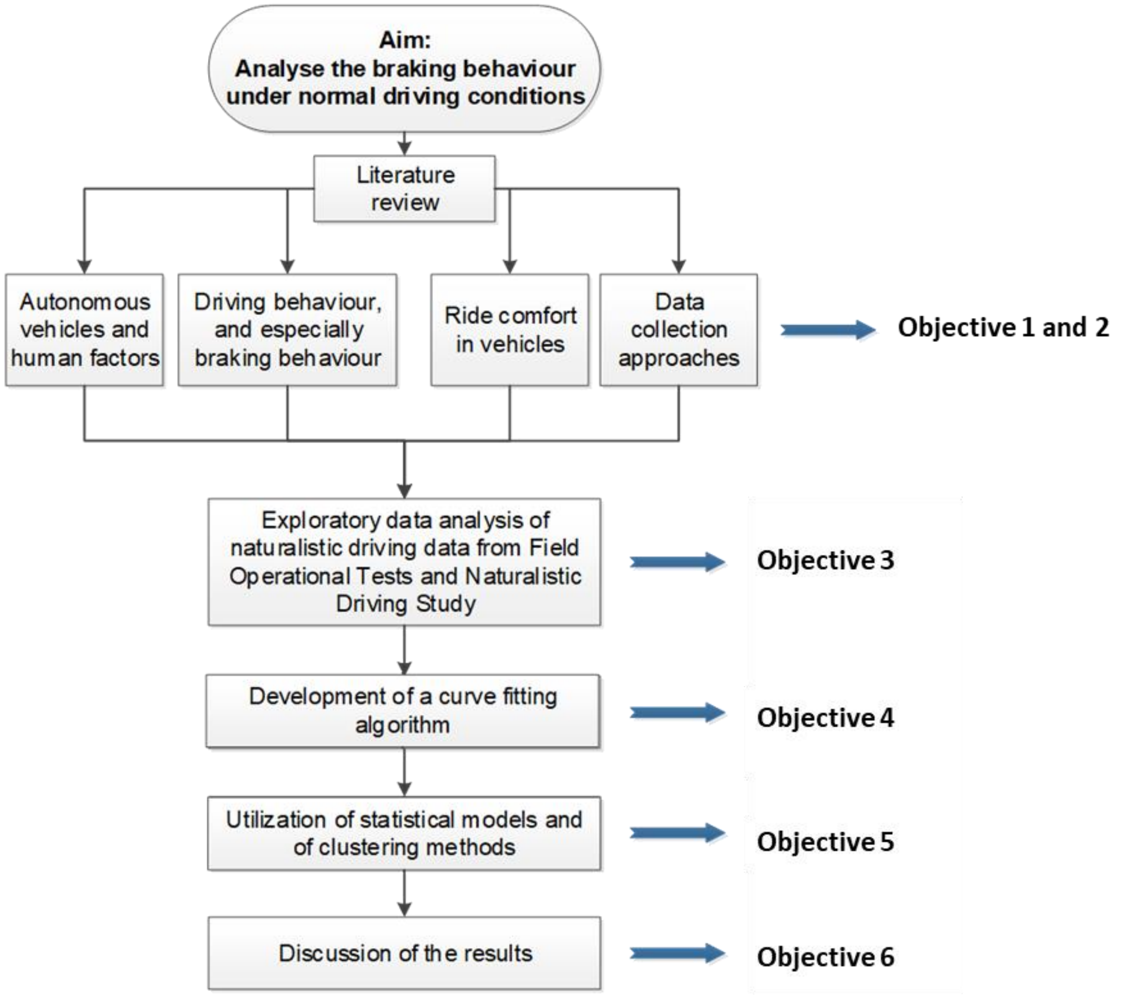


Figure 4.1: The flowchart of the research design

4.2 Deceleration Events and Deceleration Profiles

4.2.1 Detection of the deceleration events

One of the challenges of this research was to correctly detect deceleration events from a large volume of traffic data (25 million observations for the TeleFOT and OEM projects with observation frequency 100Hz and 7 million observations from the UDRIVE project with frequency 10Hz) that were obtained from the projects that were used. More specifically, it was difficult to choose an appropriate threshold which will indicate the occurrence of a deceleration event within normal driving conditions. Studies documented in the literature show that most drivers decelerate at a rate greater than 4.5 m/s^2 when confronted with the need to stop for an unexpected object in the roadway (AASHTO, 2004). Such deceleration is within the driver's capability to stay within the driving lane and maintain steering control during the braking manoeuvre.

Many studies through the literature have used different thresholds for describing a deceleration event depending on the purpose of each study and on the nature of the available data. For example, Naito et al. (2009) and Miyajima et al. (2011) applied a high threshold rate: i.e. 0.3g (i.e. 2.94 m/s^2), for describing and categorising deceleration events because the purpose of their study was to evaluate the driver's risk judging the way the driver brakes in emergency situations. On the other hand, Wu et al. (2009) focused on normal driving and therefore set a lower threshold value of 2 m/s^2 for comfortable longitudinal deceleration. These thresholds are between the limits of the thresholds using in Japan for detecting deceleration events, which are between 1.96 m/s^2 and 3.92 m/s^2 (Naito et al., 2009). Different thresholds were suggested by the Institution of Transportation Engineers (3.0 m/s^2) and by the American Association of State Highway and Transportation Officials (AASHTO) (3.4 m/s^2) (Maurya and Bokare, 2012).

Most of the deceleration rates observed in all projects in this work are relatively low and this may be due to the nature of naturalistic driving data, from the two FOTs and the UDRIVE NDS, which reflects driver's normal braking and does not include many safety-critical events. Therefore, the threshold was set at 2m/s^2, which is the lowest value found in the literature to detect deceleration events. This forms the <u>first criterion</u> in the detection of deceleration events.

Apart from the criterion in order to consider something as a deceleration event and detect it, the definition of the beginning and the end of a deceleration event plays an important role. Therefore, it was essential to set some more criteria. The beginning of the deceleration event is defined from the time onwards where absolute deceleration values are greater or equal to 0.1 m/s^2. In addition, the deceleration event ends when the absolute deceleration values are greater or equal to 0.1m/s^2 (criterion 2). That threshold was defined in order to exclude random noise to the actual event, since a deceleration rate which is less than -0.1 m/s^2 may just be part of normal driving and not of a deceleration event. By having only these thresholds two different problems arise: the first has to do with braking following by not fully releasing the brake and then decelerating again (Figure 4.2-a) and the other has to do with keeping a really small, (but still greater than 0.1 m/s^2) constant deceleration either before the braking or after which should not be included in the deceleration event in order to correctly calculate the deceleration profiles (Figure 4.2-b).

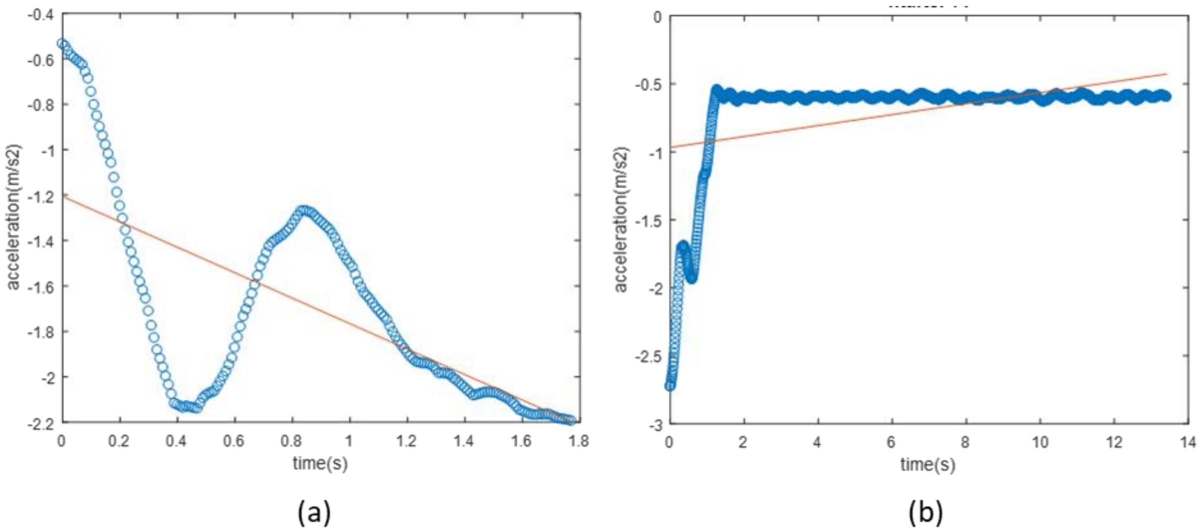


Figure 4.2: Examples of the problems during defining the deceleration events

These problems were solved by using another threshold-criterion. This threshold had to do with the rate of change of the acceleration-deceleration, i.e. jerk. Therefore, if the absolute value of the time derivative of the deceleration was smaller than 0.1 m/s^3 continuously for 0.5 sec then this will demarcate the end of the event or from this point and onwards the beginning of it (criterion 3). The values for the last threshold were obtained empirically from some of the detected deceleration events and their problematic profiles. Furthermore, this threshold agrees with the one that Murphey et al. (2009) have used to classify the driver's style using the jerk and specifically they used this threshold to specify calm from normal drivers. So, by combining the criteria 2 and 3 (Table 4.2), the start and the end of the deceleration event are defined.

Having the criteria clarified, an algorithm for the detection of the deceleration events, which satisfies those criteria (Table 4.2), was developed and was implemented through the Matlab software package. The steps that the algorithm follows are:

1. First, the algorithm detects in the dataset a deceleration event by applying the criterion 1.

2. Then, starting from the point specified from criterion 1 (i.e. a=-2 m/s^2), the algorithm searches the dataset backwards and by simultaneously applying both criteria 2 and 3, it sets the beginning of the deceleration event.
3. Finally, to define the end of the deceleration event, the algorithm finds again the point specified from criterion 1 (i.e. a=-2 m/s^2) and this times it moves forward in the dataset until the concurrent satisfaction of the criteria 2 and 3.

In addition, the algorithm computes the duration of braking events, the maximum deceleration rate (m/s^2) and the travelled distance (m) of each event.

Table 4.2: The criteria for the detection of the deceleration events

	Criterion	Purpose
1	$a \leq -2\, m/s^2$	Detection of the deceleration event.
2	$a \leq -0.1\, m/s^2$	Set the beginning and the end of the event and exclude the noise.
3	$\frac{da}{dt} \leq 0.1\, m/s^3 \;\; for \;\; duration = 0.5\, sec, (dt = 0.1s)$	Set the beginning and the end of the event and deal with the problematic profiles.

This procedure was followed to detect the deceleration events from normal driving in order to analyse them and reveal the influencing factors. Although, to analyse the comfort level of each deceleration event for the UDRIVE project, a different threshold for the maximum deceleration was set. Specifically, the first criterion changed to $a \leq -1\, m/s^2$, whereas the other two criteria remained the same. The purpose of reducing the threshold is that more soft braking events needed to be included in order to represent the most comfortable ones. The selection of the threshold for comfort analyses is explained thoroughly in Section 4.5.1.

4.2.2 Estimation of the deceleration profiles

One of the objectives of this research is to estimate the deceleration profiles in different scenarios (e.g. in different road types or in different elements). The literature review yields a variety of deceleration models (from really simple, constant deceleration to more complex linear and polynomial models (Akçelik and Besley, 2002). Deceleration value, distance and duration, together with the initial and final speeds of the event are necessary for modelling the deceleration of vehicles.

Within this PhD, three different functions are tested to represent the deceleration profile for each event, which can be assumed as typical braking patterns. For the better fit and interpretation of the functions, the deceleration event is split into two parts (Regime I and Regime II). The first part starts with the beginning of the deceleration event as was defined in the previous section and ends when the maximum deceleration occurs and in real life; this is the part where the driver presses the brake or releases the throttle. The second part begins from the maximum deceleration of the event and ends with the end of the event and depicts the release of the brake from the driver or the repress of the throttle.

The split is performed by the algorithm that was developed and implemented in Matlab. So, after the algorithm has detected the deceleration event as described in the previous section and has saved every event separately in a different file, it calculates the maximum deceleration of the event. Then, starting from the first observation of the event, it runs through the file till it meets the deceleration value that equals to the maximum one and marks that as the end of the first part of the event and the beginning of the second one. Finally, it saves each part in a different file in order to later estimate the profile for each of them. An example is shown in Figure 4.3 below.

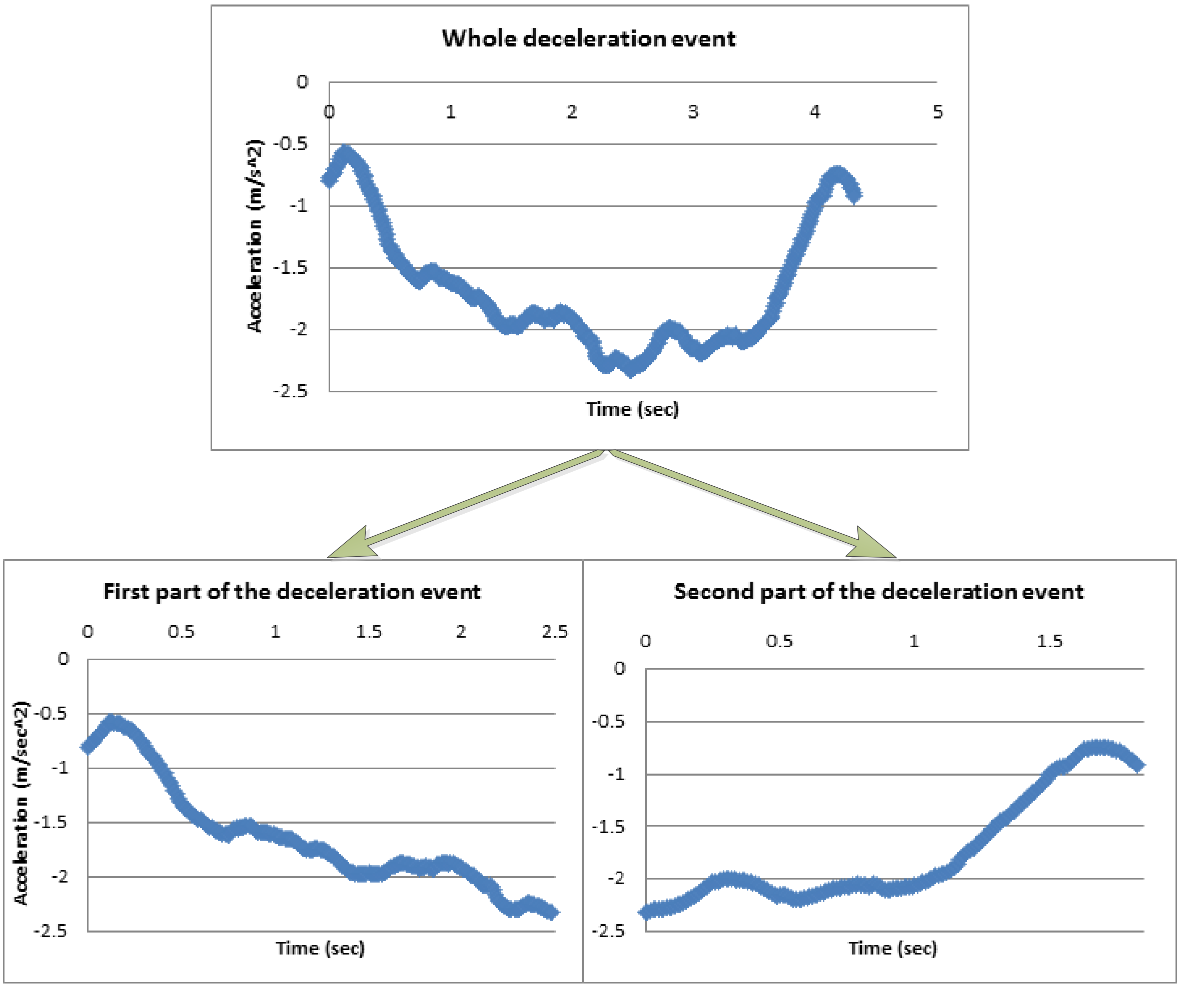


Figure 4.3: Example of the separation of the deceleration event

The next step is the estimation of the deceleration profiles. Hence, a curve fitting algorithm was developed. Three functions are tested for both parts of the deceleration events since it is of interest to understand the whole picture of the braking, i.e. how the driver press and release the brake or the throttle. The first function is the simplest and has a linear relationship between deceleration value (*a*) and elapsed deceleration time (*t*). The function is $a = p_1 \times t + p_2$ (linear equation), where p_1 and p_2 are the coefficients of the equation. In real traffic, this reflects the driver braking gradually and releasing the brake gradually too. The second function is $a = p_1 \times t^2 + p_2 \times t + p_3$ (Parabola 1-red colour in Figure 4.4) where p_1 is negative for the first part and positive for the second one. In real traffic, Parabola 1 represents for the first part of the deceleration event the situation where the driver brakes smoothly at the beginning considering enough space to stop the vehicle, though this is followed with a harder brake due to lack of space and time; for the second part it depicts that the driver presses the brake hard for some more time and after he releases it slowly. Finally, the last function is $a = p_1 \times sqrt(t) + p_2$ (Parabola 2-green colour in Figure 4.4) and represents a firm brake at the beginning of the event due to a sudden obstacle appearing, followed by gradually smoother braking since there is plenty of space to stop. As far as the releasing of the brake concerns, it illustrates that the driver releases the brake firmly. The hard press or release of the brake may also indicate that the driver obtains an aggressive driving style (Figure 4.4).

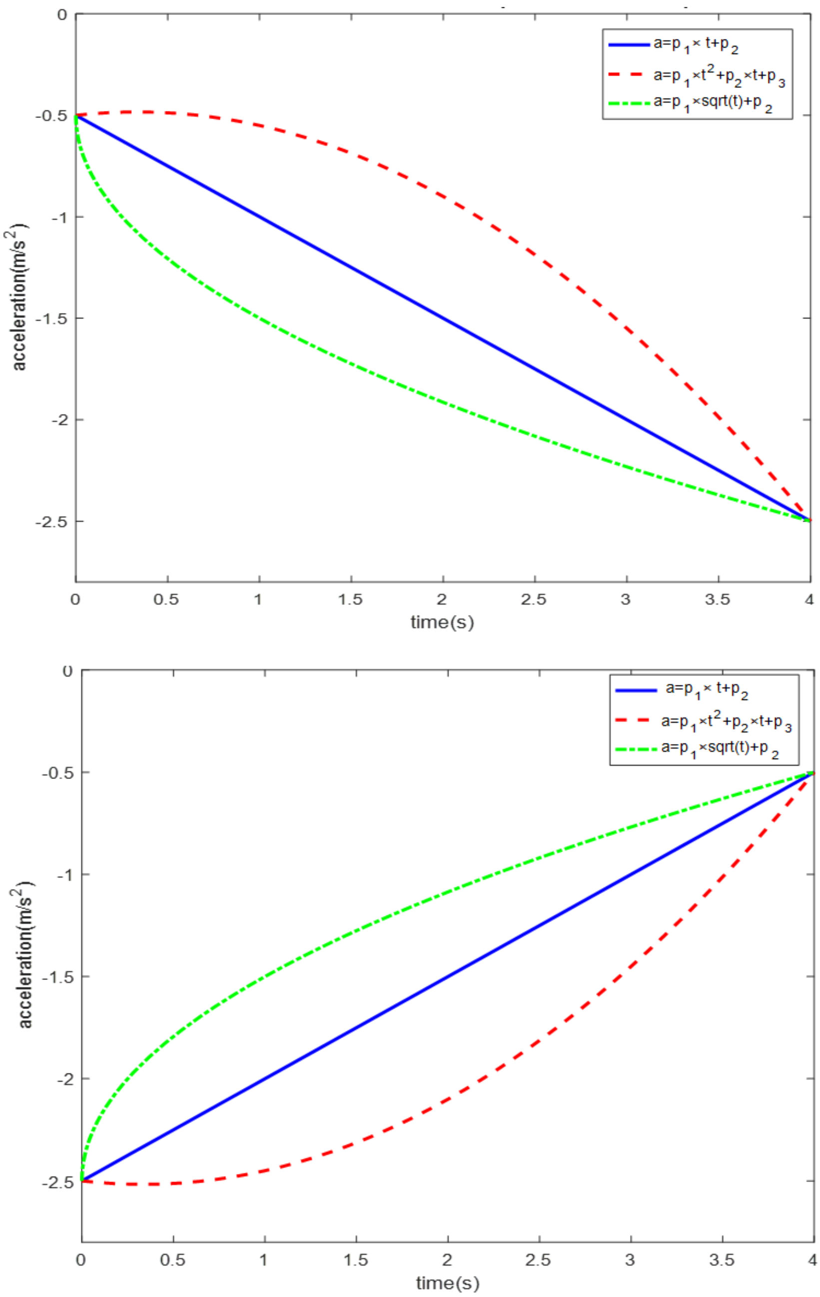


Figure 4.4: Tested functions for the first part (above diagram) and the second part (below diagram) of the deceleration event

The next step is to obtain the reference function from the tested functions described above. To judge which of the three abovementioned functions fits best to each deceleration event, the algorithm calculates the appropriate coefficients and the adjusted R square by fitting each function to the deceleration data of each event. The adjusted R^2 is a goodness of fit measure that takes into consideration the number of predictors, making it more reliable than R^2. However, to calculate the adjusted R^2, the R^2 should be found first. The R^2 is a ratio between the regression variance and the total variance of the data and is estimated by:

$$R^2 = 1 - \frac{\sum_{n=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{n=1}^{N}(y_i - \bar{y})^2} \tag{4.1}$$

where y_i is the actual observation; $\bar{y}$ is the mean value of the observations and $\hat{y}_i$ is the predicted value.

Then, the adjusted R^2 ($\bar{R}^2$) is calculated by:

$$\bar{R}^2 = 1 - (1 - R^2)\left[\frac{n-1}{n-(k+1)}\right] \tag{4.2}$$

where n is the sample size and k the number of independent variables in the regression equation.

Therefore, by comparing the adjusted R squared, the function with the maximum value is the most appropriate to represent the deceleration profile of that event and is saved as a new variable.

Up to this point, the best-fit deceleration functions for all the deceleration events have been obtained, but there is one different function for every deceleration event. Since the aim is to achieve deceleration reference functions that could describe the deceleration events in general for different scenarios, it is essential to calculate an average one for each function (i.e. linear, parabola 1 and parabola 2). Using the average of the coefficients of each event for the best-fitted function will lead to an average reference function. Aiming to explore in-depth those profiles and since the duration plays an important role, a cluster analysis was performed in SPSS for each function concluding in equations for long, medium and short deceleration events.

4.3 Multilevel modelling

4.3.1 Introduction

Many data, used in different sectors (e.g. education, social, medical, transportation) (Woltman, 2012), have a nested or clustered structure and are described as hierarchical data (Figure 4.5). Well- known form of nested data can be found in meta-analytic research, (e.g. subjects, procedures, and results data are nested within each experiment in the analysis) or in repeated measures research, where data (panel data), collected at different times and/or under different conditions, are embedded within each study participant (Osborne, 2000). More specific examples of nested data that have been studied through the literature are:

- Children within classrooms within schools;
- Patients in a medical study grouped within doctors within different clinics;
- Children within families within communities;
- Employees within departments within business locations;
- Airline passengers within flights within airports;
- Traffic measurements (speed, acceleration etc.) within trips within drivers;
- Accidents within geographic regions;
- Pilots are nested within crews which are nested within fleets.

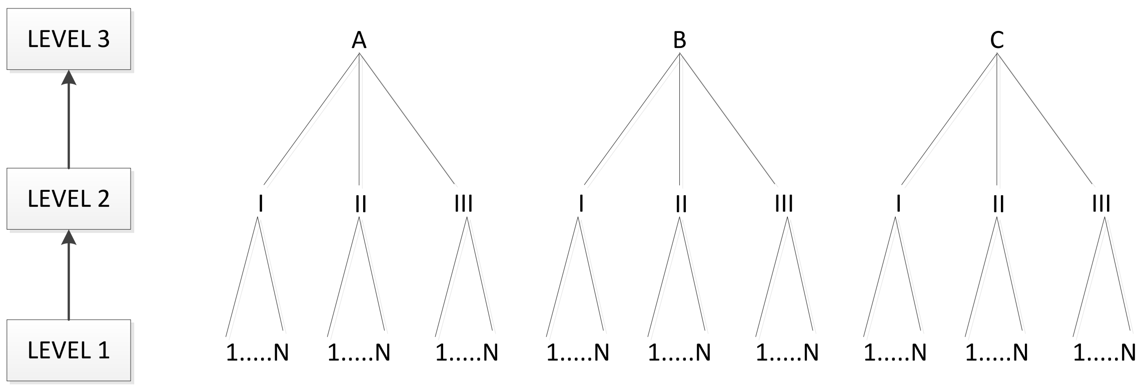


Figure 4.5: Structure of three-level hierarchical data

The analysis of hierarchical data is really challenging in the sense of selecting the most appropriate methodological approach (O'Connell and McCoach, 2004). The underlying reason is that there is a correlation among the data that belong to the same group; they seem to be more similar to each other and share some common characteristics. Therefore, nested data are not statistically independent. Most statistical analyses techniques require independence of observations as a primary assumption, making them inappropriate to analyse data with a hierarchical structure. If nevertheless, one of these methods is used, it will produce standard errors that are too small, which leads to a higher probability of rejection of a null hypothesis (Beaubien et al., 2001; O'Connell and McCoach, 2004).

The above-mentioned limitation of traditional approaches to analysing nested data can be overcome by applying multilevel models. Multilevel regression, also called hierarchical linear regression is designed for application to multilevel (hierarchical) data structures as it accounts for the statistical dependence among sequential observations in the same group (Goldstein, 2003). Moreover, multilevel models can handle unbalanced data as well as measurement occasions that in practice often vary across individuals. It is an extension of regression with the difference that the parameters are given a probability model, i.e. are allowed to vary, and it is allowed to include random effects other than those associated with the overall error term. The two key parts of a multilevel model are varying coefficients, and a model for those varying coefficients (Gelman and Hill, 2007).

Since its inception in the 1970s, multilevel regression has been widely used for analysing hierarchical data and has been developed simultaneously across many fields. Therefore, it has come to be known by several names, including hierarchical-, multilevel-, mixed level-, mixed linear-, mixed effects-, random effects-, random coefficient (regression)-, and (complex) covariance components-modelling. Multilevel regression, as mentioned above, can be used to handle clustered, grouped or data in which the measurement vary from subject to subject. It simultaneously investigates relationships within (*within-group variation*, e.g. the variance due to the differences of individuals in the same group) and between (*between-group variance*, e.g. the variance due to the differences between the observations from one group to another) hierarchical levels of grouped data. Consequently, it is more efficient in accounting for variance among variables at different levels than other existing analyses methods (Woltman, 2012).

Other approaches to deal with the analyses of hierarchical data are: the disaggregation of data, the aggregation of data and the inclusion of dummy variables to a single level model and are presented at Table 4.3 along with their challenges (Beaubien et al., 2001; Goldstein, 2003; O'Connell and McCoach, 2004; Gelman and Hill, 2007; Woltman, 2012). Disaggregation of data deals with hierarchical data issues by ignoring the structure and considering all relationships between variables to be situated at level-1 of the hierarchy (i.e. at the individual level). By bringing level 2 data down to level 1, disaggregation ignores the presence of possible between-group variation. On the other hand, aggregation of data deals with the issues of hierarchical data analysis differently than disaggregation. Instead of ignoring higher-level group differences, aggregation ignores lower-level individual differences. In aggregated statistical models, within-group variation is ignored, and individuals are treated as homogenous entities by using the average for each group.

Table 4.3: Strategies to deal with nested data

Strategy	**Consequences**
Fit a single-level model and ignore structure (disaggregation)	• the importance of context will not be measured; • too small standard errors-> incorrect inferences
Include a set of dummy variables for groups (a fixed-effects model)	• large number of groups-> large number of additional parameters to estimate; • the effects of group-level predictors cannot be estimated simultaneously with group residuals.
Fit a single-level model with group-level predictors (aggregation)	• standard errors of coefficients of group-level predictors may be severely underestimated; • no estimate of the between-group variance that remains unaccounted
Multilevel modelling (random effects)	• correct standard errors and an estimate of between-group variance.

From the Table above, it is notable that the other strategies have a lot of difficulties in dealing with nested data. Multilevel modelling is more suitable for this type of data, but this does not come without disadvantages. The motivations for using this method are:

- ✓ It provides the possibility for one variable to have an effect that varies. In many applications, it is not an overall effect of x that is of interest, but how this effect varies in the population;
- ✓ it can overtake the assumptions of traditional statistical models (i.e. independence of error, homogeneity of regression slopes) since it allows within and between-subject heterogeneity;
- ✓ the prediction is more accurate when the data vary by group. If a model ignores group effects (classical regression), it will tend to understate the error in predictions for new groups;
- ✓ it does not require same data structure for each level component and so it can handle better missing and unbalanced data; and
- ✓ it makes use of data for each and every observation or time point, increasing the power of analysis.

On the other hand, there are some difficulties in using multilevel modelling:

- ✓ It is a time-consuming method. It can accommodate any number of hierarchical levels, but the workload increases exponentially with each added level;
- ✓ it requires a different understanding of how the data are structured;
- ✓ some procedures may require specialized software; and
- ✓ the outcome variable(s) of interest must be situated at the lowest level of analysis.

As far as this research is concerned, the objective is to use a statistical model which can explain the relationship between the deceleration events under normal driving conditions and the factors affecting them. Three types of factors are considered: (1) driver factors (e.g. age, gender and driving miles per year), (2) factors relating to the trip (e.g. trip duration, car type, road type) and (3) factors related to the deceleration event (e.g. cause of braking, traffic density at this specific point). Since each driver in the used datasets had several trips and each trip had multiple deceleration events, it is obvious that the data have a hierarchical structure (the deceleration events are nested within the trips and the trips are nested within the drivers). Therefore, the deceleration behaviour can be modelled using three-level analyses i.e. the driver level, the trip level and the event level as can be seen in Figure 4.6.

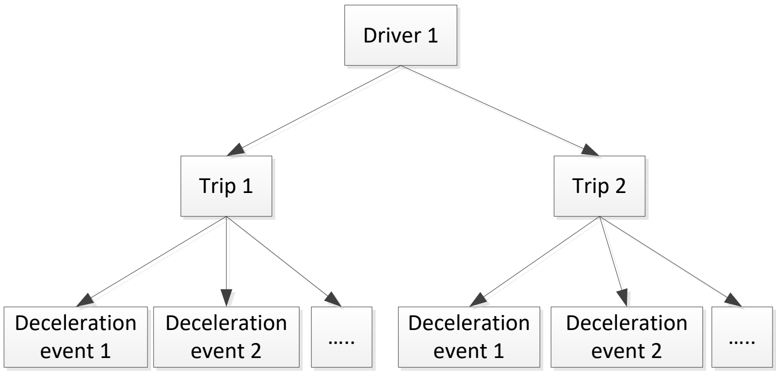


Figure 4.6: The hierarchical structure of the data of this work

Deceleration events from the same driver may have some common characteristics, for instance, if a driver is aggressive it is more possible to decelerate hard and jerkily (large deceleration value and short duration). In addition, the deceleration events are nested within trips, which may indicate some correlation among the events from the same trip (i.e. within-cluster correlation). On the other hand, there might be a variation between deceleration events from different drivers or/and different trips (i.e. between-cluster variation). Therefore, a statistical model is needed to jointly control both within- and between-cluster variations. As described above the more suitable model to overcome these problems is the multilevel mixed-effects linear regression model, and specifically a three-level random-intercept and random-coefficient model, which will be described in detail in the following section.

The multilevel model offers a more comprehensive use and a more appropriate and powerful analysis of the specific datasets than simple regression models. The mixed model allows for the full exploitation of the data that were acquired from three different studies, providing the opportunity to make use of the structure of the data and to explore as many factors as possible. It allows for dependency of deceleration characteristics for the same driver and within the same trip and examines the variation of deceleration characteristics for different drivers and different trips conducted by the same drivers. Also, it deals with the problem of consistency due to the fact that not all drivers have executed the same number of trips and not every trip has the same number of deceleration events. However, it is much more demanding in terms of software and statistical knowledge. Regarding this work, the multilevel modelling was applied using the STATA software for the two Field operational projects and the R programming language and software for the UDRIVE project.

4.3.2 Description of the model

In order to explain the multilevel model (Woltman, 2012; StataCorp, 2013), the simplest possible regression model (i.e. a model only for the mean of the dependent variable with no explanatory variables) would be described and by building up this model, it will end up at the multilevel model. So, the equation which represents the simplest regression model is:

$$y_i = \beta_0 + e_i \tag{4.3}$$

where:

y_i= dependent variable;

β_0= the mean of y;

e_i= the residuals, i.e. the difference between an individual's y value and the population mean;

Moving to the simplest two-level random effect model (equation (4.4)), the residuals are split into two components: the group-level residuals or group random effects (u_j) and the individual residuals e_{ij}.

$$y_{ij} = \beta_0 + u_j + e_{ij}$$

$$e_{ij} \sim N(0, \sigma_e^2), \quad u_j \sim N(0, \sigma_u^2) \tag{4.4}$$

where:

β_0= the overall mean of y;

u_j= the difference between group j's mean and the overall mean;

e_{ij}= the difference between y value for the i_{th} individual and the individual's group mean;

Residuals at both levels are assumed to follow normal distributions with zero means. The total variance is therefore partitioned into two components: the between-group variance σ_u^2 , based on the deviation of group means from the overall mean, and the within-group between-individual variance σ_e^2 , based on individual differences from the group means.

4.3.2.1 Testing for group effects

It is really important to test for group effects, i.e. to test if a multilevel model is more suitable to describe the data. The method that is used for this purpose is the likelihood ratio (LR) test, which is a statistical test used generally for comparing the goodness of fit of two models (the null model and the alternative one). By conducting the LR test to the models, described by the equations (4.3) and (4.4), the null hypothesis that there are no group effects: H_0 : σ_u^2=0 can be tested (i.e. H_0: single-level model is true vs. H_A: multilevel model is true). The test statistic is twice the difference in the log-likelihoods:

$$LR = 2 \times (loglikehood\ of\ the\ alternative\ model - loglikelihood\ of\ the\ null\ model)$$

In this case, the alternative model is the multilevel model and the null, the single-level one. The test statistic LR is compared with a chi-squared distribution with degrees of freedom equal to the number of extra parameters in the more complex model. The multilevel model (equation (4.4) has one additional parameter, the between-group variance σ_u^2, so there is 1 degree of freedom. Rejection of the null hypothesis implies that there are 'real' group differences, in which case the multilevel model is preferred over the single-level model. On the other hand, if the null hypothesis cannot be rejected, further exploration is still needed in order to fit a single-level model, since between-group differences may be revealed after adding explanatory variables.

4.3.2.2 Interpret variance components

There are two coefficients that describe the variance that is due to the hierarchical structure of the data: the Variance Partition Coefficients (VPCs) and the Intraclass Correlation Coefficients (*ICCs*). The ICC measures the correlation (i.e. similarity or homogeneity) of the observations within a given cluster:

$$ICC = \frac{\sigma_{\mathrm{u}}^2}{\sigma_u^2 + \sigma_e^2} \qquad (4.5)$$

The more common characteristics have the observations in the same cluster the larger the ICC. Whereas the variance partition coefficient reports the proportion of the observed response variation that lies at each level of the model hierarchy and so is due to the differences between groups. It allows establishing the relative importance of each level to the variation of the observations:

$$VPC_u = \frac{\sigma_{\mathrm{u}}^2}{\sigma_u^2 + \sigma_e^2} \text{. for level 2}$$

$$VPC_e = \frac{\sigma_{\mathrm{e}}^2}{\sigma_u^2 + \sigma_e^2} \text{, for level 1} \qquad (4.6)$$

If the observations do not statistically differ from one group to another, then the VPC equals to 0. It is noticeable that for the two-level model VPC and ICC are equivalent, but this changes in more complex models (e.g. for level 2 in a three-level model: $VPC_s = \frac{\sigma_{\mathrm{u}}^2}{\sigma_{\mathrm{v}}^2 + \sigma_u^2 + \sigma_e^2}$, $ICC_s = \frac{\sigma_{\mathrm{v}}^2 + \sigma_{\mathrm{u}}^2}{\sigma_{\mathrm{v}}^2 + \sigma_u^2 + \sigma_e^2}$).

4.3.2.3 Random intercept model

Following the description of the model, the next step is to add an explanatory variable defined at level 1 and denoted by x_{ij}. The equation becomes:

$$y_{ij} = \beta_{0j} + \beta_{10} \times x_{ij} + e_{ij} \qquad (4.7)$$

$$\beta_{0j} = \gamma_{00} + u_{oj} \qquad Level\ 2 \tag{4.8}$$

By replacing β_{0j} in the equation (4.7) with the equation (4.8), the resulting equation is the following:

$$y_{ij} = \overbrace{\boxed{\gamma_{00} + \beta_{10} \times x_{ij}}}^{\text{Fixed part}} + \overbrace{\boxed{u_j + e_{ij}}}^{\text{Random part}} \tag{4.9}$$

$$e_{ij} \sim N(0, \sigma_e^2), \quad u_j \sim N(0, \sigma_u^2) \tag{4.10}$$

This model is called a random intercept model because the intercept of the group regression lines is allowed to vary randomly across groups. The overall relationship between the dependent variable y and the explanatory variable x is represented by a straight line with intercept γ_{00} and slope β_{10}. A multilevel model can be thought of as consisting of two components: a fixed part which specifies the relationship between the mean of y and explanatory variables, and a random part that contains the level 1 and 2 residuals. The fixed and the random parts of this model are shown in equation (4.9). The fixed part is extended by adding more predictors, while the random part is extended by allowing the effect of one or more predictor to vary across groups or by allowing the within-group variance to depend on explanatory variables.

As it was mentioned above the intercept may vary from group to group, but the slope of the line β_{10} remains the same for all the groups. So, the predicted regression lines for all the different groups will be parallel as shown in Figure 4.7.

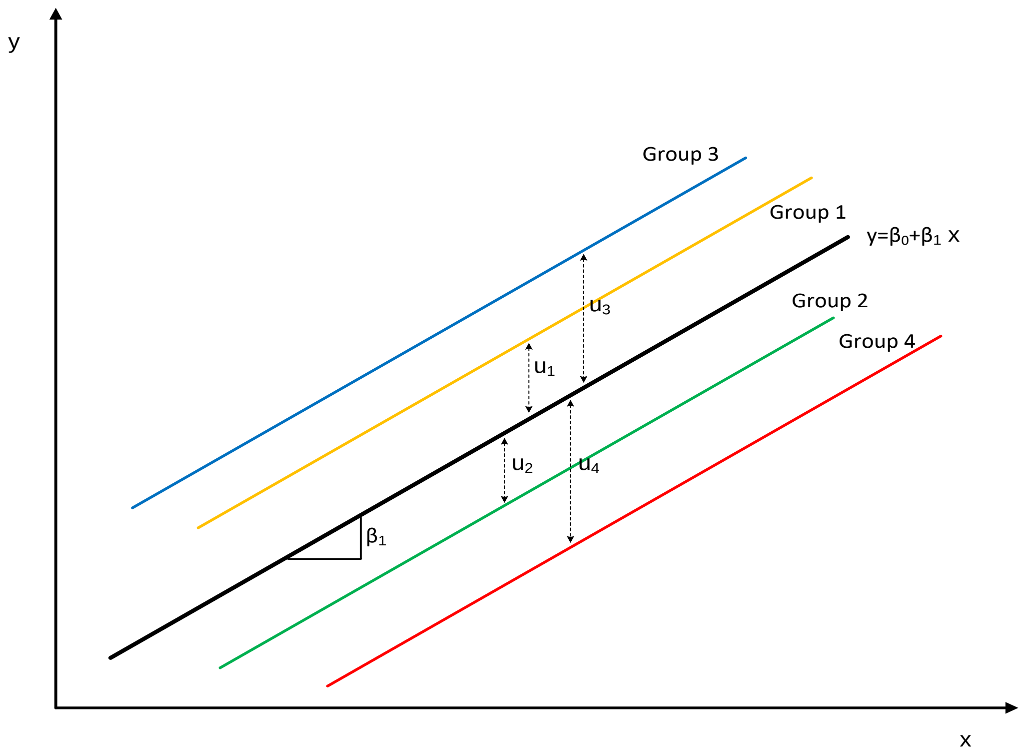


Figure 4.7: Prediction lines from a random intercept model for 4 different groups

4.3.2.4 Random Intercepts and Slopes Model (Two-level random effect multilevel model)

Sometimes the effect of the explanatory variable may differ from group to group. A random slope model allows each group line to have a different slope.

$$y_{ij} = \beta_{0j} + \beta_{1j} \times x_{ij} + e_{ij} \qquad e_{ij} \sim N(0, \sigma_\varepsilon^2) \qquad Level\ 1 \qquad (4.11)$$

$$\beta_{0j} = \gamma_{00} + u_{oj} \qquad Level\ 2 \qquad (4.12)$$

$$\beta_{1j} = \gamma_{10} + u_{1j} \qquad Level\ 2 \qquad (4.13)$$

where:

y_{ij}= dependent variable measured for i^{th} level-1 unit nested within the j^{th} level-2 unit;

x_{ij}= value on the level-1 predictor;

β_{0j}= intercept for the j^{th} level-2 unit;

β_{1j}= regression coefficient associated with for the j^{th} level-2 unit;

e_{ij}= random error associated with the i^{th} level-1 unit nested within the j^{th} level-2 unit;

γ_{00}= overall mean intercept;

γ_{10}= overall mean slope;

u_{oj}= random effects of the j^{th} level-2 unit adjusted for x_{ij} on the intercept;

u_{1j}= random effects of the j^{th} level-2 unit adjusted for x_{ij} on the slope

Now the slope of the average regression line is γ_{10} and the slope of the line for group j is $\gamma_{10} + u_{1j}$. By replacing $\beta_{0j}$and β_{1j} from the equations (4.12) and (4.13), the equation (4.11) is becoming:

$$y_{ij} = \overbrace{\boxed{\gamma_{00} + \gamma_{10} \times x_{ij}}}^{\text{Fixed part}} + \overbrace{\boxed{u_{0j} + u_{1j} \times x_{ij}}}^{\text{Random part}} + e_{0ij} \qquad e_{ij} \sim N(0, \sigma_{e0}^2), \qquad (4.14)$$

$$\begin{bmatrix} u_{0j} \\ u_{1j} \end{bmatrix} \sim N(0, \Omega_u), \quad \Omega_u = \begin{bmatrix} \sigma_{u0}^2 & \\ \sigma_{u01} & \sigma_{u1}^2 \end{bmatrix} \qquad (4.15)$$

Figure 4.8: shows the prediction lines (the average regression line and the prediction lines for four different groups) from a random slope and random intercept model.

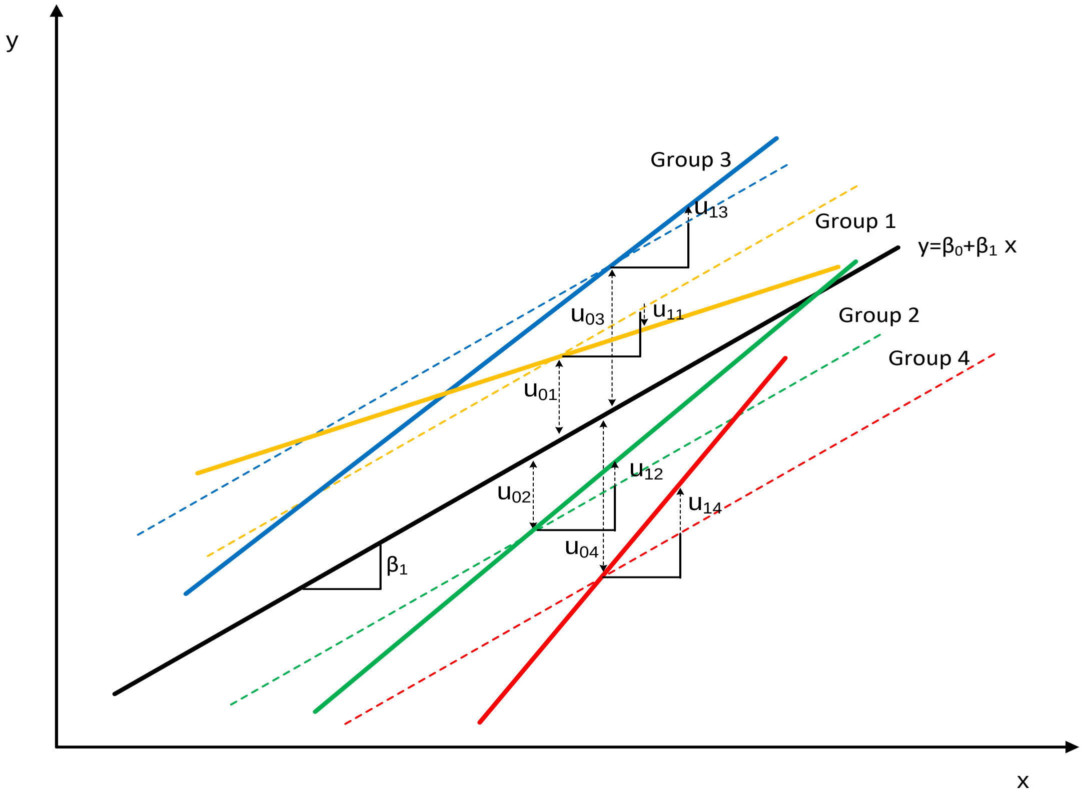


Figure 4.8: Prediction lines from a random intercept and random slope model for 4 different groups

A level 2 explanatory variable (G_j) can be included in a multilevel model in the same way as a level 1 variable. The composite equation can be expressed as:

$$Y_{ij} = \gamma_{00} + \underbrace{\boxed{\gamma_{10} \times x_{ij}}}_{\text{Level-1 predictor}} + \underbrace{\boxed{\gamma_{10} \times G_j}}_{\text{Level-2 predictor}} + \underbrace{\boxed{\gamma_{11} \times G_j \times x_{ij}}}_{\text{Cross-level term}} + u_{1j} \times x_{ij} + u_{0j} + e_{ij} \quad (4.16)$$

4.3.2.5 <u>Three-level random effect multilevel model</u>

Last but not least, the equations of a three-level mixed effect model will be displayed, so as to present how the previous equations for two-level modelling can be expanded for more levels. As mentioned above this model will be used for the two datasets. Therefore, a three-level random-effects linear regression model can be developed for a single explanatory variable (*x*) as (StataCorp, 2013):

$$Y_{ijk} = \beta_{0jk} + \beta_{1jk}x_{ijk} + e_{ijk} \qquad Level\ 1 \qquad (4.17)$$

$$\beta_{0jk} = \delta_{00k} + u_{0jk}; \quad \beta_{1jk} = \delta_{10k} + u_{1jk} \qquad Level\ 2 \qquad (4.18)$$

$$\delta_{00k} = \gamma_{000} + \vartheta_{00k}; \quad \delta_{10k} = \gamma_{100} + \vartheta_{10k} \qquad Level\ 3 \qquad (4.19)$$

The composite equation can be expressed as:

$$Y_{ijk} = \gamma_{000} + (\gamma_{100} + u_{1jk} + \vartheta_{10k})x_{ijk} + \vartheta_{00k} + u_{0jk} + e_{ijk} \qquad (4.20)$$

In which Y_{ijk} is the dependent variable for i^{th} level-1 unit nested within the j^{th} level-2 unit nested within the k^{th} level-3 unit, γ_{000} is the final model intercept, u_{0jk} is the random trip-level intercept, ϑ_{00k} is the driver-level random intercept, e_{ijk} is the event-level residual, Level-1 (event) variance of e_{ijk} is σ_e^2, Level-2 (trip) variance of u_{0jk} is $\sigma_{u_0}^2$ and Level-3 (driver) variance of ϑ_{00k} is $\sigma_{\vartheta_{00}}^2$, γ_{100} is the fixed slope coefficient for the explanatory variable *x*, u_{1jk} is the random trip-level slope coefficient for *x,* and ϑ_{10k} is the random driver-level slope coefficient for *x*. All random components are assumed to follow a normal distribution with a mean of zero and a constant standard deviation. Equation (4.20) represents a three-level random-effects linear regression model for a single explanatory variable but this can be similarly extended for multiple explanatory variables.

As far as this work is concerned, both three-level and two-level mixed effect models are used to describe the data and find the relationship between the deceleration event, more specifically the deceleration value and deceleration duration and its influencing factors. The data will be described in more detail in the Data chapter.

4.4 Cluster analysis

The next step is the creation of different scenarios based on human factors, to reflect the differences among the drivers and on the braking pattern. To accomplish that, cluster analysis will be employed. Cluster analysis is a convenient method for identifying homogenous groups of objects, sharing some common characteristics that are called clusters (Sarstedt and Mooi, 2011). The two most-used clustering techniques are hierarchical clustering and K-mean clustering, which use the hierarchical and the partitioning algorithms respectively. The hierarchical algorithm forms the clusters successively, it is a stepwise algorithm which at each step merges two objects with the least dissimilarity. On the other hand, the partitioning algorithms determine all the clusters at the same time, building different partitions. The two methods are explained in more detail in the next paragraphs.

Hierarchical clustering is one of the most straightforward clustering methods (Norušis, 2011). Most hierarchical techniques fall into a category called agglomerative clustering, which starts with each object representing an individual cluster. Then, the next step is to merge the two most similar clusters to form a new one at the bottom of the hierarchy and so on until all the objects are in one big cluster. A cluster hierarchy can also be formed with the opposite procedure (divisive clustering), i.e. all the observations form one cluster at the beginning and then they gradually split up according to their similarity till every object belongs to individual clusters (Norušis, 2011; Sarstedt and Mooi, 2011). When using hierarchical clustering, the number of clusters should be decided by the user, but it is not required before the clustering. Moreover, it can be concluded that even if it is a straightforward method, it is not suitable for a large dataset, since a distance/ similarity matrix between all pair of cases is required, i.e. the distances between all pair of cases should be calculated.

The K-mean algorithm, on the other hand, can be classified as a partitioning method and is one of the most popular clustering algorithms (Wang, 2012). It is computationally simple and can deal with large datasets. This algorithm measures dissimilarity between two objects and then assign them into k pre-decided clusters. This is one of the disadvantages of K-mean clustering method, i.e. that the number of the clusters is required before the clustering. To express (dis)similarity between objects, there have been used different measures. The most well-known one is the square of the Euclidian distance, which is the square of the straight line between them. Other distances are the Angular and Mahalanobis distance (Sarstedt and Mooi, 2011). The procedure of the algorithm conducts expectation and maximisation steps until it is converged to one solution. In the first step, the algorithm assigns all objects to k clusters whose centroids are closest to each object and in the next step, the algorithm calculates the point for each cluster that minimises the sum of the distances between this point and the objects in the cluster, which becomes the centroid for each cluster. Next, it reclassifies all cases based on the new set of means and so on. Therefore, one object can belong to a different cluster at each step, which is one more difference from the hierarchical method. This procedure is repeating until the cluster centroids do not change much between successive steps (Norušis, 2011; Jung, 2012).

Generally, K-means clustering has some advantages comparing to the hierarchical clustering; it is influenced less by outliers and irrelevant clustering variables. Furthermore, as it was mentioned earlier, K-mean clustering can handle very large-dataset in contrast to hierarchical one, since the procedure is less computationally demanding. On the other hand, K-mean algorithm can handle mostly continuous variables (interval or ratio scaled data), due to the use of the Euclidian distance. Finally, the pre-decision of the number of clusters can be challenging.

To overcome the aforementioned disadvantages, the Two-step cluster analysis was developed by Chiu et al. (2001). So, the 2-step clustering method is a scalable cluster analysis algorithm designed to handle very large datasets. It can overcome the difficulties of the other classic clustering techniques. First, it can handle both categorical and continuous variables, since it is based on the likelihood distance measure assuming that all the variables are independent. In addition, all continuous variables are assumed to follow a normal distribution and categorical variables a multinomial one (SPSS Inc., 2001; Şchiopu, 2010; Norušis, 2011). Moreover, this method can automatically determine the optimal number of clusters by calculating and comparing measures of fit such as Akaike's Information Criterion (AIC) or Bayes Information Criterion (BIC); the smaller value the better fit.

As its name reveals, this clustering technique consists of two steps: the pre-clustering step, and the clustering step (SPSS Inc., 2001; Şchiopu, 2010; Norušis, 2011; Sarstedt and Mooi, 2011). In the first stage, the algorithm aims in creating pre-clusters by undertaking a procedure where it checks if the current record should merge an existing cluster or form a new one (similar to K-mean clustering procedure). This is accomplished by the construction of a Cluster Features (CF) Tree, where the first case is being placed at the root of the tree in a leaf node that contains useful information about that case. Then, other cases are added to an existing node or are forming a new one, based on the similarities to existing nodes using the distance measure. In the process of building the CF tree, the algorithm has implemented an optional step that allows dealing with outliers, i.e. records that do not fill well into any cluster. The next stage takes the resulted leaf-nodes of the CF tree as an input and groups them using an agglomerative hierarchical clustering algorithm which allows exploring a range of solutions with a different number of clusters.

Considering the clustering procedure of this thesis. The human characteristics that will be included in the cluster analyses are the gender and the age category (19-30,31-50,51+). Specifically, the 2-step cluster analysis in SPSS will be used, due to two important advantages that have been mentioned before and are essential for this analysis. First, it can handle large dataset, by constructing a cluster features (CF) tree that summarizes the records in contrast to hierarchical clustering that is inadequate for large datasets and the two datasets that will be analysed consists of 2700 and 7160 observations. The other reason is that it can handle both categorical and continuous variables whereas K-mean clustering can only handle continuous variables and the current clustering is based on human factors and on deceleration profiles that are categorical variables. The other features that give leverage to this method, i.e. it automatically standardises all the variables, it can handle outliers and insignificant variables and it selects the best number of clusters automatically played an essential part on the selection of this method.

The procedure that it follows to select the best number of clusters is described below. The Schwarz's Bayesian Criterion is calculated for the different number of clusters. The smallest the Bayesian Information Criterion (BIC) the better the cluster analyses. The maximum number of clusters is set equal to the number of clusters where the ratio BIC_k/BIC_1 is smaller than $c1$ for the first time. In the table below the c1 has not been reached yet and so the SPSS stops at the maximum number of clusters that is set by the user, i.e. 15. Moreover, the SPSS calculates the ratio change $R(k)$ in distance for k clusters. To decide the best number of clusters, SPSS calculates the ration $R(k_1)/R(k_2)$ for the two largest values. If the ratio is larger than 1.15 the number of clusters is set equal to k1, otherwise to the largest number between k1 and k2. In this case, the 2 largest R(k) are for the 2 and 3 clusters and the ratio $R(2)/R(3)=1.14<1.15$ and therefore the 3 clusters is set as the best solution from SPSS (Table 4.4).

Table 4.4: Procedure for selecting the best number of clusters

Auto-Clustering

Number of Clusters	Schwarz's Bayesian Criterion (BIC)	BIC Change	Ratio of BIC Changes	Ratio of Distance Measures
1	19050.606			
2	15560.152	-3490.454	1.000	1.619
3	13428.661	-2131.492	.611	1.419
4	11945.290	-1483.371	.425	1.175
5	10692.548	-1252.742	.359	1.037
6	9487.064	-1205.484	.345	1.325
7	8592.616	-894.448	.256	1.121
8	7801.248	-791.368	.227	1.157
9	7126.100	-675.148	.193	1.243
10	6595.160	-530.940	.152	1.052
11	6093.612	-501.548	.144	1.167
12	5672.884	-420.728	.121	1.055
13	5277.438	-395.446	.113	1.165
14	4947.107	-330.331	.095	1.086
15	4647.895	-299.211	.086	1.021

Other useful information that is provided by the 2-step clustering is the goodness of fit which is called silhouette measure of cohesion and separation and it is based on the average distance between the object. Its value fluctuates from -1 to +1, with values less than 0.20 indicating poor solution quality, values between 0.20 and 0.50 a fair quality and values over 0.50 a good quality. Last but not least, the 2-Level clustering demonstrates the importance of each variable that was included in the procedure, showing to the user if one variable is not necessary.

4.5 Comfort level and discrete choice models

4.5.1 Calculation of comfort indices

Ride comfort is a subjective concept understood as a state achieved by the removal or absence of uneasiness and distress. There have been many attempts in the literature to evaluate the comfort inside a vehicle and to discover the factors affecting it (Martin et al. 2008; Elbanhawi et al. 2015, Bellem et al., 2016; Le Vine et al., 2015a). One of the most important and critical factors of perceived safety and comfort is the braking as a sharp deceleration is closely connected to accidents. It should be noted that deceleration is only one dimension of passengers' ride experience while braking, others include vibration and jerk (Le Vine et al., 2015a; Bellem et al., 2016).

Le Vine et al. (2015a) support that passengers of an AV will have similar behaviour with current car passengers, who start experiencing discomfort at lower rates of deceleration than car drivers. Therefore, the AV should not manoeuvre in a way that mimics exactly the human-driver operation but in a way providing greater ride comfort (Le Vine et al., 2015a). This could be taken into consideration by applying thresholds found in comfort analysis on ground public transport.

It is strongly supported that vehicle acceleration/deceleration and the time rate of change of acceleration, i.e. jerk can have a significant impact on passenger's comfort and safety (Martin and Litwhiler, 2008; Wu et al., 2009; Lu et al., 2010; Jensen et al., 2011; Powell and Palacín, 2015). As it is extendedly described in the literature review of the ride comfort there are no precise limits for comfort braking. In different words, the authors used various thresholds to achieve their objectives. For example, Gebhard, (1970) and Hoberock (1976) concluded that the range 1.08 m/s^2 to 1.47 m/s^2 (0.11g to 0.15g) is considered comfortable deceleration for more studies and regarding the jerk the value should not exceed 2.94 m/s^3 (=0.3g/s) to be perceived as acceptable. Moreover, Le Vine et al. (2015b) employed the maximum typical rates of acceleration and deceleration during revenue service for light rail speed rail, which equals 1.34 m/s^2. The limit of 2 m/s^2 was set by Abernethy et al. (1977)as the threshold of emergency deceleration, whereas in Wu et al. (2009)'s work it was the threshold of comfortable deceleration. In addition, to recognise the “hard” braking in the EuroFOT project and the 100-Car NDS, the threshold was set at 4 m/s^2.

Taking into consideration the thresholds that have been used in previous studies on comfort and since the lowest one regarding deceleration equals to 1 m/s^2 (Hoberock, 1976; Eriksson and Svensson, 2015), an algorithm that detects all the deceleration events with deceleration greater than 1 m/s^2 in absolute value was developed. This resulted in 23933 deceleration events. It is strongly supported that speed, acceleration and jerk play a crucial role to passenger’s comfort(Martin and Litwhiler, 2008; Wang et al., 2010; Jensen et al., 2011; Wu et al., 2013).

Many studies have classified events and trips as comfortable or not by using only one of those variables either deceleration or jerk (Abernethy et al., 1977; Wu et al., 2009; Vine et al., 2015) and setting different limits depicted with straight lines in Figure 4.9. Although analysing simultaneously two of them can give more accurate results in the comfort evaluation of the events.

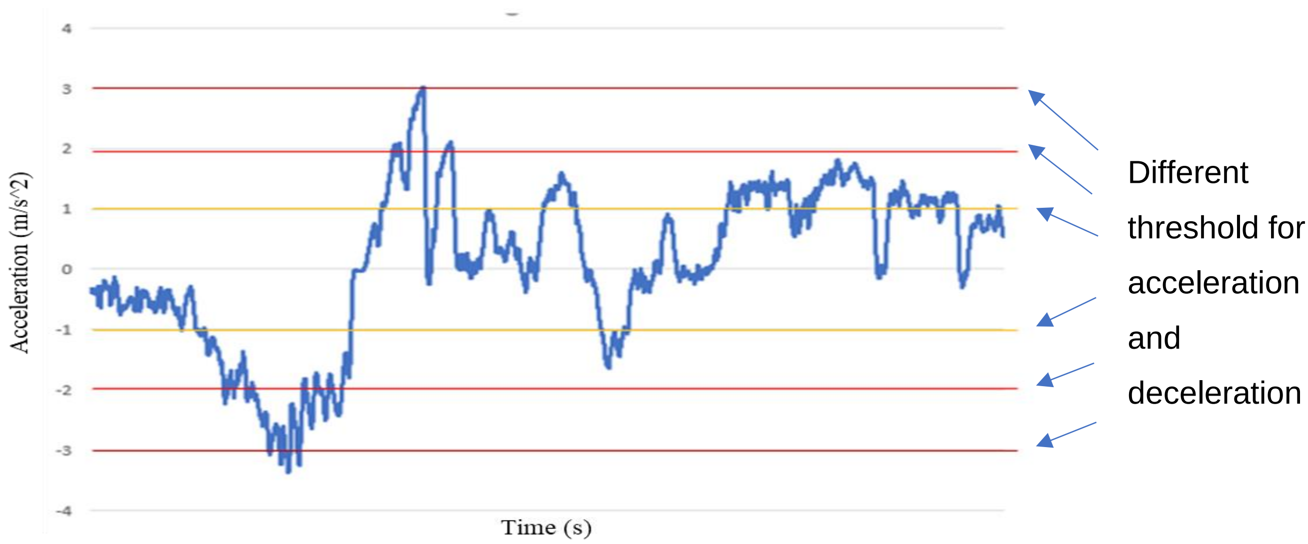


Figure 4.9: Acceleration diagram with different threshold

In this work, deceleration and jerk were employed in order to determine the comfort level of the braking events. More specifically, combining different thresholds for deceleration and jerk, the comfort categories where developed. As it was mentioned in the literature there are no determined limits that can be used to define the comfort level and each study uses different ones (Hoberock, 1976; Martin and Litwhiler, 2008; Eriksson and Svensson, 2015; Powell and Palacín, 2015). Therefore, three different sets of thresholds were used in this analysis, creating four, three and two comfort categories (Table 4.5, Table 4.6 and Table 4.7) and will be referred as classification A, B and C respectively. All three classifications were analysed and were modelled by using discrete choice modelling.

4.5.1.1 The categorisation of the events

As it was mentioned the Classifications A consists of four categories, i.e. very comfortable, slightly comfortable, slightly uncomfortable and very uncomfortable. The thresholds for the very uncomfortable zone were taken from the literature, as 4 m/s^2 was the limit for hard braking and 2.95 m/s^3 the limit of jerk to be perceived as acceptable (McLaughlin et al., 2009). The following Table presents the thresholds that defined the four categories.

Table 4.5: Thresholds for creating four comfort categories (Classification A)

Comfort Level	Deceleration (m/s^2)	Jerk (m/s^3)
Very comfortable	[-1,-2)	[0,-1)
Slightly comfortable	[-2,-3)	[-1,-2)
Slightly uncomfortable	[-3,-4)	[-2,-3)
Very uncomfortable	<-4	<-3

Next, the deceleration events should be categorised in those four categories, based on the thresholds that are presented in Table 4.5. Initially, straight lines were considered for the acceleration and jerk limits, which created phase plane limit rectangles. That resulted in assigning a deceleration event that had deceleration -2 m/s^2 and jerk close to zero to the slightly comfortable category, whereas a deceleration event that had deceleration equal to -1.9 m/s^2 and jerk equal to -0.9 m/s^3 was assigned to a more comfortable category and that was not logical. Therefore, the lines that define the comfort categories were created using ellipses based on the acceleration and jerk limits. The centre of the ellipses was set at the point (0,-1) which was the lowest values of the observations. To create the ellipses for the different comfort levels, the fact that each ellipse should pass from the adequate limits was taking into consideration. Having the form of the equation of the ellipse ($\frac{x^2}{a^2} + \frac{y^2}{b^2} = 1$) and knowing two point that the ellipse passes from, it was easy to calculate the coefficients a and b and to get the equations that separate the comfort categories (Figure 4.10). For example, to calculate the ellipse that separates the "comfortable" from the "slightly comfortable" zone, the points (-2,0) and (0,-1) where it should cross the axis were inserted in the ellipse equation and the resulted equation was: ($\frac{x^2}{4} + \frac{y^2}{1} = 1$).

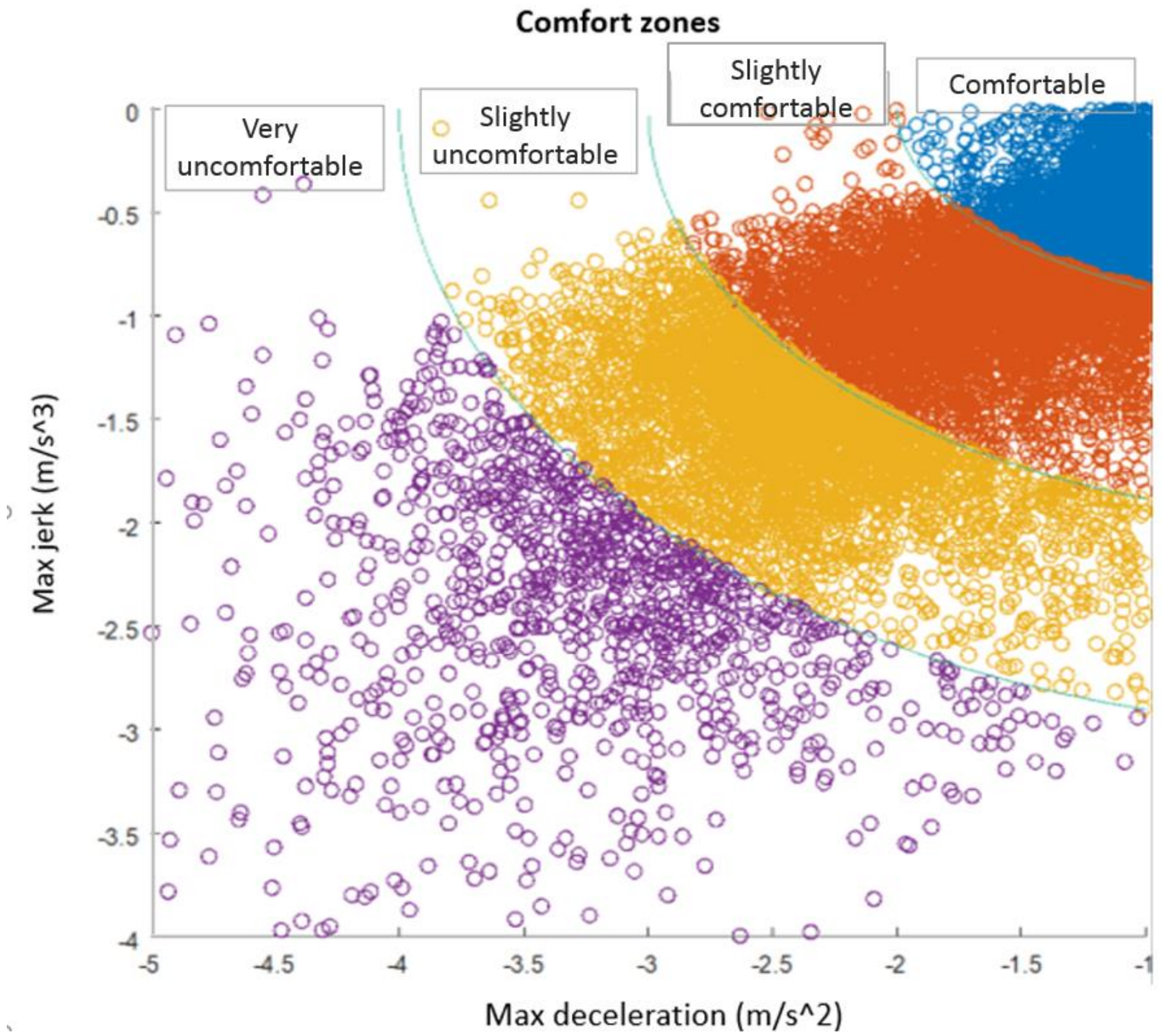


Figure 4.10: Distribution of the deceleration events at Classification A

The same approach was used to define the areas of the three and the two comfort categories. The thresholds that were used for these classifications are presented in Table 4.6 and Table 4.7 respectively.

Table 4.6: Thresholds for creating three comfort categories (Classification B)

Comfort Level	**Deceleration (m/s^2)**	**Jerk (m/s^3)**
Comfortable	[-1,-2)	[0,-1)
Neutral	[-2,-3.4)	[-1,-2)
Uncomfortable	<-3.4	<-2

Table 4.7: Thresholds for creating TWO comfort categories (Classification C)

Comfort Level	**Deceleration (m/s^2)**	**Jerk (m/s^3)**
Comfortable	[-1,-2.5)	[0,-1.2)
Uncomfortable	<-2.5	<-1.2

The procedure of assigning the deceleration events to the correct comfort category for Classification B and C is the same as for Classification A. Using the ellipse mathematical form and the adequate threshold the areas of each category were designed.

4.5.2 Description of the model

One of the primary assumptions of linear models is that the dependent variable must be continuous, unbounded and measured on an interval or ratio scale. Therefore, categorical variables cannot be modelled as dependent variables using linear models, no matter how many transformations are applied. One solution is to use discrete choice models. Discrete choice models, also called qualitative choice models are used widely in economics, in health science, in biostatistics, in transport mode preferences and in traffic safety (Pai et al., 2009; H.-A. Park, 2013; Ye and Lord, 2013; Sperandei, 2014) and can explain or predict a choice from a set of alternatives. Discrete choice econometrics is usually more challenging since discrete choice explains less the choice process than continuous-outcome choices. The logit models have been identified through the literature to be an essential tool for dealing with discrete choices (Hensher and Greene, 2003).

There are many discrete choice models, i.e. Logit, GEV (Generalized extreme value), probit, and mixed logit, but logit is by far the most widely used (K. Train, 2009). Starting with the simple binary logit model; where the dependent variable has only two categories, the multinomial logit (MNL) model and the nested logit (NL) model have been developed. The MNL model is derived under the assumption that ε_{ni} is iid extreme value for all i. The critical part of the assumption is that the unobserved factors are uncorrelated over alternatives or outcomes (also known as the independence from irrelevant alternative (IIA)), as well as having the same variance for all alternatives. However, the assumption of independence can be inappropriate in some situations (Hensher and Greene, 2003; K. Train, 2009; Ye and Lord, 2014).

To avoid the independence assumption of the MNL model, other models have been developed. GEV models, for example, are based on a generalisation of the extreme value distribution, which can take many forms. The generalisation allows the unobserved factors over alternatives to be correlated. If this correlation equals to zero, the model becomes an MNL model. Also, another GEV model placed the alternatives into groups, i.e. nests and allows the unobserved factors to have the same correlation for alternatives within a nest and no correlation for alternatives in different ones, leading to the nested logit (NL) model.

Another model category that was created to overcome the MNL model limitation is the multinomial probit models (MNP). Both those models and the GEV models existed conceptually and analytically since the 1970s. The difference of the MNP models is that they are based on the assumption that the unobserved factors are distributed jointly normal: $\varepsilon_n' = (\varepsilon_{n1}, \dots \dots .., \varepsilon_{nJ}) \sim N(0, \Omega)$. The advantage of the probit models is that they are flexible in handling correlations over alternatives and time. On the other hand, the normal distribution assumption causes some limitation, since unobserved factors may not be normally distributed.

To deal with this disadvantage, mixed multinomial logit models (MMLN) were developed. Mixed logit models allow unobserved factors to follow any distribution. The defining attribute is that the unobserved factors can be split into two parts; one that is iid extreme value distributed and one that can follow any distribution and contains all the correlation and heteroskedasticity.

To fully understand the logit models, their equations will be presented and explained. First, it should be understood that the logit of the categorical variable Y is used as the response of the regression equation:

$$\ln\left(\frac{P}{1-P}\right) = a_0+\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \tag{4.21}$$

where the logit function is the natural log of the odds that Y equals to one of the categories. Moreover, p is the probability of interested outcome; X is the explanatory variables and α and β the parameters of the logistic regression. Equation (4.21) is the simple logistic model (H. A. Park, 2013).

Generally, some of the factor affecting the dependent variable are known and observed by the researcher and some are not. The observed factors are marked X and the unobserved ε. A function y=f (X, ε) determines the relationship between the influencing factors and the choice of a category and is called utility function. This choice is not deterministic because ε is not observed. The utility function U_{ni} of the multilevel logit model can be used to express the tendency of decision-maker *i* to choose alternative *n* (Pai et al., 2009; Ye and Lord, 2014)*:*

$$U_{ni} = \propto_n + \ \beta_n X_{ni} + \ \varepsilon_{ni} \tag{4.22}$$

where:

$\propto_n$ = a constant parameter for category n, the alternative-specific constant for an alternative captures the average effect on the utility of all factors that are not included in the model.

β_n=a vector of the estimated parameters of the explanatory factors for category n; n=1,…,N representing all the comfort categories;

X_{ni}=a vector of explanatory variables affecting the comfort level for i at comfort category n (kinematic factors, driver characteristics, situational factors);

ε_{ni}= the unobserved error term that follows the Type I GEV distribution (iid extreme value); and

i=1,…., k, where k is the total number of observations, i.e. of deceleration events that are included in the model (Ye and Lord, 2013).

When the regression coefficient of an independent variable is not significantly different from 0 in the 95% confidence level (p_{value}>0.05 or t_{stat}>1.96), then this variable is removed from the model. The interpretation of the logistic regression coefficient is that it shows the change (increase if β_i>0 and decrease if β_i<0) in the predicted logged odd of having the characteristic of interest when the explanatory variable X_i change by one-unit (H. A. Park, 2013). Therefore, by taking the exponential of both sides, equation (4.21) becomes:

$$odds = \frac{p}{1-p} = e^{a_0} \times e^{b_1 X_1} \times e^{b_2 X_2} \times \ldots\ldots \times e^{b_k X_k} \qquad (4.23)$$

Increasing an independent variable X_i by one-unit and keeping all the other factors unchanged, the odds of having the category of interest will increase or decrease by a factor e^{b_i}:

$$e^{b_1(1+X_1)} - e^{b_1 X_1} = e^{b_1(1+X_1)-b_1 X_1} = e^{b_1 + b_1 X_1 - b_1 X_1} = e^{b_1} \qquad (4.24)$$

The logit probability $P_{ni}(n)$ of an observation *i* choosing category *n* is:

$$P_i(\mathrm{n}) = \frac{e^{(a_{n+}\beta_n X_{ni})}}{\sum_{\forall n} e^{(a_{n+}\beta_n X_{ni})}} \qquad (4.25)$$

Equation (4.25) shows how to calculate the probability for each comfort category.

The relation of the logit probability to representative utility is sigmoid, or S-shaped, meaning that if the utility for one alternative is relative low, then a small increase on that utility will have small impact on the probability of its being chosen whereas if this probability is close to 0.5, then any change on the utility has significant effects (K. Train, 2009).

As it was mentioned before, the MNL model has some limitations. These limitations can be overcome, by using Mixed logit model, since it allows random taste variation, unrestricted substitution patterns and correlation in unobserved factors over time. The mixed logit model is a flexible model that has been widely used after the advent of simulation techniques and the enhancement of computer power (Hensher and Greene, 2003; Ye and Lord, 2013). The utility function of the mixed logit model has the same structure as the MNL model (Equation (4.22)). The difference is that the coefficients vary over decision-makers in the population with density $f(\beta|\theta)$. The mixed logit probabilities are the intervals of the multilevel logit probabilities over a density of parameters (K. Train, 2009). In other words, a mixed logit model is any model whose choice probabilities have the following form:

$$P_i(\mathrm{n}) = \int \frac{e^{(a_{n+}\beta_n X_{ni})}}{\sum_{\forall n} e^{(a_{n+}\beta_n X_{ni})}} \; f(\beta|\theta) d\beta \tag{4.26}$$

where $f(\beta|\theta)$ is the density function of β with θ referring to a vector of parameters of the density function, i.e. mean and variance and all the other terms are as defined previously.

The mixed logit probability is a weighted average of the logit formula evaluated at different values of β across the observations, with the weights given by the density $f(\beta|\theta)$ (K. E. Train, 2009; Pai et al., 2009). In the statistics literature, the weighted average of several functions is called a mixed-function, and the density that provides the weights is called the mixing distribution. Mixed logit is a mixture of the logit function evaluated at different β' s with $f(\beta|\theta)$ as the mixing distribution.

The distribution for the coefficients should be specified and its parameters should be estimated. If there is one single issue that can cause much concern, it is the influence of the distributional assumptions of random parameters. There are different distributions that can be applied; the most popular being normal, triangular, uniform and lognormal distribution. The lognormal distribution is appealing if the response parameter needs to be a specific (non-negative) sign; however, it has a very long right-hand tail which is a disadvantage. The uniform distribution with a (0, 1) bound is sensible when we have dummy variables (Hensher and Greene, 2003). To evaluate which is the best distribution to use, multiple distributions should be used and then the outcoming models can be evaluated and compared to decide the best and most realistic one. Moreover, some logic thinking should be applied; for example, if the effect of one variable should logically be negative, a log-normal distribution might be the most appropriate choice.

Finally, to decide if an MMNL model is better than the corresponding (i.e. the one that has the same explanatory variables) MNL model, the log-likelihood test can be applied (section 4.3.2.1), since the MMNL model can be “collapse” back to the multinomial logit one. The same procedure can be used to compare different formulations of mixed logit models, provided that the new model can ‘collapse’ back into the model with which it is compared. There are two more criteria that can be used to compare the models, i.e. the AIC or Bayesian Information Criterion (BIC), where the smaller the value the better the model.

In this work, to model the level of comfort and identify the factors increasing the likelihood for a deceleration event to be perceived as uncomfortable, MNL and MMNL models were applied. The dependent variable is the comfort categories, which is a categorical variable. Moreover, the explanatory variables can be categorised at the event level variables and the driver level ones. All of them will be included in the models and the statistically insignificant ones will be removed since they do not affect the level of discomfort. The models were examined by developing code in R, using the CMC package provided by ITS Leeds (CMC (2017)) and different specifications were tested. Moreover, the distributions of the unobserved factors that will be examined are the normal, the lognormal and the exponential distribution.

4.6 Conclusion

This chapter provided a discussion of the methodology to be followed in this work. Following the research design, a statistical model (i.e. the multilevel mixed-effect model) was described in detail. This model can overcome the problem of the dependencies in the datasets and it is appropriate to describe the available data and to discover the relation between the deceleration behaviour and its affecting factors.

Moreover, the way to deal with a large amount of data was represented by detecting the deceleration event which was of interest and keeping only the data which describe this event. The problem which had to be overcome was that some data seem to be part of the event but actually were not and by including them, it would have misled the results. The different thresholds in order to overcome this problem were presented and justified.

The different deceleration profiles that were tested were presented and explained in this chapter, along with the algorithm that calculates the specific function for each event and the average reference ones. In addition, the cluster algorithms were described and specifically the 2-Step algorithm that overcomes the challenges of the large dataset and the mixture of continuous and categorical variables in the analysis.

Finally, the ride comfort and adequate thresholds for the classification of the deceleration events to different comfort level were discussed. Then, the discrete choice models and specifically the MMNL models that are capable of describing the relationship between influencing factors and comfort level are described in detail.

It should be noted that the methodology and specifically the modelling strategy was data-driven. Specifically, the statistical models that were employed were selected due to the data structure (i.e. the hierarchical structure) for the multilevel models and the desired modelled value (i.e. the comfort level) for the discrete choice models. Moreover, the criteria and the thresholds used to detect the deceleration events and to classify the comfort levels came both from theory (i.e. previous studies) and data-driven.

In conclusion, Figure 4.11: presents a flowchart of the overall methodology of this PhD.

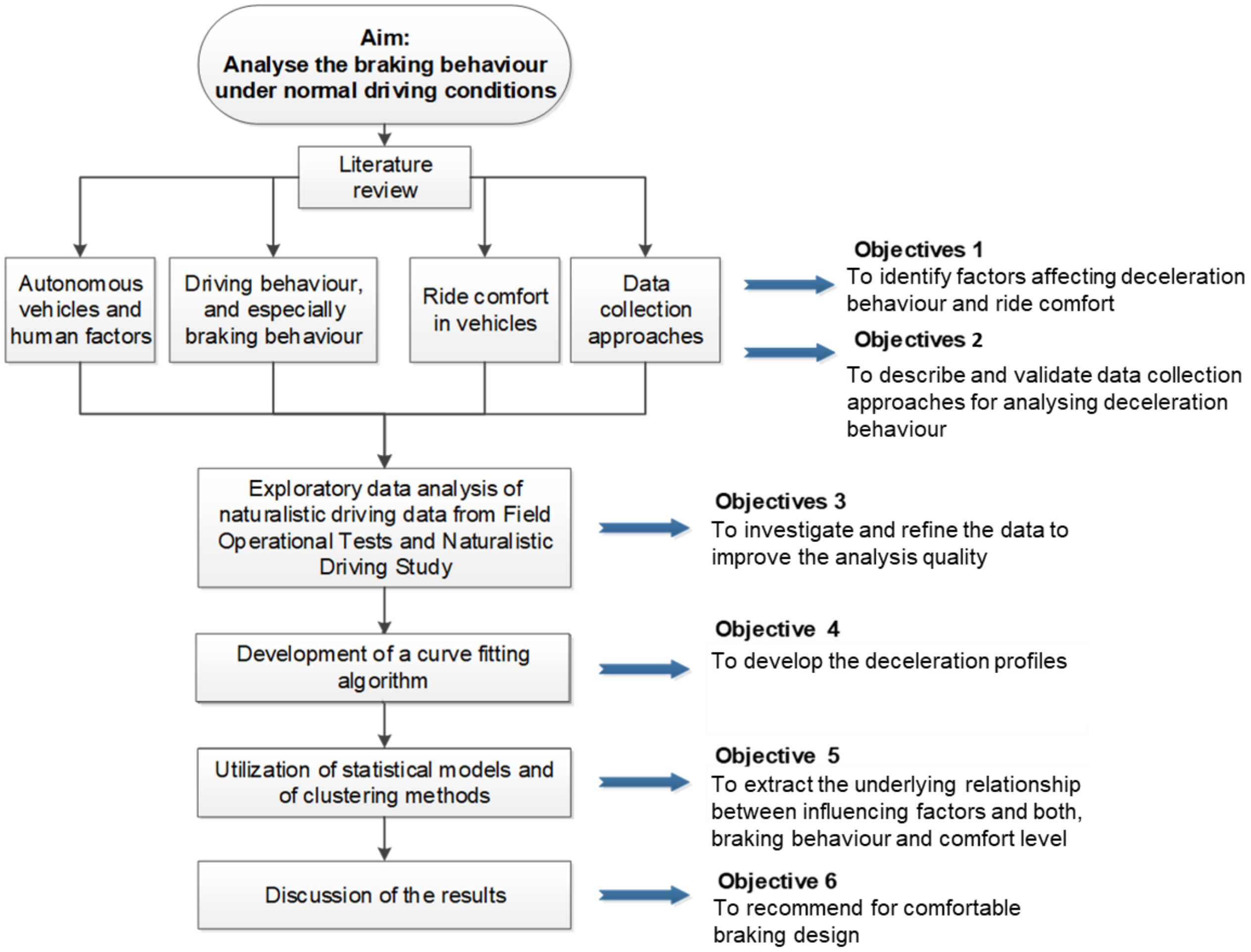


Figure 4.11: The flowchart of the methodology

5 Results of the Analyses: Deceleration Events

Employing the datasets and the methods that were discussed in Chapters 4 and 1 respectively, a series of statistical analysis have been developed by employing different mixed multilevel regression models. Those models reveal the factors that affect the deceleration events, specifically the maximum deceleration value and the duration of the event. The effect of each factor is demonstrated in detail. This chapter presents the results of the developed models in section 5.2.

In detail, the models that were tested to describe the examined variables were the random intercept two-level and three-level models and the random intercept and random slope two-level and three-level models. These models were applied to both the deceleration and the duration of the event. Each model is represented with a table that shows the coefficient estimates of the examined independent variable along with their t-statistic to prove their statistical significance and the magnitude of the effect of each variable. Moreover, in most of the cases a table that displays the LR-test to prove the most parsimonious model is presented.

The first section demonstrates the results of the calculation of the most common braking profiles for both the press and the release of the brake. The specific equations are presented in tables and plotted to be visually understood. Moreover, the results of a cluster analysis investigating in which scenarios each function is used are displayed.

5.1 Deceleration Profiles

As it was discussed in the methodology, one of this study's objectives is to reveal the most common braking profile. Three functions are tested for both parts of the deceleration events, i.e. for the press of the brake before the maximum deceleration and for the release of the brake after the maximum deceleration value. The three functions are: 1) $a = p_1 \times t + p_2$ (linear equation), 2) $a = p_1 \times t^2 + p_2 \times t + p_3$ (Parabola 1) and 3) $a = p_1 \times sqrt(t) + p_2$ (Parabola 2), where a is the deceleration value, t is the time and p_1-p_3 are the model coefficients. The best-fitted deceleration functions for all the deceleration events have been calculated and the distribution of the deceleration profiles are presented in Table 5.1. Also, the means of the adjusted R^2, which are an indication of goodness of fit, are displayed in Table 5.2 and it can be concluded that all the fitted equations show reasonable goodness of fit (Adj. R^2>0.77).

Table 5.1: Distribution of the deceleration profiles for all the datasets

REGIME I				REGIME II		
		frequency	**proportion**		**frequency**	**proportion**
OEM	fit1	490	29.30	fit1	404	23.91
	fit2	837	50.61	fit2	600	35.50
	fit3	363	20.09	fit3	686	40.59
	sum	1690		sum	1690	
TELEFOT	fit1	286	32.91	fit1	250	28.77
	fit2	292	33.60	fit2	315	36.25
	fit3	291	33.49	fit3	304	34.98
	sum	869		sum	869	
Combination (OEM+TeleFOT)	fit1	788	29.91	fit1	614	23.30
	fit2	1159	43.98	fit2	953	36.17
	fit3	688	26.11	fit3	1068	40.53
	sum	2635		sum	2635	
UDRIVE	fit1	2135	29.81	fit1	2221	31.01
	fit2	3599	50.25	fit2	1803	25.17
	fit3	1428	19.94	fit3	3138	43.81
	sum	7162		sum	7162	

Table 5.2: The mean value of the Adjusted R^2 of the fitted equations

	Adjusted R^2	
	Regime I	Regime II
TeleFOT	0.93	0.92
OEM	0.84	0.77
Combination	0.87	0.82
UDRIVE	0.82	0.79

It can be observed that the most common deceleration profile for the Regime I, which is the first part of the deceleration event from the beginning till the maximum deceleration, is the second equation, i.e. the Parabola 1. Specifically, for the OEM and the UDRIVE data, the percentage of the events following the second equations is more than 50% whereas for the TeleFOT project the proportion of the three equations is almost equal. The equation of Parabola 1 represents that the driver presses the brake smoothly at the beginning in order to evaluate the situation and then harder braking is followed. As far as Regime II is concerned, the most used profile is the third equation (Parabola 2), which depicts a firm release of the brake. More specifically, the percentage of the Parabola 2 for the UDRIVE dataset is almost 43% and for the TeleFOT dataset 41%, whereas for the data received from the OEM project the most common equation resulted to be equation 2 which represents a slower release of the brake.

In Table 5.3 the equations for the Regime I of the different datasets are presented. Those equations resulted from the average values of the equations that have been fitted for each deceleration event. Many similarities can be observed, the coefficients have almost the same values for all the datasets but TeleFOT. To illustrate the similarities and the difference, all equations are plotted in Figure 5.1. Judging from the plots, the main difference is at the duration of the events. Generally, TeleFOT events seem to have smaller duration than the others, which is depicted in the equations plotted in Figure 5.1. Moreover, parabola 2 (blue colour in Figure 5.1) and the linear equation (red colour in Figure 5.1) have shorter duration whereas Parabola 1 (green colour in Figure 5.1) depicts a longer duration to the deceleration event.

Table 5.3: Equations describing the press of the brake for all the datasets

Fit before	**Linear equation**	**Parabola 1**	**Parabola 2**
TeleFOT	$a = -2.5 \times d - 0.06$	$a = -3.4 \times d^2 + 0.35 \times d - 0.35$	$a = -1.78 \times \sqrt{d} + 0.07$
OEM	$a = -1.09 \times d - 0.22$	$a = -0.7 \times d^2 + 0.2 \times d - 0.51$	$a = -1.2 \times \sqrt{d} - 0.036$
Combination	$a = -0.96 \times d - 0.24$	$a = -0.86 \times d^2 + 0.25 \times d - 0.5$	$a = -1.19 \times \sqrt{d} - 0.03$
UDRIVE	$a = -1.12 \times d - 0.25$	$a = -0.4 \times d^2 + 0.17 \times d - 0.5$	$a = -1.46 \times \sqrt{d} - 0.16$
*where a=maximum deceleration value of the event in m/s^2 and d=duration(sec).			

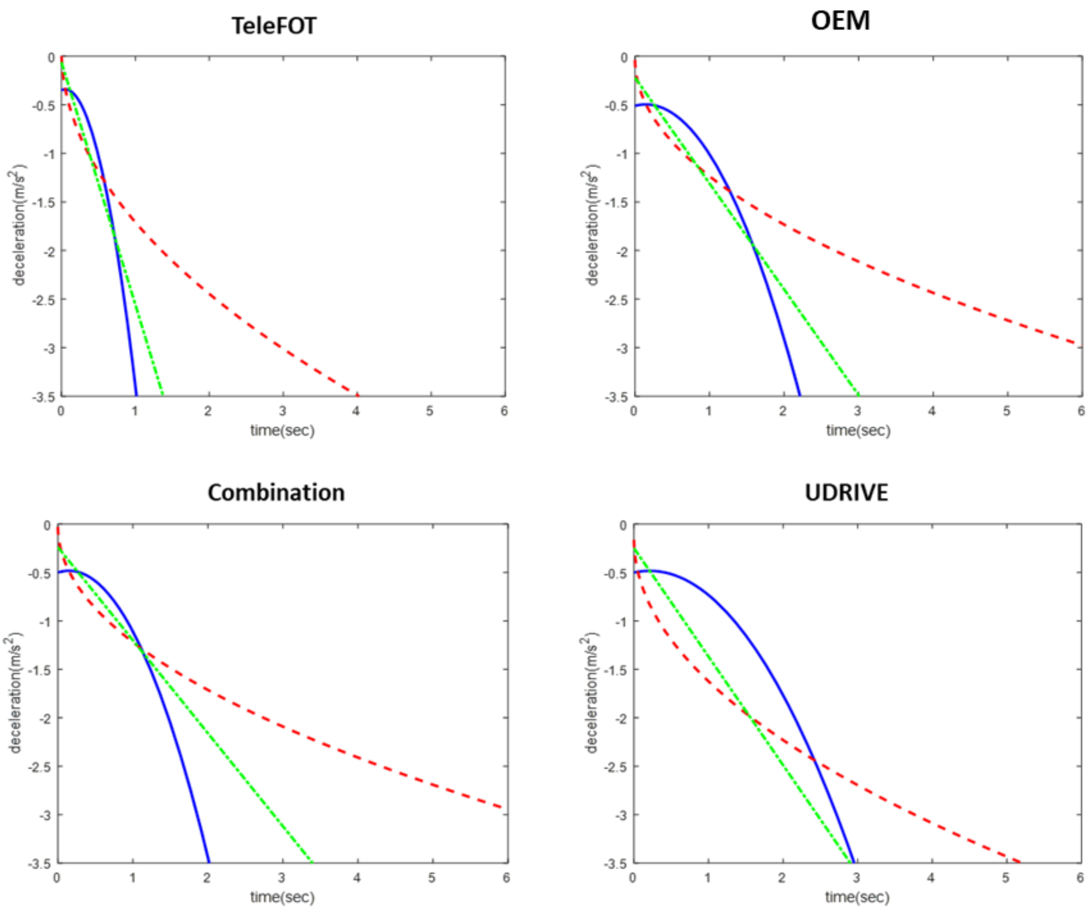


Figure 5.1: Plots of the equations representing the press of the brake

Table 5.4 includes the equations for the second part of the deceleration event after the maximum deceleration and till the end of the event (i.e. Regime II) for all the datasets, which have been plotted in Figure 5.2. The equations for all the datasets show similar characteristics; parabola 2 (blue colour in Figure 5.2) represents the shorter duration for all the datasets while parabola 1 (green colour in Figure 5.2) represents the longer deceleration events.

Table 5.4: Equations describing the release of the brake for all the datasets

Fit after	Linear equation	Parabola 1	Parabola 2
TeleFOT	$a = 2.6 \times d - 2.52$	$a = 10.23 \times d^2 + 0.13 \times d - 2.2$	$a = 2.09 \times \sqrt{d} - 2.65$
OEM	$a = 1.5 \times d - 2.64$	$a = 1.74 \times d^2 - 0.1 \times d - 2.23$	$a = 1.59 \times \sqrt{d} - 2.71$
Combination	$a = 1.38 \times d - 2.55$	$a = 1.57 \times d^2 - 0.21 \times d - 2.29$	$a = 1.05 \times \sqrt{d} - 2.5$
UDRIVE	$a = 1.6 \times d - 2.64$	$a = 1.06 \times d^2 - 0.13 \times d - 2.3$	$a = 1.51 \times \sqrt{d} - 2.59$
*where a=maximum deceleration value of the event in m/s2 and d=duration(sec).			

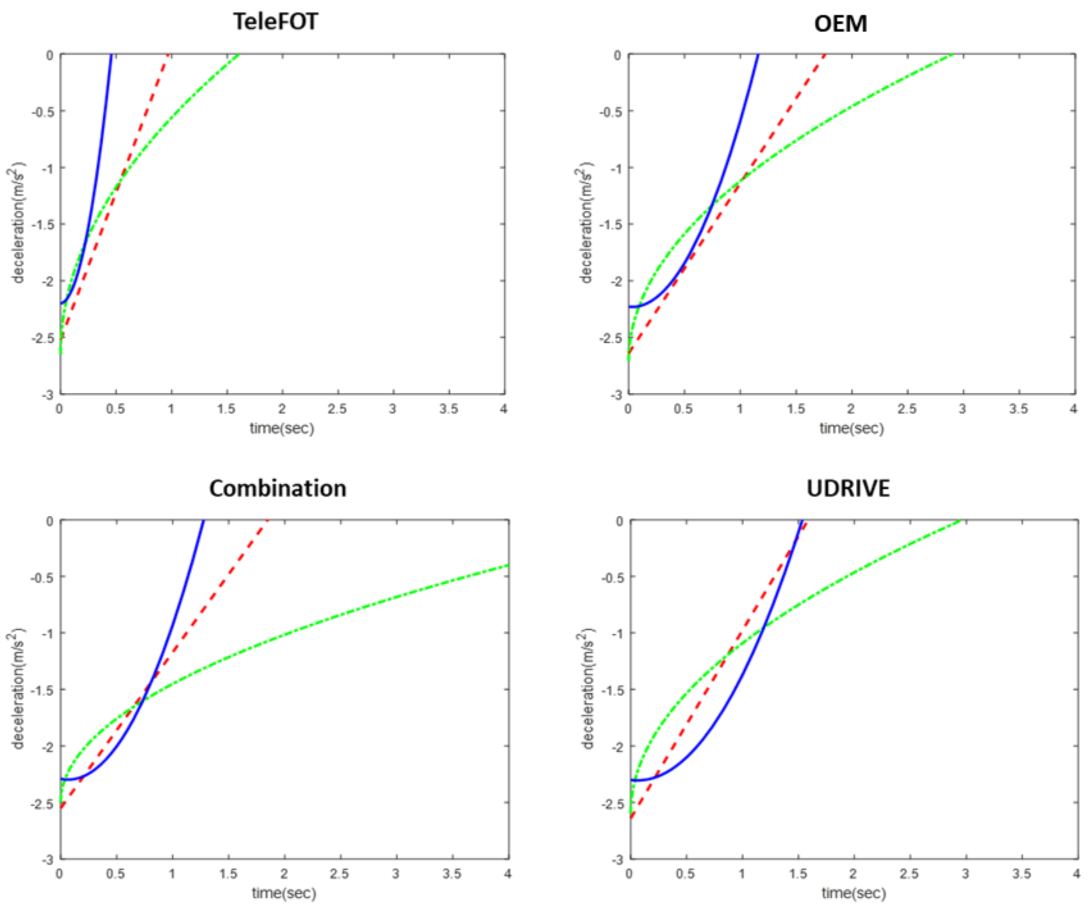


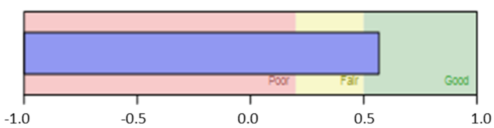
Figure 5.2: Plots of the equations representing the release of the brake

It can be observed that duration plays an important role in the profiles and the values of the coefficients. Therefore, a more detailed analysis was undertaken to investigate the formulation of the different profiles depending on the duration. To achieve that, a 2-step cluster analysis was performed for each profile and an example is displayed in

Model summary

Algorithm	TwoStep
Inputs	3
Clusters	3

Cluster Quality



Clusters

Input (Predictor) Importance

1.0 0.8 0.6 0.4 0.2 0.0

Cluster	1	2	3
Size	77.6% (2722)	18.8% (660)	3.6% (125)
Inputs	Duration (Regime I) 4.18	Duration (Regime I) 10.90	Duration (Regime I) 1.35
	p1 (Regime I) -0.31	p1 (Regime I) -0.03	p1 (Regime I) -4.25
	p2 (Regime I) 0.13	p2 (Regime I) 0.09	p2 (Regime I) 1.32

Figure 5.3. The cluster took into consideration the duration and the coefficients of the equations for each event, apart from the constant which did not show any differences based on the duration. The cluster showed fair goodness of fit and all the variables were significant. This procedure was applied in all the datasets, however only the representative results of UDRIVE dataset will be displayed for similarities reasons. The results for the first part of the deceleration are presented in Table 5.5 and Figure 5.4. The majority of the deceleration events occurred within the medium duration, a small percentage (only 3.6% of the deceleration events) for Parabola 2 happened in short duration, whereas for Parabola 3 40% of the events had a short duration and only 12.7% had a long one.

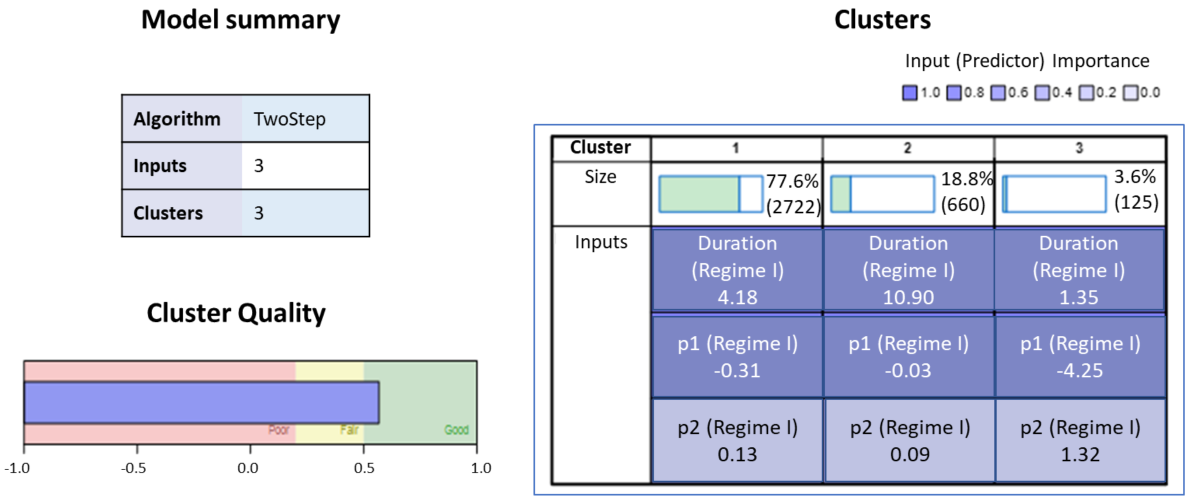


Figure 5.3: Example of the cluster analysis for Parabola 1

Table 5.5: Results of the detailed analyses of the first part of the deceleration profiles based on the duration

Deceleration events	Count	Percentage	Duration	Coefficient 1	Coefficient 2
EQUATION 1					
Short duration	393	18.6%	1.08	-3.11	NA
Medium duration	1346	63.6%	3.42	-.78	NA
Long duration	377	17.8%	8.59	-.25	NA
EQUATION 2					
Short duration	125	3.6%	1.35	-4.25	1.32
Medium duration	2722	77.6%	4.18	-0.31	0.13
Long duration	660	18.8%	10.9	-0.03	0.09
EQUATION 3					
Short duration	484	40%	1.71	-2.26	NA
Medium duration	573	47.3%	4.39	-1.02	NA
Long duration	154	12.7%	9.62	-0.62	NA

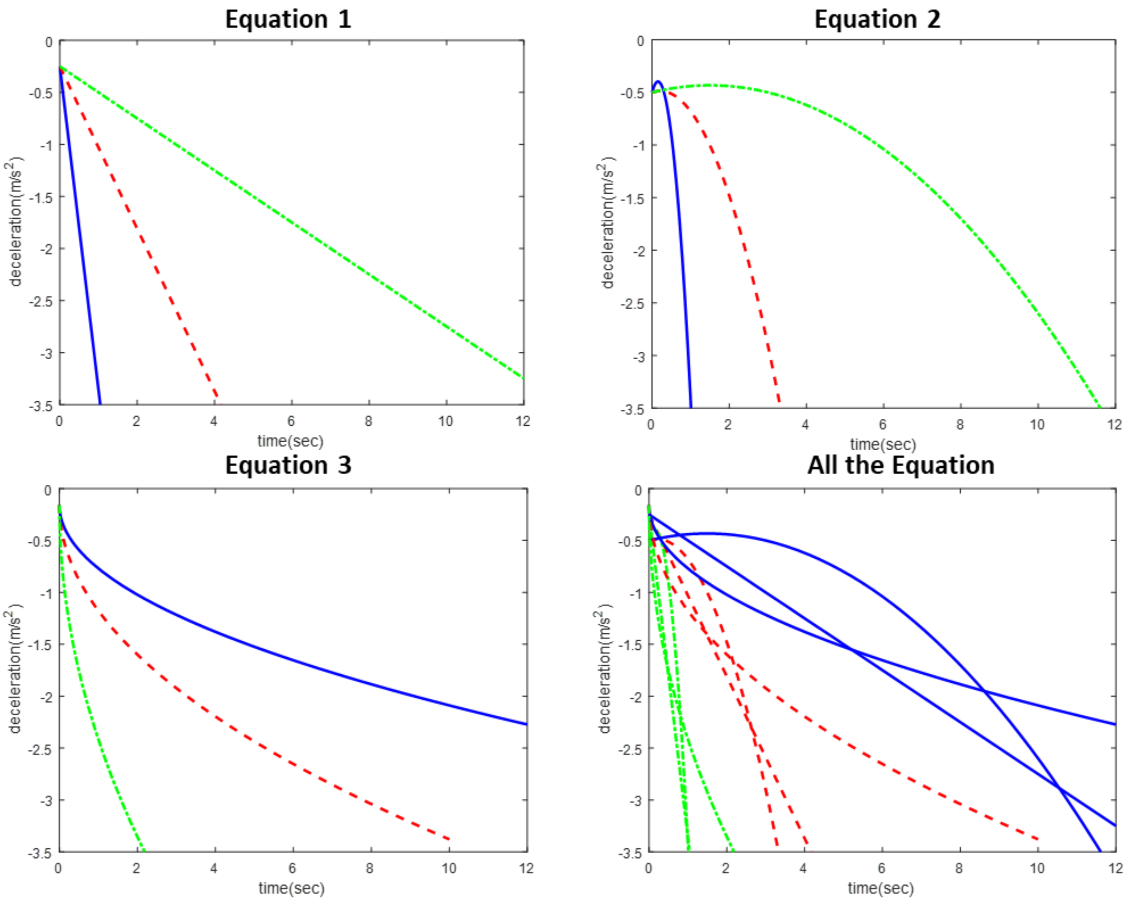


Figure 5.4: Plots of the equations for the first part of the deceleration based on the duration

The same procedure was followed for the part after the maximum deceleration, resulting in Table 5.6 and Figure 5.5. The medium duration is the dominant one with percentages from 47.3% to 67.3%, whereas short and long duration have almost equal percentages apart from equation 3 that short duration reaches 40% and long duration only 12.7%.

Table 5.6: Results of the detailed analyses of the second part of the deceleration profiles based on the duration

Deceleration events	Count	Percentage	Duration	Coefficient 1	Coefficient 2
EQUATION 1					
Short duration	318	14.5%	0.8	4.46	NA
Medium duration	1480	67.3%	2.3	1.4	NA
Long duration	402	18.3%	5.46	0.44	NA
EQUATION 2					
Short duration	357	21.8%	1.26	3.34	-0.53
Medium duration	897	54.9%	2.4	0.56	-0.05
Long duration	381	23.3%	5.9	0.09	-0.16

EQUATION 3					
Short duration	484	40%	1.71	-2.26	NA
Medium duration	573	47.3%	4.39	-1.02	NA
Long duration	154	12.7%	9.62	-0.62	NA

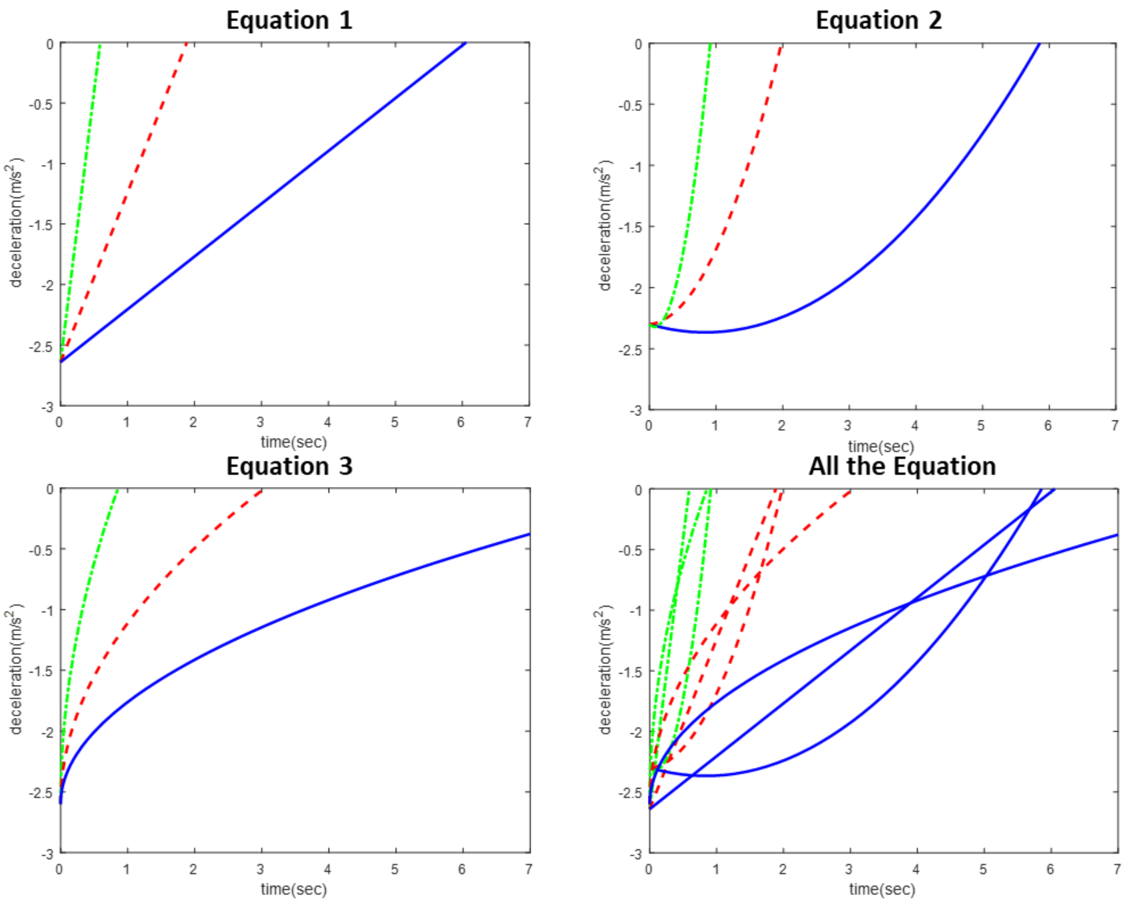
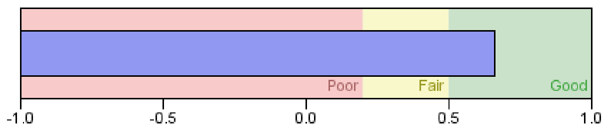
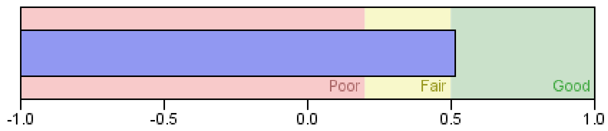
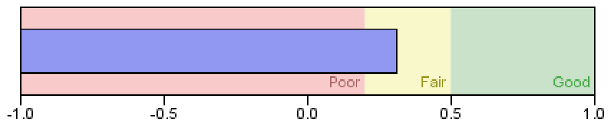
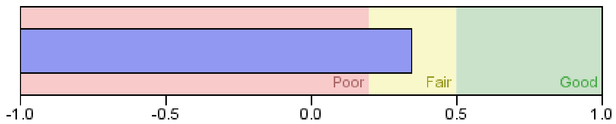


Figure 5.5: Plots of the equations for the second part of the deceleration based on the duration

After obtaining the profiles that people used to brake, it is interesting to investigate when the driver is conducting which profile. To achieve that the OEM data was utilized, and a cluster analysis was performed. For the cluster analyses, the two-step cluster method was used, and it was conducted in SPSS. Different scenarios were examined in order to determine which factors affect the profile of the deceleration and in which scenarios the driver chooses to brake with which profile. Specifically, the variables included in the cluster analyses vary in each scenario between the explanatory factors e.g. gender, age, road type etc., but the selected profile was always included and should be significant. Table 5.7 summarises the different tested scenarios.

Table 5.7: Different clusters to investigate the factors affecting the braking profile

ID	Variables	Cluster Quality outcome
1	Age_categories Driver_ID Male_or_not Road_type	Poor
2	Road_type Car_ID	3 clusters Fair quality
3	Road_type Male_or_not Age_categories	Poor(insignificant)
4	Male_or_not Age_categories	Poor (insignificant)
5	Road_type TripID	Poor (insignificant)
6	Road_type Trip_duration(min)	Too many clusters
7	Road_type Trip_duration(min) Car ID	Too many clusters
8	Road_type Initial speed Car ID	Poor(fit_bef->insignificant)
9	Road_type Initial speed	Too many clusters
10	Road_type Initial speed density	4 clusters Fair quality
11	Initial speed density	Speed not significant
12	Initial speed Density Cause of braking Traffic light	Fit not significant
13	Density Cause of braking Traffic light	Fit not significant
14	Density Cause of braking	4 clusters Fair quality
15	Cause of braking	5 clusters 

16	Cause of braking Initial speed	5 clusters 
17	Road type Cause of braking	3 clusters 
18	Density Road type	3 clusters 
19	Road type Traffic light	Too many clusters

If there were too many clusters, it was a classification giving no useful information about the use of each profile. The best results were given from the scenarios 15,16,17 and 18, supporting that the cause of braking and the road type play an important role. Specifically, from cluster 15 it was concluded that if the reason for braking is the approach of a junction, then the deceleration profile follows either a linear equation or parabola 1 whereas if there is a roundabout, parabola 1 is the most used. Moreover, if there is an obstacle the driver brakes firmly (parabola 2) or in a linear way. The clustering analysis 17 shows more combined results. Specifically, if the driver is on a rural road but s/he brakes before a junction, the deceleration follows the linear function, whereas if the driver brakes because of an obstacle, the deceleration follows parabola 1. Finally, the last good clustering analysis (analysis 18) shows that if the traffic density is low and the road type rural, the deceleration follows either parabola 1 or the linear equation, whereas if the traffic density is medium and the road type urban, the deceleration follows parabola 1.

5.2 Multilevel modelling

After identifying the deceleration profiles, a statistical analysis was undertaken in order to reveal which factors affect the deceleration events and how. The most important features describing a deceleration event are the maximum deceleration value and the duration, therefore, both features will be explored as dependent variables by separate statistical analysis. As it was discussed in the Methodology Chapter, the most appropriate statistical model based on the structure of the data is the multilevel mixed-effect model. This analysis was applied to all the datasets and the results are presented in the following sectors, named after the dataset. The procedure to reveal the best fitted statistical model in multilevel modelling is to first compare the null models, i.e. the model without having any explanatory variables, for no level, two-level and three-level using the LR-test. Then, the best linear regression model is calculated, revealing the independent factors that affect the deceleration value and duration. After that step, two types of multilevel model were estimated: (1) random-intercept model and (2) random- intercept and random- slope model for the two and the three-level depending on the results of the LR test and the intra-class coefficient. Each of the variables has been examined to determine whether or not the effect of the variable (i.e. the slope coefficient) varies across the examined level by conducting the LR test. For space purposes, not all the models can be displayed so the most parsimonious models will be presented in this Chapter for all the datasets and the result will be explained and compared. The LR test tables along with some good models can be found in the Appendix B.

5.2.1 OEM

The variables that were included in the statistical analysis for the OEM dataset, for both dependent variables, i.e. deceleration value and duration are presented in Table 5.8. The variables can be categorised into the driver, the trip and the event level.

Table 5.8: Variables including in the analysis of the OEM data

Variable's category	Variable's name	Variable's level
Car_model	Vehicle A	Trip level
Vehicle B as reference	Vehicle C	
Road_type	Rural	Trip level
Motorway as reference	Urban	
	Trip duration (min)	Trip level
	Male	Driver level
Age categories	Age_young	Driver level
Age_middle	Age_old	
Driver's reaction	Driver_reaction_1	Event level
Driver_reaction_2 as reference	Driver_reaction_3	
	Driver_reaction_4	
	Stops_at_car_block	Event level
	Traffic light	Event level
Traffic density	Medium_density	Event level

Low_density as reference	High_density	
<u>Reason for braking</u>	Roundabout	Event level
Obstacle_on_road as reference	Junction	
	Pedestrian crossing	
	Other	
	Driver ID	
	TripID	
	Distance	Event level
	Initial speed	Event level

In order to perform a three or a two-level analysis, it has to be ensured that there are enough observations to describe each level. In this case, enough trips per car/drive/road type (for the three-level modelling) and enough events per trip/car/driver/road type (if a two-level analysis is more suitable). Therefore, the adequate values were calculated and are presented in Table 5.9.

Table 5.9: Number of observations for each level of the analysis for OEM data

	Mean	Std. Dev.	Min	Max
Trips per car model	43.67	13.28	36	59
Trips per road type	43.67	0.58	43	44
Trips per driver	10.92	2.11	6	12
Events per driver	140.83	32.25	104	194
Events per road type	563.33	311.29	204	751
Events per car model	563.33	96.03	466	658
Events per trip	12.90	8.39	2	34

5.2.1.1 <u>Deceleration value</u>

First, the regression model, which is simpler than the multilevel ones, is tested. After trying different combinations for the independent variables and different model combination, i.e. log_transformation of the independent and the dependent variables with linear ones, the most parsimonious model (highest R^2 and all the variables statistically significant) was the linear-linear one. The adj. R^2 =0.1228 and so 12.3% of the deceleration values can be explained well by this model. This is not a high percentage and it is not satisfactory. Therefore, it is of high importance to test for group effects, i.e. to test if a multilevel model is more suitable to describe the data.

5.2.1.1.1 2-Level null model

First, the 2-level models will be analysed. In this dataset, there are 4 different levels (i.e. driver, trip, road type, car model level) in which the events are nested. It is important to mention that in the data, there are 12 different drivers, 131 different trips, and 3 different cars and road types. Thus, all the possible 2-level models are examined, and the results are presented in Table 5.10.

Table 5.10: LR test for the 2-Level null models of deceleration value for OEM dataset

2-LEVEL (null models)	Log-likelihood	ICC	LR	Chi Probability	Better model
Single level	-1322.89				
2-level-driver	-1306.67	0.031	26.82	3.84	yes
2-level-trip	-1289.93	0.098	50.97	3.84	yes
2-level-roadtype	-1302.92	0.025	39.93	3.84	yes
2-level-car	-1305.78	0.023	34.20	3.84	yes

The single null model (no independent variables) has been calculated too, in order to judge if there are group effects. The method that is used for this purpose is the LR test, which is a statistical test used generally for comparing the goodness of fit of two models (the null single-level model and the alternative 2-level one). By conducting the LR test to two models, the null hypothesis that there are no group effects: H0 : σ_u^2=0 can be tested (i.e. H0: the single-level model is true vs. HA: the multilevel model is true). The test statistic is twice the difference in the log-likelihoods:

$$LR = 2 \times (loglikehood\ of\ the\ alternative\ model - loglikelihood\ of\ the\ null\ model)$$

In this case, the alternative model is the multilevel model and the null, the single-level one. The test statistic LR is compared with a chi-squared distribution with degrees of freedom equal to the number of extra parameters in the more complex model. The multilevel model has one additional parameter, the between-group variance σ_u^2, so there is 1 degree of freedom. From the table above, it is concluded that we can reject the null hypothesis (LR>chi probability), which implies that there are ‘real’ group differences, so all the 2-level models are preferred over the single-level model.

Also, it can be seen from Table 5.10 that the trip-level model has the highest ICC (0.098), which means that deceleration from the same trip has some higher correlation than deceleration from the same driver or from the same car or at the same road type. Specifically, 9.8% of the variation in deceleration values lies between trips and the rest lies between events in the same trip. Respectively, the variation on the other levels can be interpreted. Moreover, the ICC of the road type and the car model level is very low, indicating that there is no strong group effect in these categories.

Moreover, on that point, it is useful to predict and examine the effect from each level. Here we present the driver effect since we have 12 drivers that are enough to detect the differences. So, from the null driver-level model, the predicted random effects and the associated standard errors for each driver were calculated (Table 5.11). Looking at these values and at Figure 5.6, 4 out of 12 drivers differ significantly from the average driver. The drivers 7 and 10 are predicted to brake the hardest, while the drivers 12 and 1 are predicted to brake softer. By observing the same graph for the trip level, it can be noted that in most of the trips the deceleration values are within the values of the average trip. Only around 10 trips differ significantly, presenting harder braking. Also, from both plots, it is obvious that the confidence intervals around the predicted effects vary greatly in their length. Finally, it should be noted that because the independent variables have not been considered yet, the effects plotted here are very likely not to reflect just driver or trip effects, but some effects from the independent variables too.

Table 5.11: Predicted random effects and standard errors for each driver for 2-Level driver model

DriverID	v1	v1se	v1rank
10	-.1383269	.0447882	1
7	-.131584	.0351041	2
9	-.0744652	.0432204	3
8	-.0586784	.0423553	4
4	-.0247064	.0429262	5
6	-.011801	.0347125	6
2	.0338556	.0393507	7
11	.0455511	.0383783	8
5	.0614487	.0411497	9
3	.0688475	.0411497	10
12	.1129857	.035427	11
1	.1168731	.0433698	12

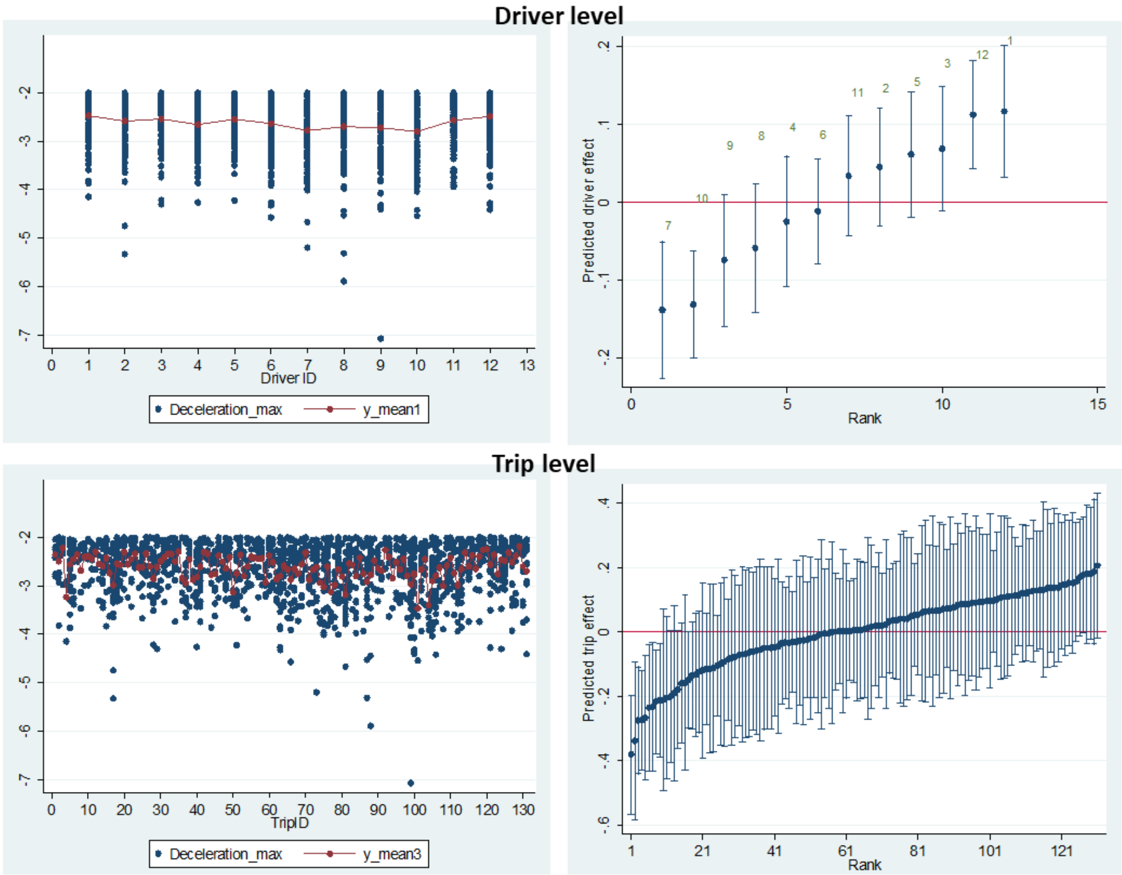


Figure 5.6: Plots representing the driver and trip effects in the deceleration values for the 2-Level null models for OEM dataset

5.2.1.1.2 3-Level null model

As it was previously discussed, the structure of the data reveals the existence of a three-level structure (events nested into trips nested into drivers). So, the three-level model was tested with the LR-test against the corresponding 2-level models, e.g. the driver-trip three-level model was tested against the 2-level driver and the 2-level trip model.

Table 5.12: LR test for the 3-Level null model of deceleration value for OEM dataset

3-level	log-likelihood	level	ICC	model	Log-likelihood of 2-level	LR-TEST	Degree of freedom	Chi prob.	Better model
model1 (driver-trip)	-1285.94	driver_id	0.027	model1 (driver level)	-1306.67	41.46	1	3.84	yes
		trip_id	0.1	model2 (trip level)	-1289.93	7.98	1	3.84	yes
				null model	-1322.89	73.90	2	5.99	yes

From Table 5.12, it can be concluded that the null three-level model is better than the corresponding null two-level ones. Although, this must be further examined as the independent variables are added to the model. The predicted effect of the driver-trip level model will be presented for a better understanding of the effect of the different levels. The predicted driver effects are listed in the following table:

Table 5.13: Predicted random effects and standard errors for each driver for the 3-Level model

DriverID	v0	v0se	v0rank
7	-.1316937	.0481766	1
10	-.1153911	.057785	2
9	-.044435	.0586832	3
8	-.0295861	.0523007	4
4	-.0202643	.0530608	5
6	-.0135994	.0479679	6
11	.0328924	.0501375	7
2	.037428	.0511774	8
5	.041648	.0510103	9
3	.0658264	.0508932	10
12	.0873516	.0493129	11
1	.0898232	.0526893	12

Comparing the driver effects in the 3-Level model with the driver effect in the 2-Level one, the values of the effect changes as well as the sequence of the drivers, implying that a different model structure affects the effects on the deceleration value.

Since there are 131 trips, the predicted trip effects are summarised rather than being listed in a table:

Variable	Obs	Mean	Std. Dev.	Min	Max
u0	131	4.49e-11	.0951444	-.2764184	.1700764

So, the trip effects range from -0.276 to 0.1701, while the driver effects range from -0.132 to 0.09 which is a smaller range. The magnitudes of the driver and the trip effects are presented in the next graph (caterpillar plot).

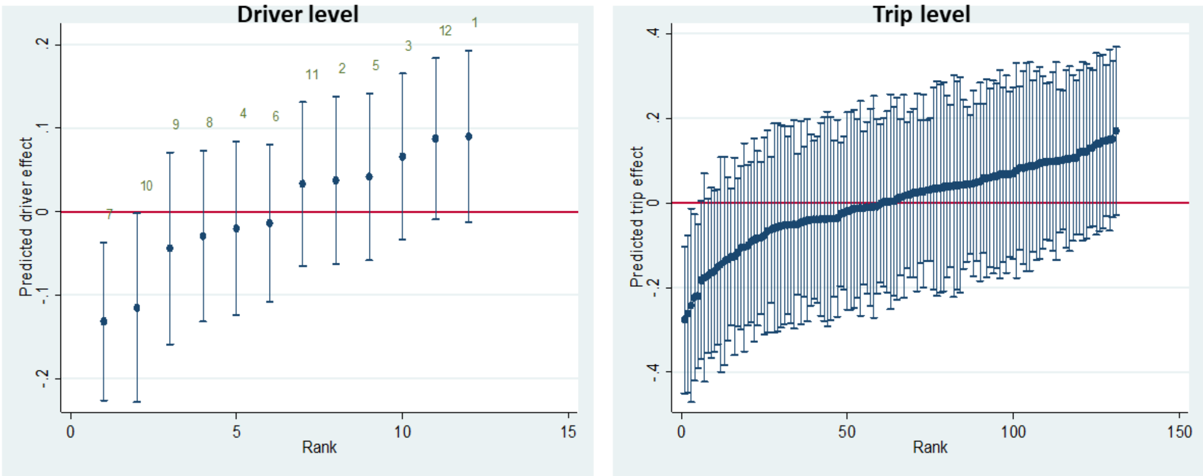


Figure 5.8: Magnitudes of the effects in the 3-Level null model for OEM data

From the plot above it is obvious that the confidence intervals around the predicted effects vary greatly in their length; drivers with fewer deceleration events (e.g. driver 9, which has 108 deceleration events) will have longer intervals than ones with a lot of events (e.g. driver 7, which has 197 events). The plot shows that only 2 out of the 12 drivers differ significantly from the average driver and one of them is close to the limit. Two drivers (7 and 10) had deceleration events with deceleration value significantly lower than the others, which means that they used to brake harder. Furthermore, it should be noted that because the independent variables have not been considered yet, the effects plotted here are very likely to reflect not just driver effects.

5.2.1.1.3 2-Level random intercept model

The next step is to start adding explanatory variables into the 2-level models (Random Intercept Models). After exploring all the different 2-level models (driver, trip, car model, road type), it is concluded that the car-level model and the road_type-level model were not suitable for these data since the ICC to both models was almost equal to 0. This signifies that none of these levels explains any of the variations in the deceleration values. The more common characteristics have the observations in the same cluster the larger the ICC. This was further supported by the LR-test that was conducted and showed that they are the worst models than the single level ones. On the other hand, both the trip and driver-level models gave better results than the single-level ones. Judging from the results, it can be concluded that both models can describe the data good (ICC for the trip-level=0.04 and for the driver-level=0.036), but from the log-likelihood and the BIC (lower value indicates a better model) it is revealed that the slightly better model is the two-level mixed model based on the drivers.

5.2.1.1.4 2-Level random intercept and random slope

Till now, driver and trip effects have been included by allowing the intercept of the regression model to vary randomly across the drivers and across the trips, but the slope of the regression line was assumed fixed across drivers and trips. Now, the random intercept model will be expanded by allowing the slope to vary randomly across the level too. Each of the variables has been examined to determine whether the effect of the variable (i.e. the slope coefficient) varies across the trips or the drivers by conducting the LR test. Only the standard deviation associated with the slope coefficients of the Vehicle C was found to be statistically significant at the driver level. Moreover, the LR-test was conducted to check if this or the simpler random intercept model is better.

It is concluded that the trip level random intercept model is the best whereas for the driver level the best model is the random intercept and random slope for the variable Vehicle C and its results are presenting in Table 5.14. It can be noted that the overall intra-class correlation (ICC) for the model is 0.03 indicating that only a 3 per cent of the variation in the deceleration value is explained by the multilevel or hierarchical data structure.

Table 5.14: Results of the Driver Level mixed effect for Vehicle C model for OEM Data

Deceleration	Coef.	z	P>z
Initial speed	-0.020	-7.86	0.000
Vehicle A	0.163	5.48	0.000
Vehicle C	0.196	4.65	0.000
Urban	0.112	4.02	0.000
Roundabout	0.168	3.78	0.000
Junction	0.117	3.16	0.002
Pedestrian crossing	-0.192	-2.28	0.022
Other	0.155	3.93	0.000
Driver reaction1	0.100	3.44	0.001
Traffic light	0.136	3.59	0.000
Stop car	-0.191	-6.95	0.000
Intercept	-2.592	-40.54	0.000

Random-effects Parameters	Estimate
DriverID: Independent	
Var (Vehicle C)	0.0097
Var (Intercept)	0.0071
Var (Residual)	0.2360
Level	**ICC**
DriverID	0.0293
Observations	1689
ll(model)	-1191.73
df	15

The most statistically significant variables affecting the deceleration events have been found to be the initial speed, the road type and the need to stop. Regarding the initial speed of the event, a 1 m/s increase in the initial speed increases the absolute value of the deceleration by 0.0204m/s^2 (harder braking), while if the road type is urban, the braking is reduced by 0.112 m/s^2 relative to other road types. Moreover, if the car needs to stop in order to avoid a collision, the absolute deceleration value is increased by 0.191m/s^2.

As far as the car model is concerned, if the Vehicle A is used, the absolute deceleration value decreases by 0.163 m/s^2 (softer braking). Since the use of the Vehicle C has a random effect (random coefficient and random slope) on the deceleration value, it can be seen that the use of the Vehicle C effect for driver j is estimated as 0.196 + u1j and the between driver variance in these slopes is estimated as 0.01. A 95% coverage interval for the driver slopes is estimated as $0.196 \mp 1.96\sqrt{0.001}$=0.04 to 0.41. Thus, it is expected to have a positive effect on 95% of the deceleration events with a slope coefficient between 0.04 and 0.41.

Moreover, since the μ=0.196 and the σ=sqrt(0.0097)=0.098,

z=0.196/0.098=2

According to the normal distribution table for z=2 -> 0.9772. This means that for 97.72% of the slopes it has a positive effect and for the rest 2.28%, the corresponding slopes show a negative effect. In terms of driver reaction, if the driver is looking forward (driver reaction 1) and not right/left or inside the car, it results in a decrease of the absolute deceleration value by 0.1 m/s^2 (softer braking).

Another statistically significant variable is the reason for braking. This variable was included in the model as a categorical variable with 5 categories with the category of braking due to a dynamic obstacle as the reference category. It can be observed that braking due to a reason other than dynamic obstacle leads to an increase in the deceleration value i.e. smoother braking and this may be because the dynamic obstacle mostly describes the unexpected and sudden braking, except for the braking due to approaching to a pedestrian crossing. For example, if the driver brakes because there is a junction instead of a dynamic obstacle the deceleration value increases by 0.117 m/s^2 resulting in softer braking. Furthermore, the existence of a traffic light plays a significant role, i.e. if there is a traffic light, the absolute value of the deceleration is decreasing, indicating softer braking. Traffic density (i.e. low, medium and high) was included in the analyses as a categorical variable with low density as the reference category, but it was not statistically significant.

The factors associated with the human characteristics were included in the model as categorical variables. More specifically, the age of the driver had three distinct categories, age_yound, age_middle and age_old; and gender had two categories, with the male drivers as the reference one. As the results indicate, none of the human factors variables was statistically significant. This is perhaps because the number of drivers (12 different drivers) was small and the number of events varied from driver to driver.

5.2.1.1.5 Three-Level random intercept model

The driver-trip model was also tested, and it was compared with the adequate two-level models by the LR-test. It was revealed that the most parsimonious model is the 2 driver-level random intercept and random slope model (Vehicle C has a mixed effect) (Table 5.14).

5.2.1.2 Duration

Next, the outcome of the statistical analysis with the dependent variable the duration is displayed. The best fitted linear regression is first calculated and it resulted to be the log-log transformation (i.e. the logarithmic transformation of the dependent and the independent variables where possible). The adjuster R^2 is 0.5565, showing a satisfactory fit. Although, the group effects should be tested to reveal if any multilevel model is more parsimonious.

5.2.1.2.1 Multi-Level null model

Similar to the analysis for the maximum deceleration value, the LR-test was conducted to test if a 2-Level model is better than a single-level model, resulting in favour of both the driver-level and the trip-level model. Moreover, the trip-level model has the highest ICC (0.126), which means that 12.6% of the variation in the duration of the deceleration event lies between the trips and the rest 87.4% lies between the events in the same trip. On the other hand, the driver-level model has small ICC (0.07), indicating that there is no driver effect on the duration. Moreover, the LR-test was performed to examine the 3-Level model against the corresponding 2-Level and single-level models, giving strong evidence that the 3-Level model overrides the driver-Level and the single level model but not the trip-level.

5.2.1.2.2 2-Level random intercept and random slope models

To create the 2-Level random intercept model, the explanatory variables were added. All the different groups were tested, i.e. driver, trip, car model, road type and it was concluded that only the trip-level model was suitable for the data, since the ICC of the other models almost equals to zero, meaning that none of these levels justified any of the variations in the duration of the deceleration events. The best 2-Level random intercept model considering trip effects is presented in Table 5.15. The next step was to test for random slope for each of the explanatory variables by conducting the LR-test and comparing the AIC and the BIC. The results showed strong evidence that none of the explanatory variables has a random slope, meaning that the 2-Level random intercept model is the most parsimonious.

Table 5.15: Results of the trip-level random intercept model of the duration for the OEM data

Ln_duration	Coef.	z	P>z
Ln_initial speed	0.7500	30.26	0.00
Roundabout	0.3120	8.19	0.00
Urban	-0.1160	-3.81	0.00
Ln_trip duration	0.3100	3.10	0.00

Junction	0.2740	8.99	0.00
Pedestrian crossing	0.2420	3.54	0.00
Other	0.2930	8.99	0.00
Driver_reaction_1	-0.1340	-5.33	0.00
Stops_at_car_block	0.1580	4.66	0.00
Traffic light	-0.1150	-3.57	0.00
Car_stops	0.3640	16.10	0.00
Intercept	-1.0780	-3.17	0.00
Random-effects Parameters TripID: Identity	**Estimate**		
var(Intercept)	0.0113		
var(Residual)	0.1524		
Level	**ICC**		
TripID	0.0688		
Obs	1689		
ll(model)	-848.4088		
df	14		
AIC	1724.818		
BIC	1800.864		

The most statistically significant variables affecting the duration of the deceleration event have been found to be the initial speed, the cause of braking and the need to stop. Since the logarithmic model is the most parsimonious the slope coefficient for each independent variable must be calculated. If the independent variable is in a logarithmic transformation as well, then the slope coefficient equals to $b_1\left(\frac{\bar{y}}{\bar{x}}\right)$ where $\bar{x}$ is the average of the independent variable and $\bar{y}$ the average of the dependent variable. Otherwise, if the independent variable is not transformed then the slope coefficient equals to $b_1(\bar{y})$. So, if the initial speed of the event increases by 1 m/s, the duration increases by 0.47sec. Moreover, if the car stops at the end of the deceleration event, the duration is longer by 3.15sec. Regarding the reason for braking, it can be concluded that braking due to a reason other than a dynamic obstacle leads to longer deceleration events, for example, if the braking happened because of a roundabout or a junction the duration increases by 2.7 sec and 2.37 sec respectively. As far as the road type is concerned, being in an urban road instead of a rural or motorway results in shorter deceleration events by 1 sec.

Traffic density (i.e. low, medium and high) and the factors associating with the driver, i.e. gender and age showed no effect on the duration of the deceleration event. On the other hand, if the driver is looking in front and not inside the car or right/left, s/he performs deceleration events that have shorter duration by 1.16 sec. This might indicate that the driver is more focused and reacts faster. Last but not least, the traffic light has a negative effect on the duration of the deceleration event, meaning that if there is a traffic light, the deceleration is shorter by 1sec, indicating maybe that when there is a traffic light the drivers delay to press the brake.

5.2.2 TeleFOT

The first thing is to test whether there are enough observations to describe each level so that a two-level and a three-level analysis can be conducted. The number of observations per each level is presented in Table 5.16. It can be observed that there are enough events per driver and per trip to perform both two-level analyses but there are not many trips per driver, i.e. mean 1.72 from 1 to 3 trips and that might be problematic in the appliance of a three-Level model. Also, it should be noted that there are 25 drivers performed 43 trips.

Table 5.16: Number of observations for each level of the analysis for TeleFOT data

	Mean	Std. Dev.	Min	Max
Trips per driver	1.72	0.73	1	3
Events per driver	33.44	26.7	4	90
Events per trip	19.44	10.72	3	42

5.2.2.1 Deceleration

The best-fitted model of the linear regression has an adjusted R^2 of 0.10. The adjusted R^2 is low, indicating that the model does not explain well the dependent variable. The most significant explanatory factors are the initial speed, “if the car has to stop” variable and the reason for braking. The next step is to search for group effects that might describe better the dataset.

5.2.2.1.1 2-Level null model

To investigate if the 2-Level model describes better the data than the single-level one, the LR test is performed resulting that there is a group effect for both drivers and trips.The predicted driver and trip effect are displayed in Figure 5.9. Observing the Boxplots for the driver effect, only one driver from the 25 differs significantly from the average driver, performing harder braking. Also, from the same graph for the trip level, it can be noted that in all the trips the deceleration values are within the values of the average trip.

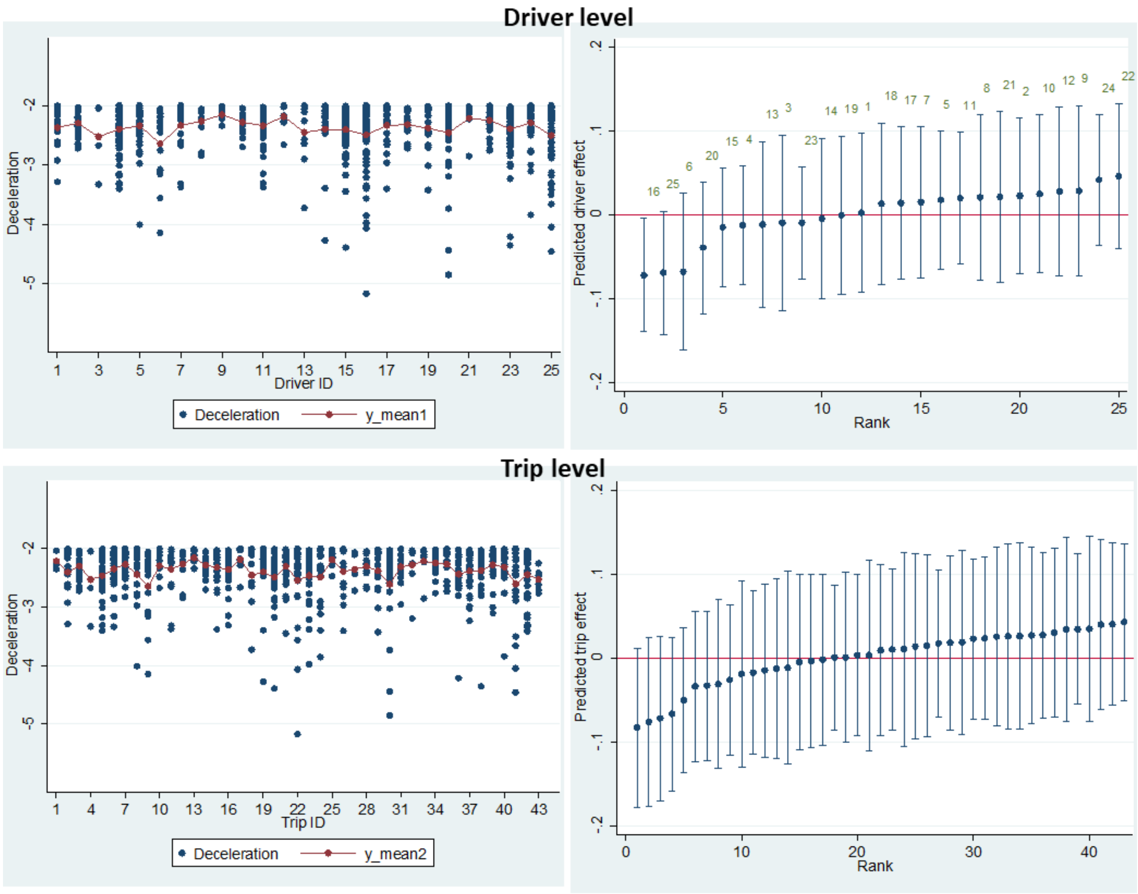


Figure 5.9: Plots representing the driver and trip effects in the deceleration values for the 2-Level null models for TeleFOT dataset

5.2.2.1.2 3-Level null model

Moving to the 3-level null model, the LR-test showed that it is not significantly better from neither the single-level model nor any of the 2-Level ones. This was further supported by the low values of the ICC for the driver level in the 3-level model.

5.2.2.1.3 2-Level random intercept

Having concluded that both driver and trip effect play a role, the 2-Level random intercept models for trip level and driver level were calculated. The results show almost the same effects of the explanatory variables to the deceleration value for both models.

Although, the trip-level model shows better fit since the ICC (0.046) is bigger than the ICC of the driver-level model (0.039).

5.2.2.1.4 2-Level random intercept and random slope

Then, it was tested if by adding a random slope to any of the independent variables, a better-fitted model would have been created. The resulted models were compared to the simpler random intercept model to prove which is the best model to describe the deceleration value. The results of the LR-Test and the comparison of the AIC and BIC concluded that the best model to describe the maximum deceleration value for the TeleFOT dataset is the trip-Level random intercept and random slope for traffic light model, which is displayed in Table 5.17.

Table 5.17: Results of the trip-Level random intercept and random slope for traffic light model for deceleration (TeleFOT dataset)

Deceleration	**Coef.**	**z**	**P>z**
Initial speed	-0.027	-7.5	0.000
Traffic light	-0.083	-1.97	0.049
Roundabout	0.176	3.51	0.000
Junction	0.151	3.29	0.001
Other	0.099	2.2	0.028
Pedestrian crossing	-0.022	-0.22	0.830
Car stops	-0.227	-6.84	0.000
Rural	0.057	1.98	0.048
Driver reaction 1	0.147	3.83	0.000
Intercept	-2.253	-40.11	0.000
Random-effects Parameters	**Estimate**		
TripID: Independent			
var(traffi~t)	0.0643		
var(Intercept)	0.0066		
var(Residual)	0.1378		
ICC **Obs** **ll(model)** **df**	0.046 837 -387.15 13		

The initial speed and if the car stops affect the deceleration value the most. Specifically, 1m/s increase in the initial speed results in 0.027m/s^2 decrease in the deceleration value and if the car stops at the end of the deceleration event leads to a decrease in the deceleration value by 0.227m/s^2. On the other hand, if the driver is looking ahead and the road type is rural, the deceleration value is increasing, resulting in softer braking. Another statistically significant variable is the reason for braking. The effect is positive if the deceleration did not happen due to a dynamic objective or a pedestrian crossing.

As far as the traffic light is concerned, the initial effect for trip j is estimated as -0.083+ u_{1j} and the between trip variance in these slopes is estimated as 0.0643 (σ=0,2536). Therefore, z=0.083/0.2536=0.327 and from the normal distribution table, it is concluded that 62.9% of the slopes of the traffic light variable give a negative effect on the deceleration value whereas the rest 37.1% a positive one.

5.2.2.2 Duration

The statistical analysis of the duration starts with the calculation of the best linear regression model, which is the ln-ln linear regression model with a satisfactory adjusted R^2 (0.56). So, 56% of the duration values can be explained well by this model.

5.2.2.2.1 Multi-level null model

To examine if there is any driver or trip effect, the LR-test was conducted to the null trip-level and drivel-level against the single-level model and there was overwhelming evidence in favour of both 2-Level models. Also, using the LR-test the 3-Level model against the 2-Level and the single level models were examined and it resulted that the 3-Level model is better than the single-level and the driver-level but not than the trip-Level one. So, the best model is the 2-trip level model.

5.2.2.2.2 2-level random intercept

The procedure continues by adding the explanatory variables to the trip-level null model and by keeping the variables that are statistically significant. Also, when the explanatory variables were added to the drivel level model, the model resulted to be inappropriate (ICC value almost equal to 0). This happened because the driver variables (age, driver experience and gender) that were added explained the differences due to the driver. Next, random slopes for the dependent variables were added to the trip-level random intercept model. The resulted models were compared with the random intercept trip-level model through the LR-test and it was proven that the best-fitted model is the random intercept trip-Level model (see Table 5.18).

Table 5.18: Trip-Level random intercept model for the Duration (TeleFOT dataset)

	Trip level		
Ln_duration	**Coef.**	**z**	**P>z**
Ln_initial speed	0.7480	28.92	0.00
Ln_trip distance	0.1800	2.72	0.01
Age_old	0.0840	2.29	0.02
Driven_miles 2	-0.2380	-2.96	0.00
Driven_miles 3	-0.1800	-2.18	0.03
Driven_miles 4	-0.1230	-1.10	0.27
Stop_at_car_block	0.0780	2.25	0.02
Rural	0.0600	2.62	0.01
Car_stops	0.4130	15.36	0.00
Driver_reaction1	-0.0850	-3.85	0.00
Intercept	-0.6720	-3.30	0.00
Random-effects Parameters	**Estimate**		
TripID: Identity			
var(Intercept)	0.004		
var(Residual)	0.095		
Level **TripID**	**ICC** 0.04		
Obs	845		
ll(model)	-217.86		
df	13		
AIC	461.7207		
BIC	523.3321		

From the results in Table 5.18, it can be noted that the initial speed and the need to stop affect the most the duration of the deceleration events. They both have a positive effect, meaning that the increase of the initial speed or if the car needs to stop leads to an increase in the deceleration duration. Specifically, if the initial speed increases by 1 m/s, the duration increases by 0.33sec and if the car needs to stop it increases by 1.76 sec. Moreover, some driver characteristics play a significant role, i.e. the age, specifically an old driver brakes longer by 0.36 sec than a middle-age one and the driving experience showing that drivers with more driven miles brake in shorter duration, indicating more experience driving style. Shorter braking is resulting when the driver looks in front just at the moment the driver started the braking and not inside the car.

The reason for braking does not affect the duration even if it was inserting in the model. Driving in a rural road instead of an urban or a motorway leads to an increase to the duration by 0.26sec. Also, stopping at a car block has a positive effect on the duration. Last but not least, the trip duration has a positive effect on the duration, meaning that 1 min increase in the trip duration results in 0.05sec increase in the deceleration duration. Finally, the ICC equals to 0.04, which means that 4% of the variation in duration values lies between the trips whereas the rest variation lies between the events on the same trip.

5.2.3 Combination of OEM and TeleFOT

5.2.3.1 Deceleration

In order to explore further factors affecting the deceleration value, the two datasets i.e. OEM and TeleFOT were combined. Therefore, the factors will not be connected only to one dataset and the results would be more generic. First, Table 5.19 displays the observations for each level to establish that it is possible to perform the multi-level analysis. Also, it should be noted that there were 37 drivers and 174 trips.

Table 5.19: Number of observations for each level of the analysis for combination dataset

	Mean	Std. Dev.	Min	Max
Trips per driver	4.70	4.55	1	12
Events per driver	73.4	67.6	3	217
Events per trip	15.6	9.9	2	42

The LR-test was performed to examine if there are any group effects in the data. Specifically, the 2-Level models showed a better fit than the single-level one. In addition, there was significant evidence that the 3-Level model (driver-trip-event level) is the most parsimonious model with ICC for driver effect equal to 0.061 and for trip effect equal to 0.124. Those values signify that 12.4% of the variation in the deceleration values can be explained by the group effect of the trip and the driver and the 6.1% only from the driver effect. From the boxplots displayed in Figure 5.10, the group effects are visualised. As far as the drivers' effect is concerned, many drivers decelerate in harder than the average driver. Also, the intervals are smaller for those drivers meaning that their braking does not vary a lot. On the other hand, considering the trips, there are some trips where the decelerations that took place were harder or softer than the ones on the average trip.

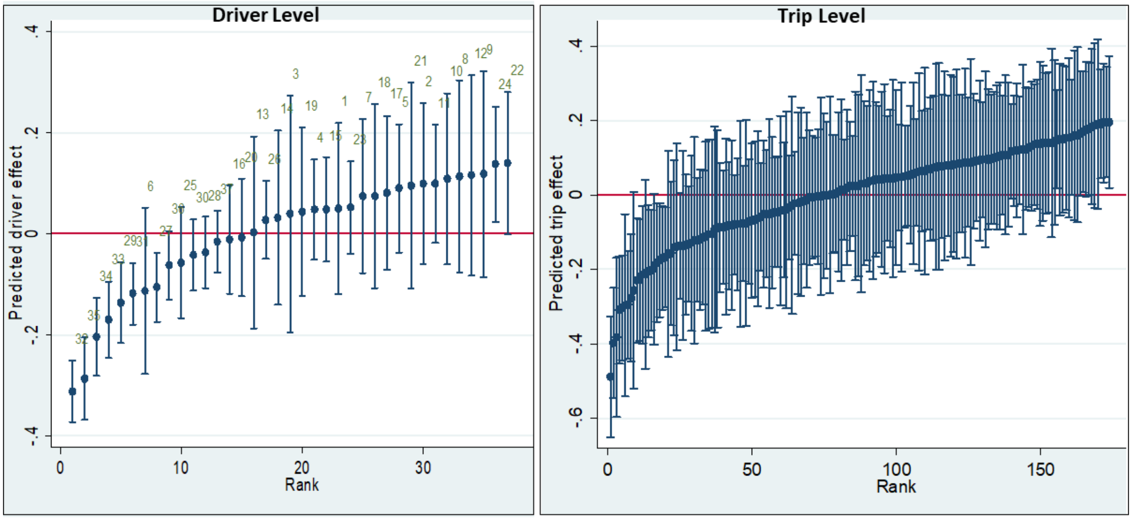


Figure 5.10: Boxplots of the group effect of the drivers and the trips for the deceleration (Combination dataset)

Continuing to the statistical analysis, after calculating the most parsimonious linear regression model (adjusted R^2=0.115) the 2-Level random intercept models were estimated both for trip and driver level, resulting in two good models with ICC=0.065 for the trip level and ICC=0.036 for the driver level. Then, random slope was added to the explanatory variables and the LR-test indicated that the best model is the driver-level random intercept and random slope for the variable Vehicle C.

Next, the best 3-Level random intercept model was estimated and was compared with the best 2-Level random intercept model, concluding that there is strong evidence in favour of the 3-Level model (LR test). By adding random slope to the variables of the 3-Level model in both driver and trip-level, the best model describing the combination data was revealed from the LR-test and by having the best values of AIC and BIC and it was the 3-Level random intercept and random slope for the variable “Car_stops” in the trip level (displayed in Table 5.20).

Table 5.20: Results of the 3-Level models for the deceleration value (Combination dataset)

	3-LEVEL RANDOM INTERCEPT MODEL			3-LEVEL RANDOM INTERCEPT AND RANDOM SLOPE		
Deceleration	**Coef.**	**z**	**P>z**	**Coef.**	**z**	**P>z**
Initial speed	-0.0004	-4.68	0.00	-0.0004	-4.60	0.00
Trip distance	-0.0116	-3.75	0.00	-0.0114	-3.71	0.00
Traffic light	-0.0524	-2.53	0.01	-0.0550	-2.66	0.01
Roundabout	0.1145	4.07	0.00	0.1127	4.02	0.00
Junction	0.0989	4.35	0.00	0.0974	4.30	0.00
Pedestrian crossing	-0.1822	-2.94	0.00	-0.1880	-3.04	0.00
Other	0.1175	4.33	0.00	0.1222	4.52	0.00
Car_stops	-0.1666	-8.44	0.00	-0.1703	-7.60	0.00
Vehicle A	0.1397	4.17	0.00	0.1397	4.20	0.00
Telefot	0.2248	5.11	0.00	0.2284	5.17	0.00
Vehicle C	0.1721	5.45	0.00	0.1614	5.08	0.00
Intercept	-2.5374	-65.21	0.00	-2.5392	-65.36	0.00
Random-effects Parameters	**Estimate**			**Estimate**		
DriverID: Identity						
var(Intercept)	0.0066			0.0069		
TripID: Identity						
var(Car_stops)				0.0162		
var(Intercept)	0.0068			0.0055		
var(Residual)	0.1954			0.1916		
Level	ICC			ICC		
DriverID	0.0318			0.034		
TripIDDriverID	0.0642			0.0608		
Obs	2715			2715		
ll(model)	-1685.99			-1681.18		
df	15			16		

The results indicate similar effects for most of the explanatory variables as the ones of the best models from OEM and TeleFOT dataset. The main difference lies in the fact the best model is a 3-Level model, where 3.4% of the variation of the deceleration value lies between the drivers, 2,68% of the variation lies between the trips and the rest 93.92% of the variation lies between the events in the same trip of the same driver. Also, the effect of the variable "Car_stops" is different, i.e. it has a random effect and specifically to 91% of the data it has a negative effect and to 9% a positive one effect that varies.

Regarding the other variables, the car model is one of the most statistically significant variables, indicating that driving any other car but Vehicle B results in softer braking by 0.16-0.23 m/s^2. Decelerating because of approaching a roundabout or a junction, increases the value of the deceleration by 0.112 m/s^2 and 0.097 m/s^2 respectively comparing to braking due to a dynamic obstacle. On the other hand, braking due to a pedestrian crossing and not due to a dynamic obstacle results in harder braking by 0.1880 m/s^2. Also, increasing the initial speed and the existence of traffic light have a negative effect on the deceleration value. Finally, no driver characteristic influences the deceleration value, but the reason might be that these characteristics were taken into consideration in the driver level.

5.2.3.2 Clustering

A different approach to analyse the data and explore the factors that affect the deceleration value is to group the data based on human factors, i.e. sociodemographic factors, to reflect the differences among the drivers, and on the braking pattern. To accomplish that, a cluster analysis was employed and specifically, the 2-step cluster analysis in SPSS was used since this method can handle categorical variables (such as gender, age categories and braking profiles) as well as big datasets. Five clusters were created as an outcome and their features can be seen in Figure 5.11. It can be noted that the size of the clusters does not have big differences (size of smaller cluster=396 and size of bigger cluster=637). Also, all the variables that were included in the cluster analysis are statistically significant. The distribution of the variables inside each cluster is displayed in the upper right part of Figure 5.11. It can be concluded that old people (cluster 1 and 3) slightly prefer the braking pattern (2) whereas young people also use the third braking pattern (3). Moreover, the different clusters present different deceleration characteristics. This can be supported by the results of the Analysis of Variance (ANOVA) test ($p=0.045<0.05$), conducted to test the differences between the means of the maximum deceleration for each cluster. Additionally, it was concluded from the Tukey's HSD test that old females brake the hardest whereas old males brake the softest.

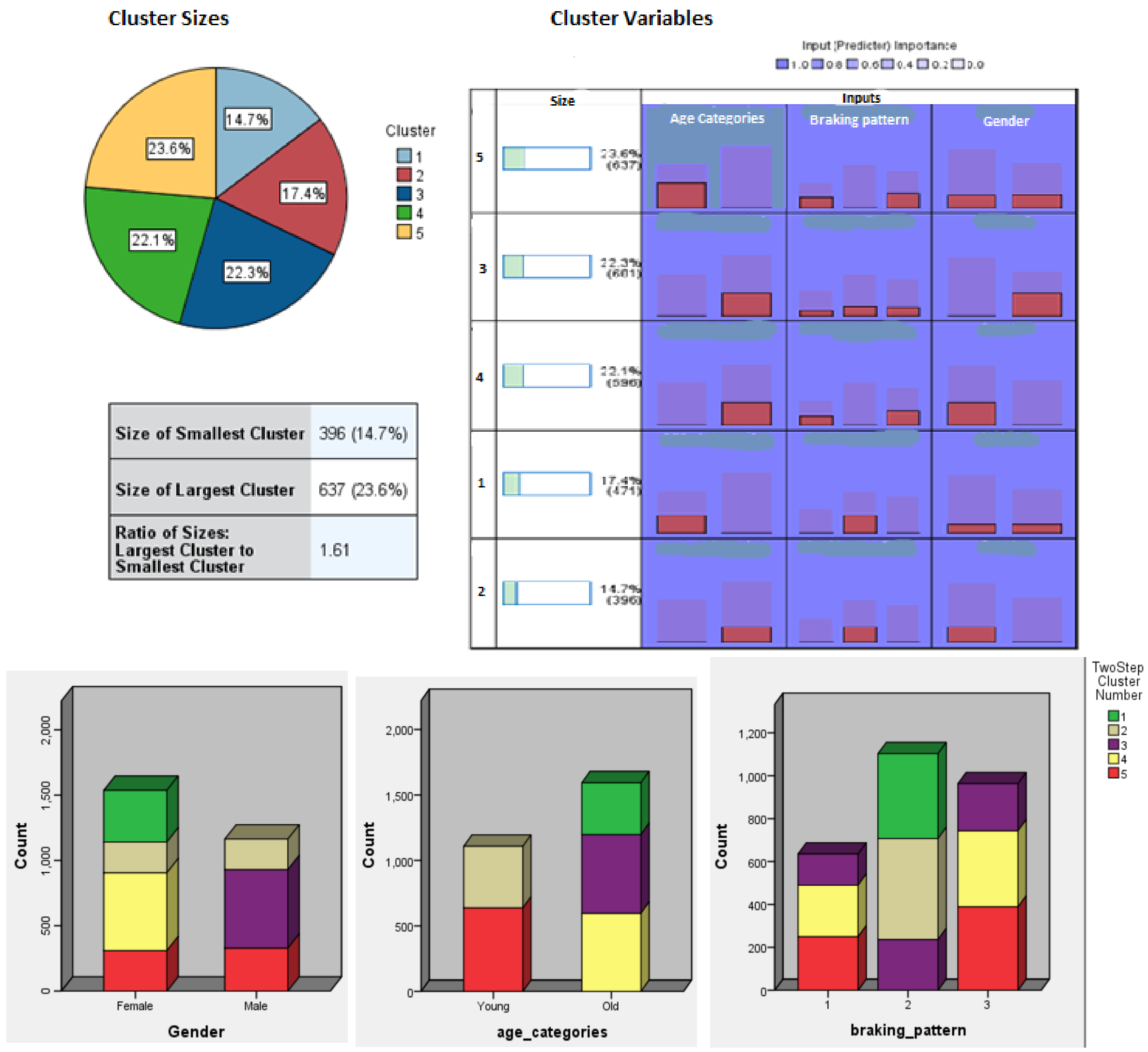


Figure 5.11: Features of the five clusters (Combination dataset)

Having the deceleration events clustered and with the aim of examining all the influencing factors of the braking behaviour, the multilevel mixed-effect model was applied to each cluster using the StataMP 13 software. The factors that were considered are (1) event-level factors, such as situational factors (reason of braking, traffic density), kinematic factors at the beginning of braking, etc. and (2) trip level factors, such as trip duration, trip distance, the model of the car. Therefore, the maximum deceleration value was analysed using statistical analysis for each cluster. Since the driver effect has been included in the clustering, the model that was used was the 2-level linear regression model based on the trip level. The explanatory variables, which include distance, initial speed, if the car should stop, traffic density and the reason for braking, were kept the same among the clusters. The results of the analysis are presented in Table 5.21. There was no evidence in favour of any random slope model in any of the clusters. The overall intra-class correlation (ICC) varies from 0.037 (cluster 1) to 0.16 (cluster 4) indicating that 3.7% and 16% of the variation in the deceleration value is explained by the trip-level hierarchical data structure. Therefore, all models show a reasonable goodness-of-fit.

Table 5.21: Results from Multilevel linear regression models in the 5 clusters (Combination dataset)

	Cluster1		Cluster2		Cluster3		Cluster4		Cluster5	
Deceleration	Coef.	z	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Distance	-0.018	-2.44	-0.020	-4.29			-0.012	-1.86		
Initial speed	-0.012	-1.89			-0.024	-6.39	-0.012	-1.69	-0.033	-6.33
Traffic light							0.126	2.45		
Roundabout			0.164	2.65	0.106	2.16			0.164	2.35
T_junction			0.112	2.13			0.071	1.62	0.161	2.55
Cross_junction			0.145	1.97	0.133	2.28			0.178	1.96
Pedestrian crossing					-0.255	-1.63			-0.553	-3.42
Other			0.109	1.9	0.117	2.58	0.097	1.87	0.117	1.69
Car_stops	-0.198	-4.32	-0.100	-2.22	-0.217	-5.73	-0.174	-4.2	-0.263	-4.81
Intercept	-2.237	-33.7	-2.482	-61.1	-2.150	-38.8	-2.345	-31.3	-2.158	-26.9
Number of observations	396		471		601		596		637	
ICC	0.037		0.055		0.07		0.16		0.11	
AIC	424.6		840.9		657.4		756.3		764.8	
BIC	448.3		880.7		697.0		795.8		806.9	
LogLik	-206.3		-411.5		-319.7		-369.2		-372.4	
df	6		9		9		9		10	

The most statistically significant variables affecting the deceleration value for almost all the models are the initial speed and if the car should stop. Increasing the initial speed by 1m/s leads to harder braking (the decrease varies from 0.012 to 0.033m/s^2) and if the car needs to stop, the deceleration value decreases from -0.1 to 0.263m/s^2. Another important factor is the cause of braking. Specifically, approaching a roundabout or a junction results in softer braking compared to a dynamic obstacle, whereas approaching a pedestrian crossing leads to harder braking. Furthermore, for cluster 4 the existence of a traffic light made the braking softer. The traffic density was revealed to be insignificant for all the clusters.

5.2.4 UDRIVE

The last dataset that was analysed is the UDRIVE dataset. UDRIVE is an NDS, so it consists of data that gathered unobtrusively in a natural setting. Specifically, the data that was analysed comprise 49 drivers and 470 trips. Therefore, this dataset can reveal more realistically the factors affecting the deceleration event, i.e. the maximum deceleration value and the duration. First, the multilevel statistical analysis was applied for both the dependent variables. Moreover, the explanatory variables include driver characteristics, i.e. age category, gender, and two indicators of personality; the AISS_total and the DBQ_total and DBQ_aggressive_violations, trip characteristics, such as car model and trip duration and event characteristics, for example, speed, steering angle, jerk, TTC, THW, space headway etc.

It can be concluded that if all the explanatory variables are concluded in the model, then fewer observations will be considered since variables such as TTC, THW and space headway were only available when there is a car in front of the car of interest. Therefore, two statistical analyses where undertaken, in the first one (Statistical Analysis I), all the explanatory variables were included, leading to less observations (3,655 instead of 7,160) and in the second analyses (Statistical Analysis II) all the observations were included by taking out the variables that were missing from observations. The results of the statistical analysis II can be directly compared to the results of the previous datasets since almost the same variables are included, whereas the statistical analysis I can be used to reveal previously unexplored factors affecting the deceleration events.

5.2.4.1 Deceleration value

First, the group effects were tested by comparing the 2-Level and the 3-Level against the single-Level and it resulted that the 2-Level model is better than the single-level and the 3-Level is better than all the others, indicating that a 3-Level model might be the most parsimonious.

5.2.4.1.1 Statistical analysis I

Initially, the simplest linear regression model is calculated, resulting in a model with adjusted R^2=0.42 (satisfactory percentage), AIC=3450, BIC=3555.6, df=16 and LogLikelihood=-1708.05. Then, the explanatory factors were inserted in the driver-level model and the trip-Level model calculating the 2-Level random intercept models that had strong evidence of being better than the linear regression model. Next, all the variables were tested for a random effect, but only the maxspeed and the max_jerk resulted in having a mixed effect. The comparison of the model was accomplished by conducting the LR test and it can be concluded, that the most parsimonious models are the driver-Level and the trip-Level random intercept and random slope for the variables maxspeed and max_jerk model. The best models from the trip and the driver level are presented in Table 5.22.

Table 5.22: Results of the Drivel-Level models for the deceleration value (UDRIVE dataset)

Model:	**Driver-Level random intercept and slope model**		**Trip-Level random intercept and slope model**	
Fixed effects:				
	Coeff.	t-value	Coeff.	t-value
Intercept	-1.3507	-29.85	-1.4703	-34.62
Age_young	Insignificant		0.0187	0.79
Age_middle	Insignificant		0.0357	2.37
Car_model	Insignificant		0.0507	3.07
Initial speed	-0.0085	-14.28	-0.0085	-15.84
Initial TTC	0.0011	3.75	0.0011	4.01
Speed_limit_2	0.0098	0.58	0.0066	0.41
Speed_limit_3	0.0994	3.14	0.0834	2.65
Speed_limit_4	0.0164	0.72	0.0032	0.14
Speed_limit_5	0.0749	2.32	0.0553	1.70
Initial headway	-0.0011	-3.12	-0.0009	-2.50
Car_stops	-0.1934	-13.86	-0.1864	-13.67
Max_steering angle	Insignificant		-0.0003	-1.87
Max_jerk	0.5176	25.36	0.4953	31.53
Traffic conjestion	0.1518	7.69	0.1372	7.10
Random effects:				
	StdDev:		StdDev:	
(Intercept)	0.2193		0.3503	
Initial speed	0.0021		0.0032	
Max_jerk	0.1154		0.1929	

Residual	0.3765	0.3577
AIC	3369.939	3240.124
BIC	3481.608	3382.813
logLik	-1666.97	-1597.06
ICC	0.78	0.767

From the results presented in Table 5.22, it can be noted that the most significant factors affecting the deceleration value are the initial speed, the car_stops variable, the maximum jerk and the existence of traffic congestion for both models. Regarding the initial speed, it has a mixed effect on the deceleration value and its effect for driver j is estimated as -0.0085 + u1j and the between driver variance in these slopes is estimated as 0.0021 and its effect for trip i equals to -0.0085+u1i and the between trip variation is 0.0032. The initial speed effect is negative for the 100% of the data but the size of the effect varies. Also, an increase in the initial TTC leads to softer braking. The same result has braking due to traffic congestion.

As far as the max_jerk is concerned, its effect for driver j is estimated as 0.5176 + u1j and the between driver variance in these slopes is estimated as 0.1154 and its effect for trip i equals to 0.495+u1i and the between trip variation is 0.1929. It must be noted that during the braking the jerk is negative, and its increase means a slower rate of deceleration. A 95% coverage interval for the driver slopes is estimated as $0.5176 \mp 1.96 * 0.1154$=0.29 to 0.74 and for trip slopes from 0.12 to 0.87. Thus, it is expected to have a positive effect on the 95% of the deceleration events with a slope coefficient between 0.04 and 0.41 for the driver-level model and between 0.12 and 0.87 for the trip-level model. Also, the positive effect of the max deceleration accounts for 100% of the data.

The age category and the car model play a significant role only in the trip-level model. In detail, drivers that belong to the age category 31-50 tend to brake softer than the ones in the age category 50+. Also, driving a premium car leads to an increase in the deceleration value. Moreover, increasing the speed limits have a positive effect on the deceleration value, indicating the importance of the road type in the braking.

Last but not least, the ICC value is really high for both models, indicating that both driver and trip groups play an important role in the variation of the deceleration value.

Furthermore, it can be concluded from the indicators AIC and BIC as well as from the log-likelihood that the trip-level model explains better the deceleration value.

Exploring the three-level models, it can be concluded that the three-Level random intercept model is better than both the driver-level and the trip-level random intercept model but when random slope is being added to the explanatory variables, the best three-level model, which is the three-level random intercept and random slope for the variables maxspeed and max_jerk is worse than the adequate model of the trip-level.

5.2.4.1.2 Statistical analysis II

The same procedure was followed in the statistical analysis II, generating first the linear regression model with a satisfactory adjusted R^2=0.34. After examining all the possible levels (Trip-Level, Driver-Level and Three-Level) by adding all the available factors and by allowing random slope to all of them, the best model was revealed which was the trip-Level random intercept and random slope for the variables maxspeed, following a car and max_jerk model (presented in Table 5.23). The ICC value of the model is really high, indicating that there is a strong trip effect on the deceleration value and in detail that 92.57% of the variation of the deceleration value lies between the trips.

Table 5.23: Results of the most parsimonious model for deceleration value in statistical analysis II (UDRIVE dataset)

Model:	**Trip-Level random intercept and slope model**	
Fixed effects:		
	Coeff.	t-value
Intercept	-1.5209	-37.45
Car model	0.0408	2.75
Trip distance_km	0.0012	1.83
Initial speed	-0.0092	-20.40
Speed_limit_2	-0.0053	-0.34
Speed_limit_3	0.0366	1.28
Speed_limit_4	0.0554	3.02
Speed_limit_5	0.0469	1.52
Following_a_car	0.0797	5.70
Car_stops	-0.1882	-15.99
Max_jerk	0.4555	31.20
Traffic congestion	0.1353	6.44

One lane road	-0.0426	-3.25
Random effects:	StdDev:	
(Intercept)	0.5120	
Initial speed	0.0048	
Following_a_car	0.1451	
Max_jerk	0.2266	
Residual	0.4338	
AIC	9223.563	
BIC	9388.6	
logLik	-4587.782	
ICC	0.9257	

The initial speed, the car_stops variable and the max_jerk are the factors that influence the deceleration value the most. Regarding the car_stops variable, it has a negative effect on the deceleration value. Both the initial speed and the maximum jerk have a random effect on the dependent variable. In more details, the maxspeed effect for trip j is estimated as -0.0092 + u1j and the between trip variance in these slopes is estimated at 0.0048, so the z=1.92 and from the normal distribution table the percentage 97.26% is obtained, showing the percentage that the maxspeed has a negative effect which varies. Calculating the same values for the max_jerk, leads to the conclusion that max_jerk affect positively 97.8% of the data, also a 95% coverage interval for the trip slopes is estimated as $0.4555 \mp 1.96 * 0.2266$=0.11 to 0.9.

Moving to the least significant variables, if there is traffic congestion, the deceleration value increases by 0.1353m/s^2. Also, if the road has only one lane, the braking is harder by 0.0426 m/s^2. The following a car variable has a random effect too, equals to 0.0797+ u1j for the average trip and being positive for 70.8% of the observations and negative for the rest of them.

The age category plays no significant role in the deceleration value, whereas driving a smaller car than a premium one results in increasing the deceleration value by 0.04m/s^2. As far as the speed limits are concerned, only the speed limit 4 which indicates being in a motorway affect significantly the dependent variable. Specifically, braking in a road with speed limit 4 (motorway) instead of speed limit 1 (urban road), results in softer braking by 0.0554 m/s^2. Maybe the reason for that is that in urban roads unexpected dynamic obstacles, like pedestrians or bicycles might be the reason for braking leading to harder and faster braking.

5.2.4.2 Duration

The modelling of the duration of the deceleration event is following, undertaking both statistical analyses. Initially, the LR-test for the multilevel models is presenting, showing that any multilevel model is better than the single-level model and that the three-level model outmatches the 2-Level models, but this might change as the explanatory variables and the random slopes are added.

5.2.4.2.1 Statistical analysis I

After examining all the possible transformations for the linear regression model, the ln-ln model appeared to be the best model with adjusted R^2=0.604, meaning that 60.4% of the variation in the duration can be explained well by the model. The most affecting factors were found to be the log_speed, the car_stops and the max_jerk. After that, the 2-Level and 3-Level random intercepts and random slopes model were estimated and the appropriate LR-tests were conducted, showing that the variables max_jerk and car_stops have a random effect.

Table 5.24: Results of the best multilevel models for Duration in Statistical analysis I (UDRIVE dataset)

Model:	**Driver-Level random intercept and slope model**		**Trip-Level random intercept and slope model**		**Three-Level random intercept and slope model**	
Fixed effects:	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
(Intercept)	-1.6488	-18.25	-1.6041	-20.54	-1.6261	-18.07
Trip duration_m	0.0031	2.77	Insignificant		Insignificant	
Trip distance_km	-0.0021	-2.88	Insignificant		Insignificant	
Day	-0.0358	-2.26	-0.0377	-2.22	-0.0351	-2.07
Ln_initial speed	0.8892	49.97	0.8993	57.68	0.8915	51.45
Initial TTC	-0.0011	-4.38	-0.0010	-4.06	-0.0010	-4.03
Initial THW	0.0096	2.22	0.0096	2.28	0.0080	1.90
Speed_limit_2	0.0387	2.48	Insignificant		0.0321	2.11
Speed_limit_3	0.0671	2.39	Insignificant		0.0500	1.81
Speed_limit_4	0.0145	0.72	Insignificant		0.0004	0.02
Speed_limit_5	0.0053	0.18	Insignificant		-0.0122	-0.42
Following_a_car	0.1976	6.32	0.1969	6.45	0.1927	6.31
Car_stops	0.4617	26.70	0.4620	31.12	0.4580	27.02
Speed violation	Insignificant		-0.0290	-1.85	Insignificant	
Max_steer_angle	0.0007	5.90	0.0007	6.03	0.0007	6.10
Max_jerk	0.1604	11.29	0.1647	12.93	0.1639	11.23

Traffic conjestion	0.1239	6.81	0.1310	7.76	0.1261	7.26
Pedestrian	0.0724	4.79	0.0671	4.71	0.0682	4.68
One lane road	-0.0392	-3.04	-0.0369	-3.14	-0.0305	-2.42
Intersection	0.0886	7.71	0.0881	8.00	0.0888	7.99
RANDOM EFFECT	**Driver id**		**Trip id**		**Driver id**	
	StdDev:		StdDev:		StdDev:	
(Intercept)	0.1568		0.3071		0.1119	
Car_stops	0.0691		0.1686		0.0503	
Max_jerk	0.0812		0.1453		0.0611	
Residual	0.3373		0.3137		NA	
					Trip_id in Driver_id	
(Intercept)	NA		NA		0.2873	
Car_stops	NA		NA		0.1372	
Max_jerk	NA		NA		0.1501	
Residual	NA		NA		0.3138	
AIC	2656.935		2511.9		2511.44	
BIC	2819.068		2642.848		2610.99	
logLik	-1302.47		-1234.947		-1223.72	
ICC	0.178		0.224		**ICC(DRIVER)**	0.065
					ICC(TRIP)	0.427

From Table 5.24 it can be concluded that the explanatory variables are almost the same for the three models with similar effects. One exception is that the duration and the distance of the trip are statistically significant (having a positive and a negative effect on the duration respectively) for the Driver-level model but not for the other two, maybe because in the other two models the effect of those two variables is included in the trip level effect. In all the models, the existence of traffic congestion, of pedestrians and of intersection results in longer braking. Moreover, the increase in the steering angle during the braking, leads to an increase in the duration, showing that if the car is turning while braking, the deceleration lasts longer (softer braking). A similar effect with the steering angle has the increase of the speed, specifically 1 km/h increase in the initial speed, results in around 0.14 sec increase in the duration for all three models.

Braking at day leads to shorter duration braking, maybe due to the better conditions of light and the confidence that they cause. If there is a car in front at the moment of braking, the duration of the deceleration is increasing, showing maybe that the driver starts braking earlier and is more alert that he might need to stop. Also, the TTC at the beginning of the braking has a significant negative effect on the duration. Moreover, if the event occurs in one-lane road, its duration decreases by 0.23 to 0.29 seconds.

Considering the variables the max_jerk and the car_stops, they have a random effect in the duration for all three models. The max jerk effect for the average driver j is estimated as 0.1604+ u1j in the driver-Level model and for the average trip i as 0.1647+ u1i in the trip-Level model. Also, 97.5% of the slopes coefficients of the max jerk were found to be positive in the driver-Level model and the corresponding percentage in the trip-Level model was 87%. The effect of the max _jerk on the duration is plotted in Figure 5.12, where the intercept and the slope vary in the driver and the trip level. Almost the same effect has the max jerk in the three-level models both for the driver and the trip level. The car stops variable has a positive effect on the duration for all the 3 models, but this effect varies with the average one to be around 3.48 sec increase on the duration if the car has to stop.

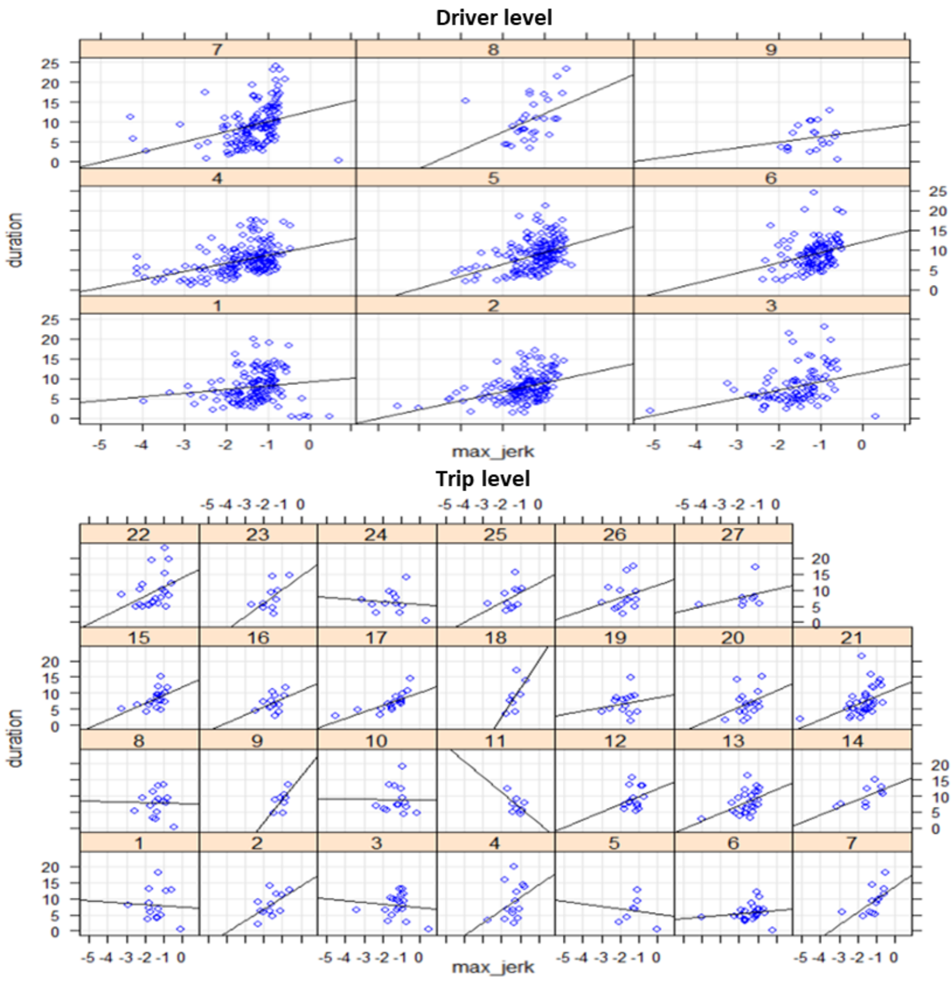


Figure 5.12: Random effect of the max_jerk in the duration for the driver and the trip level

Finally, all three models show high goodness of fit, although looking at the log-likelihood, the indicators of fit, AIC and BIC and the ICC, the three-level model is concluded to better the other models. The ICC of the best model underlines the importance of both the trip and the driver group and shows that 6.5% of the duration variation lies between the drivers and 36.2% of the variation lies between the trips.

5.2.4.2.2 Statistical analysis II

Following the same procedure in the statistical analysis II, the best linear regression was once more the ln-ln one with adjusted R^2=0.5260, which is smaller than the one form statistical analysis I indicating that the explanatory variables that were left out (e.g. TTC, THW) are affecting the duration. After examining all the possible models, i.e. trip, driver and three-Level random intercept and random slopes, the model three-Level random intercept and random slope for the variables max_jerk and car_stops concluded to be the most parsimonious and is presenting in Table 5.25.

Table 5.25: Results of the most parsimonious model for Duration in Statistical analysis II (UDRIVE dataset)

Model:	**Three-Level random intercept and slope model**	
FIXED EFFECT:		
	Coeff.	t-value
(Intercept)	-1.7353	-24.78
Day	-0.0562	-3.63
Ln_initial speed	0.8937	63.51
Speed_limit_2	0.0435	2.88
Speed_limit_3	0.0678	2.53
Speed_limit_4	0.0099	0.59
Speed_limit_5	0.0590	2.08
Following_a_car	0.1618	14.00
Car_stops	0.5539	30.20
Max_steer_angle	0.0008	11.41
Max_jerk	0.0937	4.76
One_direction road	-0.0457	-2.22
Traffic congestion	0.1061	5.33
Pedestrian	0.0671	4.60
One lane road	-0.0826	-4.34
Intersection	0.1664	15.81
RANDOM EFFECT Formula: ~max_jerk + car_stops | driver_id		

	StdDev:
(Intercept)	0.2165
Max_jerk	0.0972
cCr_stops	0.0871
Formula: ~1 | trip_id %in% driver_id	
(Intercept)	0.4067
Max_jerk	0.2168
Car_stops	0.1479
Residual	0.4101
AIC	8422.16
BIC	8621.6
logLik	-4182.08
ICC(DRIVER)	0.124
ICC(TRIP)	0.434

Comparing the result of Statistical analysis I (Table 5.24) and of Statistical analysis II (Table 5.25), similar explanatory factors, apart from the ones that were not included in the analysis II, and effects can be observed. In more details, the most statistically significant factors are the log_speed, the car_stops, the following_a_car, the intersection and the max_steering_angle whereas the max_jerk is less significant than it was in the analysis I. All the above variables have a positive effect on the duration, with the max_jerk and the car_stops to have random effects. On the one hand, the car_stops variable has a positive effect that varies on the duration for 100% of the observations in both driver and trip level. On the other hand, the max_jerk was calculated to have 83.5% positive slopes in the drivel-level and 66.7% positive slopes in the trip-Level. The ICC of the model shows the importance of both the trip and the driver group since 12.4% of the duration variation lies between the drivers and 31% of the variation lies between the trips.

5.2.4.3 Clustering

Similar to the analysis of the “combination” dataset, to examine in depth the effects that the driver characteristics might in the deceleration events, the data were clustered based on 3 age groups (18-30,31-50,>50) and gender and braking profile. Again, the 2-step cluster analysis in SPSS was employed to achieve that and the results gave good cluster quality with all the variables significant and 5 clusters, with almost similar size. The distribution of each variable in the clusters is presenting in Figure 5.13. Moreover, the different clusters present different deceleration characteristics.

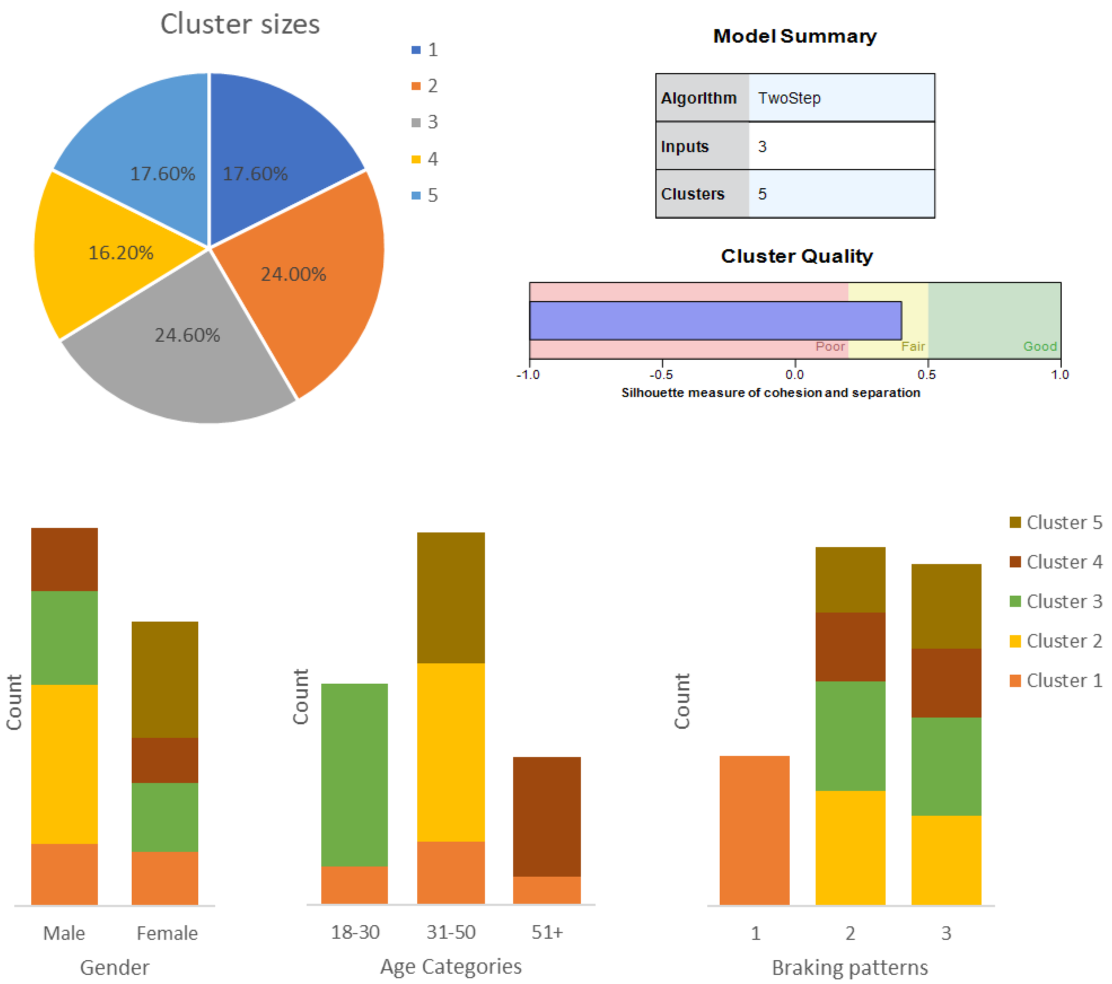


Figure 5.13: Features of the five clusters (UDRIVE dataset)

Next step is the statistical analysis of each cluster applying the multilevel mixed effect model using the statistical software R. The factors that were considered are: (1) event-level factors, such as situational factors, kinematic factors at the beginning of braking, etc. and (2) trip level factors, such as day or night, the model of the car. Therefore, the maximum deceleration value was analysed using statistical analysis for each cluster. Since the driver effect has been included in the clustering, the model that was used was the 2-level mixed effect model based on the trip level. The results from the analysis are presented in Table 5.26 for statistical analysis I and Table 5.27 for statistical analysis II. There was overwhelming evidence in favour of the trip-Level random intercept and random slope models for both statistical analyses. All the models show a reasonable goodness-of-fit since the overall intra-class correlation (ICC) was higher than 0.16 for all the models.

Table 5.26: Results from multilevel linear regression models in the 5 clusters in the statistical analysis I (UDRIVE dataset)

	Cluster 1		Cluster 2		Cluster 3		Cluster 4		Cluster 5	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
(Intercept)	-1.2967	-12.11	-1.3372	-20.87	-1.4158	-19.89	-1.5245	-20.42	-1.2572	-18.14
Day					-0.0824	-2.30				
Urban	0.0782	1.97								
Car model			0.1180	3.89						
Initial speed	-0.0091	-7.68	-0.0079	-9.80	-0.0102	-10.44	-0.0064	-6.25	-0.0086	-10.19
Speed_limit_2					0.0319	1.04				
Speed_limit_3					0.1367	2.20				
Speed_limit_4					-0.0305	-0.69				
Speed_limit_5					0.0923	1.36				
Initial headway			-0.0022	-3.65			-0.0013	-1.71		
Initial TTC	0.0018	2.54			0.0009	1.63			0.0012	2.01
Car_stops	-0.2665	-7.08	-0.2404	-10.39	-0.1979	-7.61	-0.1403	-4.66	-0.1541	-5.27
Max_jerk	0.5851	12.30	0.5698	20.07	0.3926	15.92	0.3948	14.00	0.6348	20.96
Arrive at traffic congestion	0.1406	2.54								
Traffic congestion			0.1537	4.96	0.1396	3.60	0.1379	3.50	0.1173	2.77
Random effects:										
	StdDev		StdDev		StdDev		StdDev		StdDev	
(Intercept)	0.4715		0.3455		0.3647		0.5362		0.1987	
Initial speed	0.0049		0.0041		0.0050		0.0058		0.1704	
Max_jerk	0.2289		0.2122		0.1861		0.2617		0.0024	
Residual	0.3612		0.3339		0.3303		0.3173		0.3509	
AIC	495.86		943.95		751.09		653.44		688.84	
BIC	563.92		1034.9		837.61		712.57		749.14	
logLik	-231.9		-454.0		-357.6		-313.7		-331.4	
ICC	0.826		0.734		0.793		0.808		0.169	
Number of observations	520		1158		904		698		764	
Number of groups	68		208		320		299		162	

Table 5.27: Results from Multilevel linear regression models in the 5 clusters in the statistical analysis II (UDRIVE dataset)

	Cluster 1		Cluster 2		Cluster 3		Cluster 4		Cluster 5	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
(Intercept)	-1.553	-12.67	-1.329	-22.61	-1.379	-26.22	-1.946	-24.54	-1.3555	-15.54
Car model			0.0805	2.99						
Day					-0.059	-2.35				
Trip duration									0.0054	2.75
Initial speed	-0.008	-5.96	-0.011	-14.47	-0.011	-15.20	-0.004	-4.15	-0.0097	-14.06
Speed_limit_2			0.0498	1.81	0.0216	0.82				
Speed_limit_3			0.0296	0.57	0.0446	0.88				
Speed_limit_4			0.0737	2.27	0.0549	1.72				
Speed_limit_5			0.1559	3.08	0.1259	2.37				
Following_a_car	0.1608	4.81	0.0794	3.26	0.0529	2.57	0.1190	2.81		
Car_stops	-0.193	-6.04	-0.224	-11.11	-0.222	-11.05	-0.101	-3.20	-0.1879	-8.08
Max_steering_angle	0.0006	3.33								
Max_jerk	0.5118	10.24	0.5669	22.31	0.3984	18.62	0.3193	12.96	0.6030	21.53
Traffic congestion			0.1181	3.65	0.1241	3.27	0.1548	3.07	0.1103	2.74
Intersection					-0.056	-2.91			-0.0560	-2.50
Random effects:										
	StdDev		StdDev		StdDev		StdDev		StdDev	
(Intercept)	0.8254		0.3785		0.3628		0.8575		0.3371	
Initial speed	0.0087		0.0044		0.0048		0.0069		0.0035	
Max_jerk	0.3270		0.2133		0.2300		0.2184		0.2029	
Following_a_car	0.1008		0.1521		0.6890		0.4061		N/A	
Residual	0.4988		0.3582		0.3623		0.4443		0.3645	
AIC	2000.6		1633.3		1761.1		1857.4		1204.4	
BIC	2077.7		1764.1		1887.0		1943.3		1276.4	
logLik	-985.3		-792.6		-857.6		-911.7		-588.19	
ICC	0.864		0.768		0.713		0.939		0.734	
Number of observations	1263		1719		1759		1158		1263	
Number of groups	71		212		382		363		182	

The most significant factors for all the clusters resulted to be the kinematic ones and specifically, the initial speed, the max jerk and the car_stops. The initial speed and the max jerk were found to have random effects in all the models and in detail their average effect varies from -0.004 to -0.011m/s^2 for the initial speed and from 0.3193 to 0.6348m/s^2. Their effect varies a lot, specifically for the effect of the max speed is negative to 71% till 100% of the observations in the different clusters and the effect of the max_jerk is positive to 85.31% till 100% of the observations in the different clusters. Other statistically significant variables are the initial TTC and THW in the first analysis, the following_a_car variable in the second one that gave random effect to 4 out of 5 clusters, the traffic congestion and the intersection in some clusters. Generally, the results agree with the results from the Combination dataset and from the previous multilevel analysis.

5.3 Summary

This chapter has presented the results of the analyses of the three datasets regarding the deceleration events. In detail, the outcome of the estimation of the braking functions and the results of the models that have been developed to examine the effect of the driver, trip and event factors on the deceleration value and duration are displayed. The most used deceleration profile, which is assumed to make drivers feel comfortable while braking (i.e. with the absence of uneasiness and distress since the data does not include any safety-critical events), is the Parabola 1 for the press of the brake that represents in real life a smooth braking at the beginning followed by a harder one. In detail, this profile was used in 48.6% of the cases, whereas the linear and the parabola 2 were used in 30% and 21.4% respectively. As far as the release of the brake is concerned, the most used profile is the parabola 2 with 42.5% use against 29.5% and 28% for the linear and the parabola 1 functions. Parabola 2 depicts a firm release of the brake at the beginning followed by a slower rate of deceleration.

The main findings using the multilevel mixed effect models on the deceleration value are:

- The structure of the data (how many drivers conducted how many trips) affect the best fitted multilevel model. For example, in the OEM data that 12 drivers conducted around 10 trips each the best model resulted to be the driver-level whereas in the TeleFOT dataset where 25 drivers conducted 1-2 trips the best model was a trip-level model. When each driver conducts only one till two trips, the common characteristics of the deceleration events belonging to one driver cannot be really examined due to lack of data while the trip dependencies can be better analysed. On the other hand, having 10 trips per driver provides enough data to reveal the dependencies of the deceleration events from the same driver.

- Higher initial speed and if *the car has to stop* variable affect negatively the deceleration value and are some of the most statistically significant variables.
- The reason for braking has a significant effect, i.e. braking because the car approaches a roundabout or a junction results in softer braking comparing to dynamic obstacles, whereas braking because of a pedestrian crossing or a traffic light decreases the deceleration value.
- The make and model of the car are proven to play an important role in the deceleration value.
- Braking while driving in a rural road and not in a motorway for TeleFOT dataset and in an urban road instead of a motorway for OEM dataset results in smaller absolute deceleration values, i.e. softer braking. On the other hand, considering the road speed limits in the UDRIVE dataset, it was found that the higher the road speed limit the softer the braking which contradicts the results from the other two datasets. This antithesis might be due to the varied independent variables in each dataset and to the differences on the way this variable was obtained in each dataset. Particularly, in TeleFOT study it was obtained empirically by watching the videos, in OEM study it was given as a trip variable (i.e. each trip was conducted either to a motorway, an urban or a rural area) and in UDRIVE study it was obtained as road speed limits for each event.
- When the driver was looking ahead at the time the braking starts gives softer braking compared to the cases when the driver looks inside the car.
- The driver characteristics, i.e. age, gender, driving experience (available only for the TeleFOT project) and driving behaviour (expressed as driver reaction for the TeleFOT and OEM project), the traffic density and trip characteristic with the exception of car do not affect significantly the deceleration value.

Some important results that were obtained from the statistical analysis of the duration of the deceleration event are:

- The best-fitted model for the duration was found to be the logarithmic-logarithmic model,
- Trip-level seemed to have a greater effect on the variation of the duration since either the trip or the three-level models were the most parsimonious for the

different datasets and around 5% and 35% of the variation of the duration were between the trips for the trip-level and the three-level model respectively.

- If the driver is looking ahead and not inside the car or right/left when the braking is starting, then the duration is shorter.
- The driver experience has a negative effect on the duration, meaning the more experience the driver has the shorter the braking.
- Driving in one-lane road and driving during the day result in a reduction of the duration of the braking.
- If the reason for braking is not a dynamic obstacle, the braking lasts longer.
- The initial speed and if the car stops are again statistically significant, having a positive effect on the duration.
- Higher steering angle during the braking results in an increase of the duration.
- Longer trip duration leads to a longer duration of the deceleration events.
- Driver factor and traffic density are proven not to affect the duration of the braking.

In addition, the findings described in this Chapter show that driver deceleration cannot be effectively modelled by applying average rates since the deceleration value and duration vary a lot depending on the vehicle kinematics, the reason for braking, the driver reaction and other situational factors.

6 Results of Comfort Modelling

To model the level of comfort and identify the factors increasing the likelihood for a deceleration event to be perceived as uncomfortable, the logit model was applied. The dependent variable is a categorical variable representing comfort categories such as comfortable, neutral and uncomfortable. Moreover, the explanatory variables are categorised at the event level variables and the driver level ones. All of them are included in the models and the statistically insignificant ones are removed since they do not affect the level of discomfort.

The structure of the dataset is the following: each driver made multiple trips, and in each trip, there are multiple deceleration events. Therefore, the data could be handled as panel data. Although, since we intend to explore the factors in an event level, the panel data form was not taken into consideration and each deceleration event was analysed as an individual.

Last but not least, it should be noted that two statistical analyses were undertaken; In the first one (i.e. Statistical Analysis I), all the explanatory variables were included, leading to fewer observations. Specifically, from 23,933 deceleration events that were identified, 5,843 events were included in the model. Many events happened without the existence of a leading vehicle and so, the variables TTC, THW, headway cannot be calculated. In addition, some drivers did not complete the questionnaire. In the second analyses (Statistical Analysis II) all the observations were included by taking out the variables that were mentioned before.

As it was mentioned above, the MNL model is applied to analyse the comfort level of the deceleration event so as to identify influencing factors. Since the data cannot include all the important variables and the fact that there are missing factors in relation with the reason for braking, the driver's risk perception and mental status etc., additional heterogeneity for the effect of the independent variables should be introduced (Pai et al., 2009). It is unrealistic to assume that all the influencing factors have a fixed effect on the comfort level of the deceleration events. Therefore, a methodological approach that allows for the possibility that the effect of the explanatory variables varies across the observations is adapted. So, a mixed logit model is applied to the dataset and by conducting the LR-test, it is decided if this is a better model than the multinomial logit one.

Therefore, this chapter presents the results of the discrete choice modelling of the comfort level of deceleration events. The explanatory variables and their specific effect are explained.

6.1 Classification A (4 categories)

6.1.1 Statistical analysis I (All variables)

First, a multinomial logit statistical model was applied to the data with the Classification A and the results are presented in Table 6.1. The number of observations is 5,843 as it was mentioned in the previous section. Moreover, the Adj. Rho squared equals to 0.2079, which shows a very satisfactory model fit for the MNL model. Taking into consideration that the factors affecting comfort are difficult to capture as comfort depends on the personal view of each driver, the model fit is satisfactory. In the beginning, all the variables were inserted into the model. After estimating the model, the variables that have a statistically significant effect at the 5% significance level were retained. The results are presented in Table 6.1. The parameter coefficients can be exponentiated to interpret the results in relative risk ratio's or odds. The "Very comfortable" category was kept as the reference category and the results are interpreted with respect to this category.

Table 6.1: Results of the logit model for Statistical Analysis I and Classification A

Model variables	Slightly comfortable	Slightly uncomfortable	Very uncomfortable
Alternative-specific constant	2.1317 (12.92)	2.4893 (8.91)	2.0077 (4.60)
TTC	-0.0101 (-6.88)	-0.0181 (-8.31)	-0.0320 (-7.11)
THW	-0.6097 (-11.74)	-1.2091 (-10.74)	-1.5082 (-7.92)
Space headway	0.0452 (9.56)	0.0871 (9.84)	0.1001 (7.89)
Traffic congestion	0.2530 (3.44)		

Initial speed	-0.0263 (-8.2)	-0.0417 (-7.85)	-0.0427 (-5.66)
Motorway	-0.2899 (-2)	-0.4008 (-1.92)	
Intersection	0.4091 (6.29)	0.5084 (5.98)	0.4745 (3.53)
Male	-0.1494 (-2.39)	-0.2670 (-3.23)	
Age 18-30		-0.2168 (-1.96)	-0.5795 (-2.62)
Age 30-50		0.1098 (1.97)	
Model statistics			
LL (start):	-8100.118	Rho-squared (0):	0.211
LL(0):	-8100.118	Adj.Rho-squared (0):	0.2079
LL(final):	-6390.799	AIC:	12833.6
Number of observations:	5843	BIC:	13007.1

The values of the alternative specific constants suggest that the average effect of the unmeasured variables tends to increase the probability of a braking event to be slightly comfortable, slightly uncomfortable or very uncomfortable. The probability is larger for an event to be slightly uncomfortable.

The effect of TTC is clear, showing that longer TTC results in higher odds of having a more comfortable braking event. When TTC is increased by 1 second, the odds of the event to be "very uncomfortable" are 1.03 times higher than being "very comfortable". THW was found to have a strong negative effect on all the categories, meaning that if the THW is increased the probability of an event to be uncomfortable is reducing. In this case, when the THW is increased by 1 second, the odds of the event to be "very comfortable" are 4.5 times higher than being "very uncomfortable", revealing that THW has a stronger negative effect to the comfort of the deceleration event than TTC. Moreover, an increase in space headway leads to higher odds that an event is very uncomfortable. The magnitude of the THW variable is larger than the one of the space headway, which may indicate that the event is affected more from the THW than from the space headway.

Next, when the event is happening in a moment where there is traffic congestion, there are 1.3 more odds that the event is "slightly comfortable" compared to the reference category. As far as the initial speed is considered, its increase is resulting in smaller odds of an event to be very uncomfortable. The initial speed does not have a really strong effect on the comfort of the deceleration event. This result might indicate that when the speed is high, the driver is more sensible in smaller deceleration and jerk and so the limits of the categories should be smaller for these cases. This is further supported with the effect of the motorway, showing that if the event is happening on the motorway in comparison to urban roads, its odds of being “very comfortable” are 1.3 and 1.5 higher than being “slightly comfortable” and “slightly uncomfortable” respectively. The category “urban” did not have a significant effect. Considering the situational factors, the existence of a pedestrian, a cyclist or a PTW did not show any statistically significant effect on the comfort of the deceleration event, whereas the existence of an intersection, increases the probability of an event not to be “very comfortable”.

Lastly, the results of the driver characteristics revealed that age and gender play a significant role to the comfort level of the deceleration event, while the AISS_total and the DBQ_all_violation that reveal the personality of the driver do not. More specifically, if the driver is a male then the odds of an event to be ”very comfortable” are higher than being “slightly comfortable” or “slightly uncomfortable”. Also, when drivers are 18-30 years old compared to 50+, it is less possible to have uncomfortable deceleration events. This might be because drivers at that age are more careful since they do not have the experience. On the other hand, drivers aged 30-50 are more likely to have a “slightly uncomfortable event” than the ones aged 50+.

As it was mentioned above, a mixed logit model was also applied to allow variation on the effect of the explanatory factors. Table 6.2 presents the log-likelihood of the mixed logit models, allowing heterogeneity on the effect of different factors. So, the procedure that was followed was allowing random effect to all the factors one by one working on the multinomial model with only significant variable presented in Table 6.1. Also, the log-likelihood test is presented, and the best model is the one that had the biggest value of twice the difference of its log-likelihood minus the log-likelihood of the multivariate logit model. In this case, the mixed logit model that allows mixed effect of THW turned out to be the best (see Table 6.2).

Table 6.2: Log-likelihood test for different mixed logit models for Statistical Analysis I and Classification A

Model	Log-Likelihood	2*(LogLik-$LogLik_{base\ model}$)	Chi-Square test
Discrete model	-6390.8		
Mixed effect for THW	-6378.20	25.2	7.81 (df =3) Best model
Mixed effect for SPEED	speed std deviation->not significant		
Mixed effect for TTC	-6346.93 (insignificant variables)	87.74	It
Mixed effect for TTC and SPEED	speed std deviation->not significant		
Mixed effect for space headway	-6387.16	7.28	5.99 (df =2) Better model
Mixed effect for TC	-6389.52	2.56	7.81 (df =3) Worse model
Mixed effect for INTERSECTION	-6390.59	0.42	7.81 (df =3) Worse model
Mixed effect for AGE	-6389.11	3.38	7.81 (df =3) Worse model

*at 95% confidence level

Next, the results of the best-mixed logit model are displayed in Table 6.3. It is noticed that the Adj. Rho squared is slightly higher (i.e. equals to 0.209) compared to the MNL model. Also, the AIC and BIC are slightly lower, supporting further that the mixed logit model is a better model than the multinomial logit one. The model has a few outliers. The worst outlier is an observation with ID 50, which has only a 0.4% probability per choice.

Table 6.3: Results of the best-mixed logit model for Statistical Analysis I and Classification A

Model variables	Slightly comfortable	Slightly uncomfortable	Very uncomfortable
Alternative-specific constant	2.5116 (11.96)	3.4018 (8.96)	3.4706 (5.40)
TTC	-0.0113 (-6.92)	-0.020 (-8.28)	-0.0349 (-7.34)
THW	-0.7768 (-9.86)	-1.7845 (-7.78)	-2.6159 (-5.39)

THW: standard deviation	-0.3112 (-3.69)	-0.4676 (-3.85)	-0.6543 (-3.62)
Space headway	0.0553 (9.22)	0.1115 (9.27)	0.1326 (6.78)
Traffic congestion	0.3089 (3.51)		
Initial speed	-0.0318 (-8.47)	-0.0535 (-8.39)	-0.0578 (-5.73)
Motorway	-0.3281 (-2.06)	-0.4237 (-1.8)	
Intersection	0.4469 (6.09)	0.5466 (5.72)	0.4863 (3.25)
Male	-0.1516 (-2.20)	-0.2861 (-3.08)	
Age 18-30		-0.2668 (-2.11)	-0.6215 (-2.54)
Age 30-50		0.1127 (1.79)	
Model statistics			
LL (start):	-8100.118	Rho-squared (0):	0.2126
LL(0):	-8100.118	Adj.Rho-squared (0):	0.209
LL(final):	-6378.208	AIC:	12814.42
Number of observations:	5843	BIC:	13005.93

The values of the alternative specific constants suggest that the average effect of the unmeasured variables tends to increase the probability of a braking event to be slightly comfortable, slightly uncomfortable or very uncomfortable. It can be observed that the effect of the unobserved variables is stronger to this model comparing to the multinomial logit one.

Comparing the results presented in Table 6.1 and in Table 6.3, it can be concluded that the variables have almost the same effects. For example, the TTC and the initial speed have a negative effect on the probability that a deceleration event is uncomfortable whereas the intersection and the existence of traffic congestion have an opposite effect. While the positive impact of the headway is slightly stronger in this model. Also, the effect of the younger drivers is bigger in this model, meaning that if the driver is 18-30 years old, the odds of a deceleration event to fall into the “very comfortable” category are 1.86 times higher than falling into the “very uncomfortable” category compared to if the driver was in the age category 50+.

The findings with regards to THW illustrate a strong negative effect on all the categories. In addition, THW was found to have a heterogeneous effect for all the comfort categories. Although, since the standard deviation is 2.5 till 4 times smaller than the coefficient, the impact of THW is negative across all the observation, with the small exception on the “slightly comfortable” category, where it has a positive effect on the 0.62% of the observations. So, increasing the THW has a negative effect, whose value is varying, to all the categories compared to the “very comfortable” category. Although, it should be noted that the normal distribution, which was the chosen distribution that the coefficient was allowed to fluctuate, might have enforced these results.

The predicted probabilities of the comfort categories against the THW are illustrated in Figure 6.1, in order to better understand the impact of THW to each of the categories. Probabilities for the uncomfortable categories, i.e. “slightly uncomfortable” and “very uncomfortable” are dropping significantly as the THW is increasing. Although, it can be noted that the decrease of the probabilities is not constant and that if the THW is more than 3.3 seconds the probability of an event to be uncomfortable is less than 0.1. The probabilities of the “slightly comfortable” category are increasing until the THW reaches the value of 1.8 seconds and then decreases for the rest of the values.

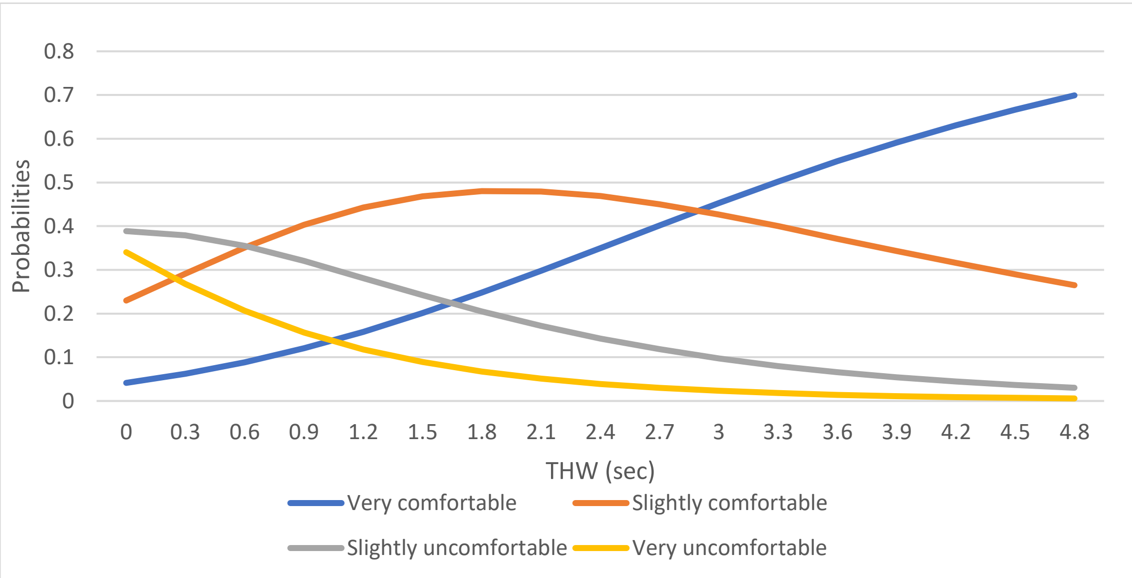


Figure 6.1: Predicted probabilities for THW based on the best-mixed logit model for Statistical Analysis I and Classification A

It was previously mentioned that the distribution, which was considered to specify the functional form of the parameter density function, in the previous model was the normal distribution. This might have imposed some results on the heterogeneous effect and so, other distributions were considered, i.e. the negative lognormal and the triangular distributions and the results are displayed in Table 6.4 and Table 6.5.

Table 6.4: Results of the mixed logit model using lognormal distribution for Statistical Analysis I and Classification A

Model variables	Slightly comfortable	Slightly uncomfortable	Very uncomfortable
Alternative-specific constant	2.478 (11.78)	3.3087 (6.70)	3.3805 (4.97)
TTC	-0.0111 (-6.88)	-0.0198 (-8.03)	-0.0341 (-7.45)
THW	0.0927 (1.44)	0.7316 (4.17)	1.0867 (4.93)
THW: standard deviation	-0.2745 (-4.06)	-0.2567 (-2.00)	0.2902 (3.03)
Space headway	0.0535 (9.38)	0.1071 (7.91)	0.1266 (6.77)
Traffic congestion	0.3078 (3.51)		
Initial speed	-0.0309 (-8.38)	-0.0516 (-7.66)	-0.0550 (-5.77)
Motorway	-0.3306 (-2.08)	-0.4181 (-1.78)	
Intersection	0.4467 (6.11)	0.5454 (5.52)	0.4787 (3.22)
Male	-0.1546 (-2.24)	-0.2891 (-3.08)	
Age 18-30		-0.2597 (-2.02)	-0.6291 (-2.58)
Age 30-50		0.1114 (1.77)	
Model statistics			
LL (start):	-8100.118	Rho-squared (0):	0.2126
LL(0):	-8100.118	Adj.Rho-squared (0):	0.209
LL(final):	-6379.457	AIC:	12814.42
Number of observations:	5843	BIC:	13007.93

Table 6.5: Results of the mixed logit model using triangular distribution for Statistical Analysis I and Classification A

Model variables	Slightly comfortable	Slightly uncomfortable	Very uncomfortable
Alternative-specific constant	2.4012 (11.98)	2.9275 (8.64)	2.5552 (5.6)
TTC	-0.0108 (-6.86)	-0.0189 (-8.46)	-0.0327 (-7.18)
THW: a	-2.3623 (-9.74)	-1.7730 (-5.46)	-2.0197 (-8.00)
THW: b	0.6320 (3.42)	-0.699 (-1.42)	-0.8695 (-2.64)
Space headway	0.0523 (9.16)	0.0982 (9.7)	0.11 (8.13)
Traffic congestion	0.2925 (3.50)		
Initial speed	-0.0303 (-8.26)	-0.0473 (-8.33)	-0.048 (-6.06)
Motorway	-0.3117 (-2.02)	-0.3992 (-1.82)	
Intersection	0.4378 (6.15)	0.5287 (5.81)	0.4761 (3.41)
Male	-0.1514 (-2.26)	-0.2743 (-3.14)	
Age 18-30		-0.2364 (-2.0)	-0.5936 (-2.62)
Age 30-50		0.1093 (1.80)	
Model statistics			
LL (start):	-17598.85	Rho-squared (0):	0.2117
LL(0):	-8100.118	Adj.Rho-squared (0):	0.2081
LL(final):	-6385.651	AIC:	1229.3
Number of observations:	5843	BIC:	13022.82

The negative lognormal distribution allows the THW to have only a negative impact on the comfort categories that fluctuates its value. The equation of the coefficient is: $= -e^{(\mu+\sigma\times r_N)}$, where r_N ~N(0.1). Therefore, the coefficient of the THW is positive and if the equation is calculated, it results in similar coefficients with the ones of the normal distribution. As it can be observed from Table 6.4 and Table 6.5 the log-likelihood of those models is larger than the one that uses the normal distribution, meaning that these models are slightly worse and the normal distribution appears to give the best statistical fit. Furthermore, it can be observed that the rest of the variables have almost the same coefficients. Table 6.5, shows the results when a triangular distribution was considered, and it can be noticed that the effect of the THW is negative for the uncomfortable categories and mostly negative for the "slightly comfortable" category that agrees with the results of the model with the normal distribution. In Figure 6.2, the density of beta (β) of the "slightly comfortable" category for the three different distributions is displayed. It can be observed that if the effect is not forced to be negative by using the negative log-normal distribution, it becomes positive for a small percentage (in both normal and triangular distributions).

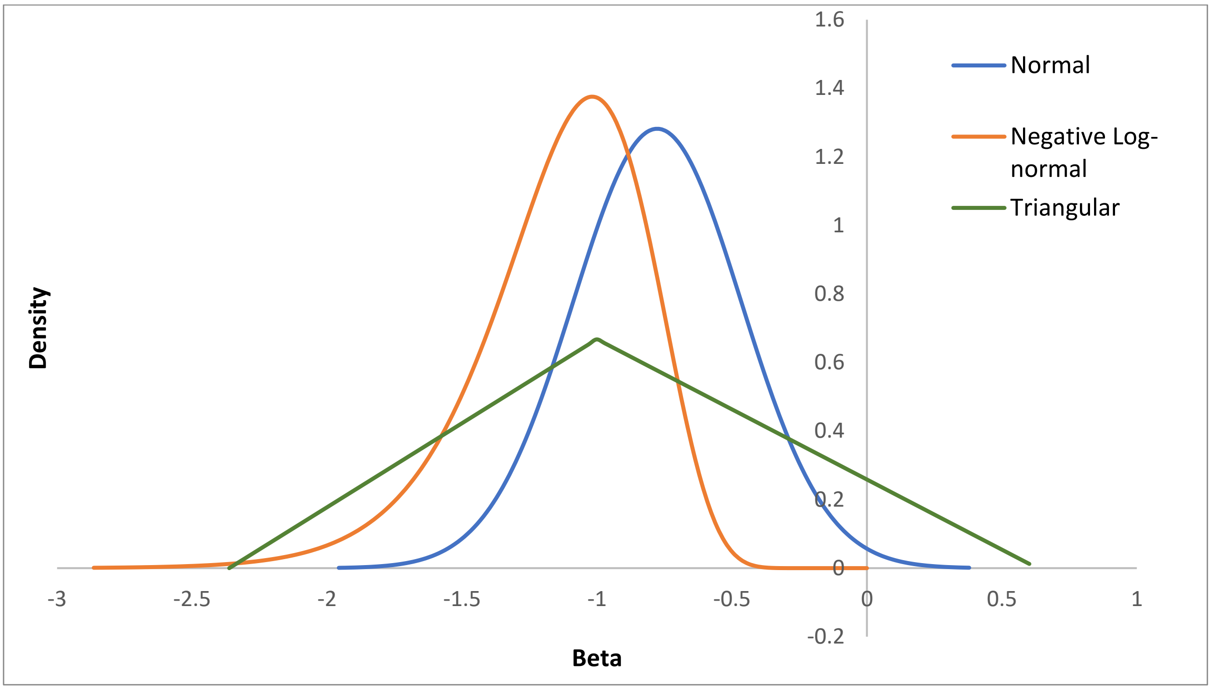


Figure 6.2: The density of beta (β) considering three different distributions for the "slightly comfortable" category

6.1.2 Statistical analysis II (All observations)

As it was mentioned in the methodological approach, the logit models have been applied again to the same dataset with the same comfort classification. The variables that were not available for all the observations, either because the car does not follow any other car (i.e. TTC, THW, space headway not available) or because the information was not available for all the drivers (e.g. AISS_total and DBQ_all violations), were excluded from the explanatory variables of the model. This resulted in having available all the observations, i.e. 23,933 observations and exploring the other variables that may affect the event when the situation is not the following car situation.

Similar to the statistical analysis I, an MNL model was first applied, and the results are presented in Table 6.6. The adjusted R^2 equals to 16.64, which shows a good fit, considering that there are plenty of factors affecting the deceleration comfort level that is not captured from the model. Moreover, the adjusted R^2 is smaller than the corresponding adjusted R^2 from statistical analysis I. This can be justified since for this analysis some explanatory variable were excluded.

Table 6.6: Results of the logit model for Statistical Analysis II and Classification A

Model variables	**Slightly comfortable**	**Slightly uncomfortable**	**Very uncomfortable**
Alternative-specific constant	0.178 (2.88)	-0.7723 (-14.01)	-2.5993 (-25.77)
Traffic congestion	0.2716 (6.33)		
Initial speed	-0.0014 (-1.93)		0.0159 (12.78)
Urban	-0.0684 (-2.11)		
Motorway	-0.4484 (-5.62)	-0.5723 (-5.21)	-0.4923 (-3.54)
Pedestrian	0.256 (5.6)	0.2138 (3.54)	0.3069 (3.74)
Intersection	0.7046 (22.42)	0.9143 (21.66)	1.071 (18.5)
Male	-0.1213 (-3.99)	-0.2645 (-6.35)	-0.1265 (-2.24)
Age 18-30		0.167 (4.34)	
Age 31-50		0.1438 (4.9)	
Lane	-0.1915 (-4.59)	0.4421 (-8.47)	-0.244 (-3.37)
Model statistics			
LL (start):	-33178.2	Rho-squared (0):	0.1671
LL(0):	-33178.2	Adj.Rho-squared (0):	0.1664
LL(final):	-27632.6	AIC:	55313.27
Number of observations:	23933	BIC:	55507.26

The values of the alternative specific constants suggest that the average effect of the unmeasured variables tends to decrease the probability of a braking event to be slightly uncomfortable or very uncomfortable compared to “very comfortable”. Whereas, it has the opposite effect on the “slightly comfortable” category.

The results indicate a positive effect of traffic congestion on a deceleration event to fall in the “slightly comfortable” category instead of the “very comfortable” one. This result is similar to the one from statistical analysis I. Next, the initial speed affects the categories “slightly comfortable” and “very uncomfortable”. To the first category, it has a negative effect, vice versa to the “very uncomfortable” category it has a positive effect. That means, that when the initial speed is increased by one unit, the odds to be “very uncomfortable” are 1.02 more than being “very comfortable”. This is an interesting finding since it comes in contrast to the statistical analysis I.

As far as the type of road is concerned, the motorway has a negative effect on the discomfort of a deceleration event to all the comfort categories compared to rural roads. Moreover, if a deceleration event is happening in an urban road, there are fewer probabilities of it to be “slightly uncomfortable” instead of “very comfortable”.

Considering the situational factors, the existence of a pedestrian plays an important role. Specifically, if there is a pedestrian, the odds of an event to be “slightly comfortable”, “slightly uncomfortable” and “very uncomfortable” are respectively 1.29, 1.24 and 1.36 more than to be “very comfortable”. The effect of the pedestrian is important since it was not captured in the previous statistical analysis. A cyclist or a PTW didn’t show any statistically significant effect on the comfort of the deceleration event. On the other hand, the existence of an intersection has a strong positive impact on the discomfort of an event. For example, the odds of a “very uncomfortable” event are 2.92 higher than a “very comfortable” event, when there is an intersection.

Table 6.6 proves that the driver characteristics have an impact on the comfort level of a deceleration event. For example, male drivers seem to have more probabilities to brake in a “very comfortable” way compared with females. The driver’s age has a bit different effect than the one that was revealed in the Statistical analysis I. Specifically if a driver is 18-30 years old compared to 50+, it is more possible to have “slightly uncomfortable” deceleration event.

A mixed logit model was applied to this statistical analysis too. Mixed logit models allowing different explanatory variables were tried and the best statistically fitted model is the mixed logit model that allows initial speed to have a heterogeneous effect (i.e. 2*(LogLik-$LogLik_{base\ model}$)=113.2> 3.84 probability of chi-square for df=1). Table 6.7 displays the results of that model. The adjusted R^2 is higher than the MNL model's, supporting further that the mixed model is better fitted. Also, the model doesn't seem to have extreme outliers, since the worst outlier is an observation with ID 389, which has a 16.6% probability per choice.

Table 6.7: Results of the mixed logit model with allowing random effect for speed for Statistical Analysis II and Classification A

Model variables	Slightly comfortable	Slightly uncomfortable	Very uncomfortable
Alternative-specific constant	0.178 (2.88)	-0.7723 (-14.01)	-2.4787 (-23.36)
Traffic congestion	0.2772 (6.45)		
Initial speed	-0.0014 (-1.86)		0.0112 (7.25)
Initial speed: standard deviation			-0.0099 (-11.4)
Urban	-0.0641 (-1.97)		
Motorway	-0.4474 (-5.6)	-0.5721 (-5.21)	-0.452 (-3.01)
Pedestrian	0.256 (5.57)	0.2135 (3.54)	0.2928 (3.49)
Intersection	0.7043 (22.42)	0.9143 (21.66)	1.0832 (18.29)
Male	-0.1223 (-4.02)	-0.2647 (-6.35)	-0.1366 (-1.84)
Age 18-30		0.1635 (4.19)	
Age 31-50		0.1366 (4.6)	
Lane	-0.1922 (4.61)	0.4419 (-8.47)	-0.268 (-3.53)
Model statistics			
LL (start):	-27898.6	Rho-squared (0):	0.1688

LL(0):	-33178.2	Adj.Rho-squared (0):	0.1681
LL(final):	-27576.5	AIC:	55202.89
Number of observations:	23933	BIC:	55404.97

Comparing the results presented in Table 6.7 with the ones in Table 6.6, one can observe that the coefficients are almost the same. That means that the effects of the explanatory variables remain the same. The only difference is that speed has a heterogeneous effect on the "very uncomfortable" category. Particularly, it has a positive effect on 87% of the observations and a negative one on the rest 13%.

6.2 Classification B (3 categories)

6.2.1 Statistical analysis I (All variables)

The second classification splits the deceleration events into three categories: "comfortable", "neutral" and "uncomfortable". The category "comfortable" was kept as the reference category. The number of the observations remains the same, 5,843 observations. First, an MNL model was applied, and the outcome is presented in Table 6.8. It can be observed that the adjusted Rho squared is 0.134, which is lower than the one from the model applied for classification A but it is still satisfactory for logistic regression models. That means that the available influencing factors affect less the comfort level of the deceleration event when having three categories.

Table 6.8: Results of the logit model for Statistical Analysis I and Classification B

Model variables	Neutral	Uncomfortable
Alternative-specific constant	2.2688 (14.87)	2.8993 (12.57)
TTC	-0.0105 (-7.03)	-0.0224 (-10.60)
THW	-0.6199 (-13.71)	-1.3257 (-14.38)
Space headway	0.0471 (11.00)	0.0897 (12.09)
Traffic congestion	0.2489 (3.39)	
Initial speed	-0.0262 (-8.68)	-0.0418 (-9.06)

Motorway	-0.3753 (-2.50)	-0.5159 (-2.50)
Pedestrian	0.4261 (6.62)	0.4472 (5.32)
Intersection	-0.1985 (-3.12)	-0.1899 (-2.25)
Age 18-30		-0.2856 (-3.22)
Model statistics		
LL (start):	-6419.192	
LL(0):	-6419.192	
LL(final):	-5541.113	
Number of observations:	5843	
Rho-squared (0):	0.1368	
Adj.Rho-squared (0):	0.134	
AIC:	11118.23	
BIC:	11238.34	

With regards to the values of the alternative specific constants, they suggest that the average effect of the unmeasured variables tends to increase the probability of a braking event to be neutral or uncomfortable. The TTC and the THW have a negative effect, meaning that the larger the TTC or the THW, the fewer probabilities of a deceleration event to be neutral or uncomfortable instead of comfortable. It can be noted from Table 6.8 that the THW has the strongest effect of all the explanatory variables since its magnitude is the highest in absolute value. For example, if the THW increases by 1 sec, the odds of an event to be “comfortable” are 3.76 times higher than to be “uncomfortable”. The effect of the space headway is positive, i.e. when increasing the space headway by 1 unit, the odds of an “uncomfortable event” are 1.09 higher than of a “comfortable” event.

Furthermore, the initial speed and the motorway have a negative effect on the discomfort level of a deceleration event. So far, the results are similar to those from Statistical analysis I at four comfort categories. Although, when having three categories the existence of a pedestrian has a significant effect, in contrast to when having four categories. Specifically, the deceleration event is more likely to be “neutral” or “uncomfortable” than “comfortable” when there is a pedestrian. Also, the probabilities of an event to be more uncomfortable are reducing if the reason for braking is an intersection.

As far as the driver characteristics are concerned, only one age category is significant at the “uncomfortable” category. It can be explained as if the driver is between 18-30 years old, the odds of having a “comfortable” deceleration event are 1.33 more than having an “uncomfortable” one. Comparing to the four categories results (Table 6.1), it can be noted that the driver characteristics have a bigger influence in the four categories classification since the gender and the age 30-50 variable are statistically significant.

To try to explain better comfort level at the classification B by allowing heterogeneous effects on the explanatory variables, mixed logit models were applied. The log-likelihood of the different mixed logit models, as well as the log-likelihood test, are demonstrated in Table 6.9. It is indicated from Table 6.9 that the mixed model allowing THW to have a mixed effect is significantly better than the MNL model, whose outcome is displayed in Table 6.10. The adjusted R^2 is slightly higher and both the AIC and the BIC are smaller than the MNL model, supporting further the fact that the mixed model has a better statistical fit. The model has some outliers, with the most extremes to have 0.44% and 2.6% probability per choice.

Table 6.9: Log-likelihood test for different mixed logit models for Statistical Analysis I and Classification B

Model	Log-Likelihood	2*(LogLik-$LogLik_{base\ model}$)	Chi-Square test
Discrete model	-5541.11		
Mixed effect for THW	-5527.19	27.84	5.99 (df =2) Better model
Mixed effect for SPEED	-5541.11	0.004	5.99 (df =2) Worse model
Mixed effect for TTC	-5509.34 not significant		
Mixed effect for space headway	-5539.12	3.98	5.99 (df =2) Worse model
Mixed effect for MOTORWAY	-5540.3	1.62	5.99 (df =2) Worse model
Mixed effect for INTERSECTION	-5540.46	1.320	5.99 (df =2) Worse model

Table 6.10: Results of the best-mixed logit model for Statistical Analysis I and Classification B

Model variables	Neutral	Uncomfortable
Alternative-specific constant	2.6512 (12.93)	4.1083 (10.97)
TTC	-0.0117 (-7.27)	-0.0255 (-9.88)
THW	-0.7846 (-10.29)	-2.0971 (-9.47)
THW: standard deviation	-0.3011 (-3.91)	-0.5697 (-5.50)
Space headway	0.0587 (9.47)	0.1220 (10.00)
Traffic congestion	0.3113 (3.51)	
Initial speed	-0.0321 (-8.53)	-0.0568 (-9.01)
Motorway	-0.398 (-2.48)	-0.5118 (-2.11)
Pedestrian	0.4679 (6.47)	0.4818 (4.94)
Intersection	-0.2061 (-2.97)	-0.2202 (-2.26)
Age 18-30		-0.4075 (-3.07)
Model statistics		
LL (start):	-6419.192	
LL(0):	-6419.192	
LL(final):	-5527.189	
Number of observations:	5843	
Rho-squared (0):	0.139	
Adj.Rho-squared (0):	0.1358	
AIC:	11094.38	
BIC:	11227.84	

From Table 6.10, it can be observed that the effects of the explanatory factors are almost similar to the MNL model. The difference come at the magnitude of the alternative-specific constants, which is larger, especially for the “uncomfortable” category. This increase implies that the unobserved factors affecting the comfort level increase a lot the probability of an event to be uncomfortable. In addition, the findings with regards to THW illustrate an even stronger negative effect on all the categories, which vary across the observations. Since the standard deviation is 2.6 and 3.7 bigger than the mean for the “neutral” and the “uncomfortable” category respectively, it can be concluded from the normal distribution table that for the “neutral” category THW has a negative effect at the 99.53% of the observations and for the “uncomfortable” category at almost 100%. Therefore, the effect of the THW is negative, but its magnitude is varying.

In Figure 6.3, the predicted probabilities of the three comfort categories against the THW are displayed. After a point for the THW, around 3 seconds, the probabilities of all the categories have a continuous trend, i.e. the comfortable category is increasing and the other two are decreasing. To illustrate better the probabilities before that point, a zoom-in version of that plot is presented in Figure 6.4. The probability of the “uncomfortable” category drops really a fact at the first two seconds followed by a smoother drop, whereas the probabilities of the “comfortable” category are increasing in a constant way till around the 5th second. Lastly, the most interesting picture is that of the “neutral” category probabilities, which are increasing till the THW equals to 1.8sec and the start decreasing, showing the heterogeneity of the effect of THW to the “neutral” category.

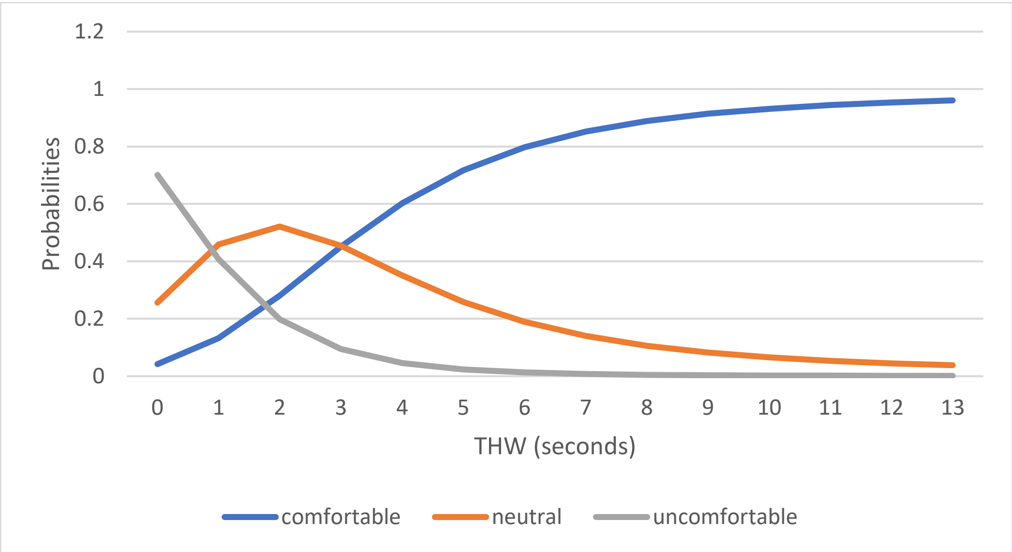


Figure 6.3: Predicted probabilities for THW based on the best-mixed logit model for Statistical Analysis I and Classification B

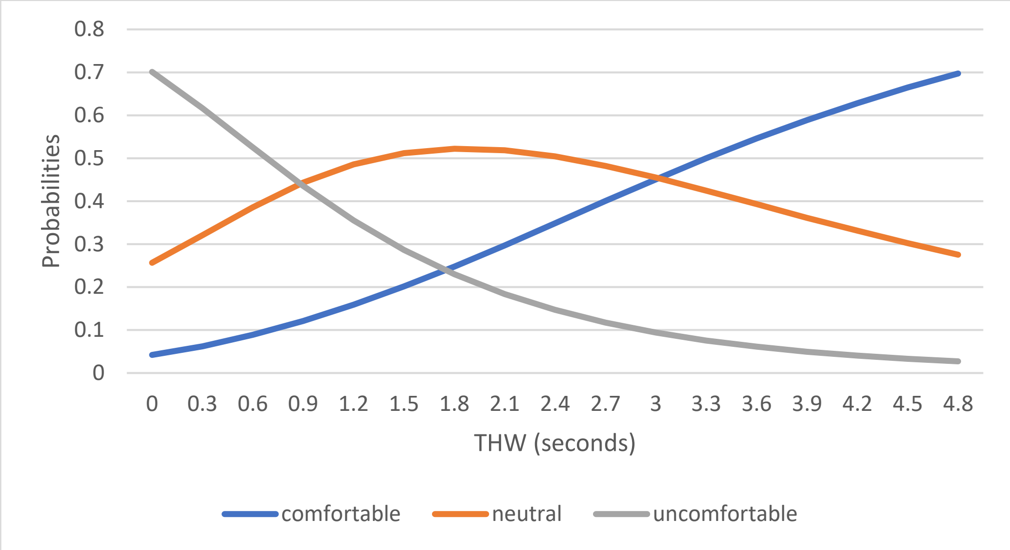


Figure 6.4: Zoom in version of Figure 6.3

6.2.2 Statistical analysis II (All observations)

Following the same methodological approach as in classification A, an MNL model was applied to the dataset with the three comfort categories using only the affecting factors available for all the observations. The outcome of the model is displayed in Table 6.11. The adjusted R^2 has dropped from 0.134 at Statistical analysis I to 0.10, implying that the explanatory variables used at the Statistical analysis I might explain better the comfort level. Moreover, the number of observations plays an important role in the Adjusted R^2, i.e. having more observations, 23,933 instead of 5,843, can lead to a smaller Adjusted R^2.

Table 6.11: Results of the logit model for Statistical Analysis II and Classification B

Model variables	Neutral	Uncomfortable
Alternative-specific constant	0.2334 (4.94)	-1.0268 (-14.53)
Traffic congestion	0.2848 (6.29)	0.1632 (2.48)
Initial speed		0.0056 (6.30)
Urban	-0.0719 (-2.43)	
Motorway	-0.4803 (-6.32)	-0.5238 (-5.00)
Pedestrian	0.2680 (5.92)	0.2150 (3.67)

Intersection	0.7378 (23.90)	0.9340 (23.06)
Male	-0.1351 (-4.52)	-0.1995 (-5.02)
Age 18-30	0.1820 (4.76)	
Age 31-50	0.1318 (4.5)	
Lane	-0.2217 (-5.40)	-0.3171 (-6.13)
Model statistics		
LL (start):	-26293.09	
LL(0):	-26293.09	
LL(final):	-23654.95	
Number of observations:	23933	
Rho-squared (0):	0.1003	
Adj.Rho-squared (0):	0.0997	
AIC:	47345.9	
BIC:	47491.4	

The magnitude of the alternative-specific constants signifies that the average effect of the unmeasured variables, increase the probability of a deceleration event to be "neutral" instead of "comfortable" and vice versa decrease the probability to be "uncomfortable" instead of "comfortable".

The traffic congestion has a positive effect, meaning that when there is traffic congestion when the deceleration event is taking place, then the probability of this event to be "neutral" or "uncomfortable" is greater than to be "comfortable". The initial speed affects only the "uncomfortable" category in a way that when the initial speed increases the odds of the "uncomfortable" category increase too. As far as the road type is concerned, if the deceleration event is taking place in a motorway or in the urban road instead of rural ones, the probability of this event to belong to the comfortable category increases.

Regarding the situational factors, both pedestrians and intersections have a positive effect on the event's discomfort, i.e. increase the odds of the event to belong to the "neutral" or the "uncomfortable" category instead of the "comfortable" one. Moreover, if the road has only one lane, then the probabilities of an event to be "uncomfortable" are decreasing.

Finally, driver characteristics became significant again. In detail, if the driver is male, the odds of a "comfortable" event are 1.15 and 1.22 higher than of a "neutral" and "uncomfortable" event respectively. Also, the age of the driver affects the "neutral" category: when the driver's age is less than 50, the probabilities of having a "neutral" event are higher than having a "comfortable" one compared to the reference age category.

Next, the results of the mixed logit model are presented in Table 6.12, showing that the mixed logit model allowing heterogeneous effect at the factor intersection is slightly better than the MNL one. Specifically, the adjusted R^2 is almost the same, whereas the AIC is larger and the BIC smaller. That doesn't give significant proof that this model is statistically significantly better than the MNL model. The log-likelihood test gives small evidence that this model is better ($2*(LogLik-LogLik_{base\ model})=13.58>3.84$ critical value of chi-square distribution for df=1).

Table 6.12: Results of the mixed logit model with allowing random effect for intersection for Statistical Analysis II and Classification B

Model variables	Neutral	Uncomfortable
Alternative-specific constant	0.22221 (3.99)	-1.0539 (-14.56)
Traffic congestion	0.3663 (6.79)	0.1568 (2.34)
Initial speed		0.0062 (6.72)
Urban	-0.0779 (-2.18)	
Motorway	-0.5406 (-6.31)	-0.5334 (-5.03)
Pedestrian	0.3411 (6.00)	0.2000 (3.37)
Intersection	1.023 (7.3)	0.9361 (23.00)
Intersection: standard deviation	3.0424 (2.93)	
Male	-0.1416 (-4.04)	-0.1970 (-4.91)
Age 18-30	0.2178 (4.65)	
Age 31-50	0.1226 (3.27)	

Lane	-0.2222 (-4.51)	-0.3151 (-6.03)
Model statistics		
LL (start):	-26293.09	
LL(0):	-26293.09	
LL(final):	-23648.16	
Number of observations:	23933	
Rho-squared (0):	0.1006	
Adj.Rho-squared (0):	0.0999	
AIC:	49334.31	
BIC:	47487.89	

Comparing the results presented in Table 6.12 with Table 6.11, it is noted that the magnitudes of the influencing factors are similar, so the interpretation is the same. Regarding the existence of an intersection, it has a mixed effect on the "neutral" category. In detail, for 63.31% of the observations, the intersection increases the probability of a "neutral" event, whereas for the rest 36.69% it has an opposite effect.

6.3 Classification C (2 categories)

6.3.1 Statistical analysis I (All variables)

The last classification has two comfort categories: "comfortable" and "uncomfortable". The category "comfortable" was kept once more as the reference category. Since the dependent variable has only two categories, the model becomes a binary MNL model. Table 6.13 presents the results of this model, the adjusted Rho squared equals to 0.062, which means that the Classification C might not be the best classification to explore the comfort influencing factors.

Table 6.13: Results of the logit model for Statistical Analysis I and Classification C

Model variables	Uncomfortable
Alternative-specific constant	2.1343 (15.15)
TTC	-0.0127 (-9.46)
THW	-0.7343 (-14.69)
Space headway	0.0554 (12.58)

Initial speed	-0.028 (-9.68)
Motorway	-0.3353 (-2.44)
Intersection	0.3654 (6.57)
Male	-0.1764 (-3.15)
Age 18-30	-0.2796 (-3.44)
Model statistics	
LL (start):	-4050.059
LL(0):	-4050.059
LL(final):	-3799.933
Number of observations:	5843
Rho-squared (0):	0.0618
Adj.Rho-squared (0):	0.0595
AIC:	7617.87
BIC:	7677.92

The influence of the unobserved factors is higher probabilities of an event to belong to the “uncomfortable” category. Both TTC and THW have a positive effect on the comfort level of a deceleration event. Increasing the THW by 1 sec leads to 2.09 higher odds of a “comfortable” instead of an “uncomfortable” event. Regarding the driver characteristics, being a male driver aged 18-30 reduces the probability of having an “uncomfortable” deceleration event. When the driver brakes because of an intersection, the odds of being an “uncomfortable” event are 1.44 times higher than being “uncomfortable”. Furthermore, motorway and initial speed have a negative impact on the “uncomfortable” category.

The next step is to allow for heterogeneous effect to all the explanatory factors. The log-likelihood along with the test is demonstrated in Table 6.14. It is obvious that the model that allows TTC and THW to have a mixed effect is the best but the most complex too. Also, the mixed model that allows only TTC to have heterogeneous effect seems to have a good fit. Therefore, both models are presented below in Table 6.15.

Table 6.14: Log-likelihood test for different mixed logit models for Statistical Analysis I and Classification C

Model	Log-Likelihood	2*(LogLik-LogLik$_{base\ model}$)	Chi-Square test
Discrete model	-3799.93		
Mixed with THW	-3790.78	18.3	3.84 (df =1) Better model
Mixed with SPEED	-3798.84	2.18	3.84 (df =1) Worse model
Mixed with TTC	-3780.42	39.02	3.84 (df =1) Better model
Mixed with space headway	-3844.52	-89.18	3.84 (df =1) Worse model
Mixed with MOTORWAY	-3799.87	0.12	3.84 (df =1) Worse model
Mixed with INTERSECTION	-3797.34	5.18	3.84 (df =1) Better model
Mixed with TTC and THW	-3776.04	47.78	5.99 (df =2) Better model

Table 6.15: Results of the mixed logit model (TTC) for Statistical Analysis I and Classification C

	Mixed logit model with TTC having heterogeneous effect (1)	Mixed logit model with TTC and THW having heterogeneous effect (2)
Model variables	**Category**	
	Uncomfortable	**Uncomfortable**
Alternative-specific constant	4.4230 (5.68)	5.0560 (5.43)
TTC	-0.0379 (-4.43)	-0.0376 (-4.55)
TTC: standard deviation	0.1141 (3.49)	0.0971 (3.54)
THW	-1.5248 (-5.41)	-1.8078 (-5.17)
THW: standard deviation	NA	-0.5518 (-3.65)
Space headway	0.1219 (5.05)	0.1469 (4.80)
Initial speed	-0.0507 (-4.88)	-0.066 (-4.72)
Motorway	-0.9614 (-2.53)	-0.8948 (-2.40)

Intersection	0.6331 (3.96)	0.6592 (3.98)
Male	-0.3488 (-2.52)	-0.3854 (-2.59)
Age 18-30	-0.6208 (-2.75)	-0.6431 (-2.82)
Model statistics		
LL (start):	-4050.059	-4050.059
LL(0):	-4050.059	-4050.059
LL(final):	-3780.416	-3776.041
Number of observations:	5843	5843
Rho-squared (0):	0.0666	0.0677
Adj.Rho-squared (0):	0.0641	0.0649
AIC:	7580.83	7574.08
BIC:	7647.56	7647.49

Firstly, the adjusted R^2 has been slightly increased with the binary mixed logit models from 0.0618 to 0.0666 for the mixed model (1) and 0.0677 for the mixed model (2). Also, the indicators of goodness of fit, AIC and BIC have been decreased showing that the mixed model (2) is the best-fitted model.

From Table 6.15, it can be noted that the magnitudes of the alternative-specific constants are larger than in the binary MNL model, indicating that the effect of the unobserved factors on an event being “uncomfortable” is bigger and positive. The TTC has a heterogeneous effect on the “uncomfortable” category for both models. In detail, TTC has a negative effect on the 62.93% of the observations and a positive one on the rest 37.07% for the mixed model (1). For the mixed model (2) the percentage that TTC has a negative effect is 65.17%. To better illustrate the mixed effect of TTC, the probabilities of the two comfort categories against the TTC have been plotted in Figure 6.5 and Figure 6.6 for the mixed model (1) and (2) respectively. Small differences can be identified in the Figures, the initial probabilities are slightly different. In both figures, the probabilities change rapidly at the beginning till TTC=4sec and then have a smoother change.

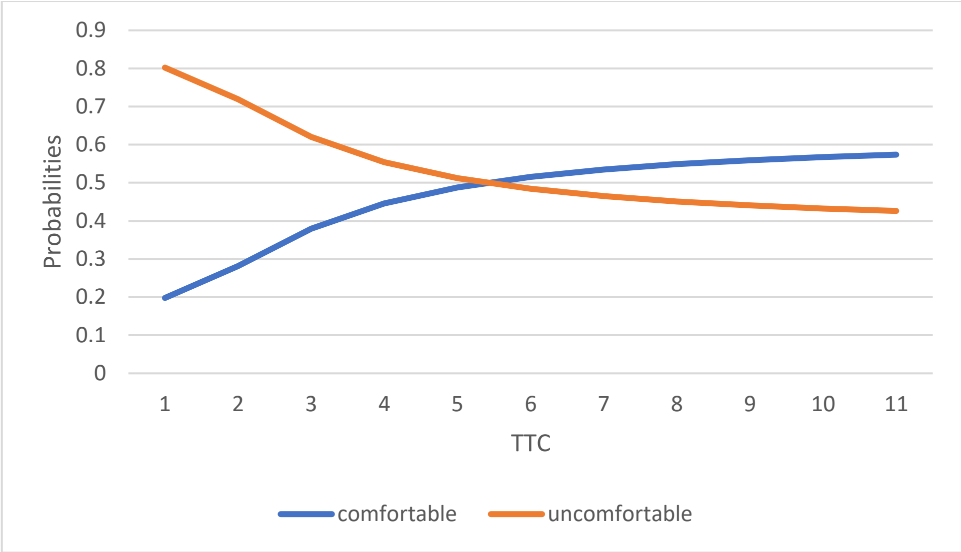


Figure 6.5: Predicted probabilities for TTC based on the TTC mixed logit model for Statistical Analysis I and Classification C

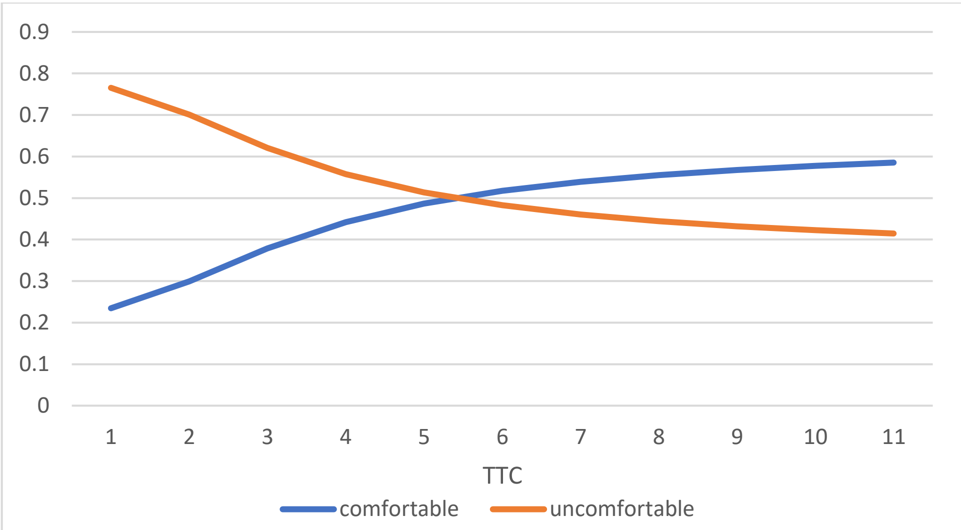


Figure 6.6: Predicted probabilities for TTC based on the mixed logit model (TTC and THW random effect) for Statistical Analysis I and Classification C

Regarding mixed model (1), the THW has a constant negative effect which is stronger than in MNL model, since 1 unit increase will result in 4.6 higher odds of a “comfortable” event rather than an “uncomfortable” one. The THW in the mixed model (2) has a fluctuated effect: it is negative for all the observations since the mean is more than three times bigger than the standard deviation but its value changes, sometimes it affects the event stronger whereas other times it has a small effect on the comfort level of the event. Figure 6.7 depicts the graph of the probabilities of the two comfort categories against the THW and it can be concluded that the probabilities change in an almost constant rate.

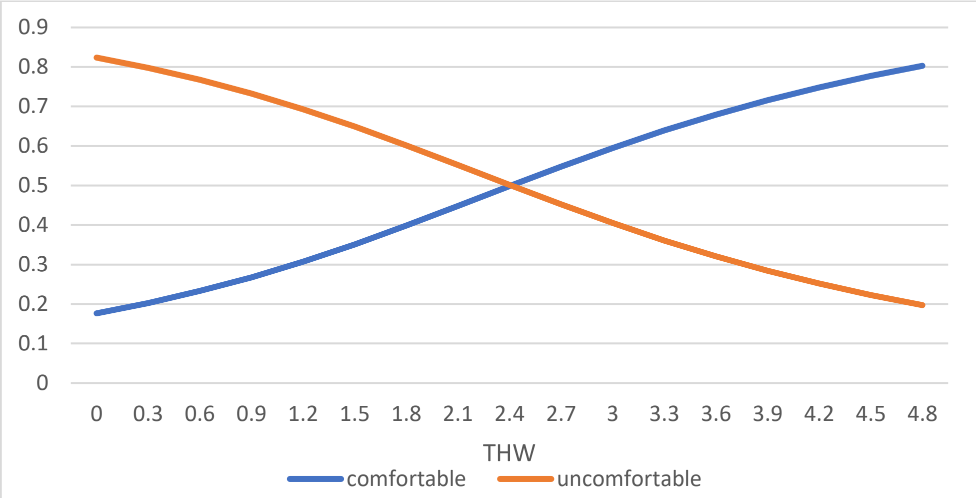


Figure 6.7: Predicted probabilities for THW based on the mixed logit model (TTC and THW random effect) for Statistical Analysis I and Classification C

The rest influencing factors have similar magnitudes for both mixed models. For example, the probabilities of an "uncomfortable" event are increasing if the space headway increases or if the reason for braking is the approach of an intersection. On the other hand, if the initial speed increases or the event is happening in a motorway, the probabilities of an "uncomfortable" event are decreasing. Last but not least, if the driver is female or older than 50 years old, the odds of having an "uncomfortable" event are higher.

6.3.2 Statistical analysis II (All observations)

The last step of the analyses is to apply a binary mixed model to all the observations using Classification C. As it can be noted from Table 6.16, the adjusted R^2 is really low, indicating that the model doesn't have a reasonable fit. Therefore, the results are presented in Table 6.16, but they won't be further analysed.

Table 6.16: Results of the logit model for Statistical Analysis II and Classification C

Model variables	Neutral
Alternative-specific constant	-0.112 (-2.32)
Traffic congestion	0.1081 (2.5)

Initial speed	0.0024 (3.83)
Motorway	-0.3885 (-5.44)
Pedestrian	0.1378 (3.55)
Intersection	0.6321 (23.58)
Ptw	0.4925 (3.04)
Male	-0.1724 (-6.51)
Lane	-0.2498 (-7.15)
Model statistics	
LL (start):	-16589.09
LL(0):	-16589.09
LL(final):	-16205.84
Number of observations:	23933
Rho-squared (0):	0.0231
Adj.Rho-squared (0):	0.0226
AIC:	32429.69
BIC:	32502.43

6.4 Summary

This Chapter has presented the results of the classification of the events in different comfort levels and the modelling of comfort level during a deceleration event. Specifically, the relationship between the comfort levels and different explanatory variables, such as driver characteristics, kinematics and situational variables is explored.

The main findings of the statistical analysis of the comfort level applying Logit Multinomial and the Mixed Logit Multinomial models are:

- The categorisation of the deceleration events into 4 comfort categories, i.e. very comfortable, slightly comfortable, slightly uncomfortable and very uncomfortable is proven to be a better categorisation than 3 or 2 comfort categories with the later to be the worst.

- Comparing the adjusted Rho squared of the best models for statistical analysis I and II, it can be concluded that statistical analysis I gave better results, indicating that the variables that were included in this analysis, i.e. THW, TTC, headway have a significant effect on the comfort level.
- The average effect of the unmeasured variables tends to increase the probability of a braking event to be one of the uncomfortable categories.
- Assuming that the functional form of the parameter density function follows the normal distribution gives better results than the (negative) lognormal or the triangular distribution.
- The initial speed has a complicated effect, in detail in the statistical analysis I, its increase lead to fewer odds of an event to be in the uncomfortable categories, whereas in the statistical analysis II it had a mixed effect leading to more chance to be very uncomfortable for 80% of the observations.
- Smaller TTC and smaller THW result in higher odds for uncomfortable events, with the effect of the THW to vary.
- If the driver is a woman or is more than 50 years old, there are more odds to perform more uncomfortable braking events.
- Driving in the motorway leads to more comfortable events.
- Braking because of a pedestrian or intersection lead to more uncomfortable events
- If there is traffic congestion, there are more odds to have a neutral than a comfortable event.

The differences in the results for the different categorisation showed the importance of picking up the appropriate thresholds to define the comfort levels. The outcomes of the discrete modelling showed that there are many variables that affect the comfort level of a deceleration event and that some of them have a mixed effect. Also, the significance of the variables that are connected to a leading vehicle (e.g. TTC, THW) is obvious comparing the two statistical analyses. Finally, the outcomes demonstrate that the comfort level of a deceleration event is sensitive mostly to the kinematic and situational variables.

7 Discussion and Recommendations

This thesis aims to examine the deceleration behaviours of drivers under normal driving conditions to ensure comfortable braking design. This has been addressed by analysing the deceleration events from naturalistic driving data and by concentrating on three points:

- ✓ Identification of the deceleration profiles
- ✓ Developing relationships between the components of the deceleration event, i.e. the deceleration value and the duration and their influencing factors.
- ✓ Exploration of the factors that affect the comfort level of the driver while braking.

Appropriate algorithms were developed to detect deceleration events and identify the deceleration profiles using data from three different studies (see Chapter 4). Then suitable statistical models were employed to develop the underlying relationship between influencing factors and braking behaviour and comfort level. The results of the statistical analyses were presented in Chapters 5 and 6. The influencing factors were event-level factors: kinematic and situational factors, trip-level factors: trip duration, length and car and driver-level factors: driver's age and gender. The aim of this section is to further discuss the results and findings from Chapters 5 and 6 to provide a better understanding and to critically synthesize the findings and relate them to the existing literature. The following section of the Chapter firstly discusses the deceleration profiles that were identified, followed by a detailed review of the effects of the influencing factors on the deceleration value and the deceleration duration. Next, the comfort evaluation is explained along with the influence of the examined factors in the comfort level. Moreover, recommendations and policy implications in light of the findings are presented. Finally, a summary of this chapter is provided.

7.1 The deceleration profiles and the influencing factors of deceleration behaviour

Chapter 5 presented the results of the fitting algorithm that identified the deceleration profiles. Many attempts have been made in the literature to model the deceleration (Bennett and Dunn, 1995; Ma and Andréasson, 2008; Maurya and Bokare, 2012).

Constant acceleration models, linear-decreasing models, polynomial acceleration models have been studied (Bennett and Dunn, 1995). It was concluded in this thesis that a single equation is not suitable to fit the deceleration for the whole duration. Accordingly, the event was split into two regimes: one before the maximum deceleration and one after that. The same procedure was followed by Maurya and Bokare (2012), who described the deceleration against speed with dual regime models for all the vehicle types but cars. Moreover, Ma and Andréasson (2008) separated the deceleration event in many regimes using pattern classification.

Within this PhD project, the deceleration value was fitted against time. Three equations were examined: a linear equation ($a = p_1 \times\ t + p_2$), a second-order polynomial ($a = p_1 \times t^2 + p_2 \times t + p_3$) and a non-linear equation $a = p_1 \times sqrt(t) + p_2$. Parabola 1 represents in real life that the driver brakes smoothly at the beginning and then harder braking is followed. This might be due to the time that the driver needs to evaluate the situation and the available distance to brake. Considering the Regime II (i.e. the part after the maximum deceleration value), the most common deceleration profile was concluded to be the non-linear equation (Parabola 2), which reflects a firm release of the brake. It should be noted that all the equations showed satisfying goodness of fit. For instance, the adjusted R^2 values range from 0.82 to 0.93 for the equations of Regime I and from 0.77 to 0.92 for the equations of Regime II. Finally, the values of the coefficients of the best-fitted equations were calculated and presented in Chapter 5.

In contrast to the work within this PhD, where the deceleration value was fitted against the time of the deceleration event, other studies have tried to model the deceleration value against other variables, such as approaching speed, speed difference, distance headway and acceleration of the leading vehicles. More specifically, Bennett and Dunn (1995) suggested a model for predicting acceleration that includes the deceleration time and the approach speed, Maurya and Bokare (2012) modelled the deceleration against the speed using three equations (a linear, an exponential and a second-order polynomial) and Ma and Andréasson (2008) modelled the braking regimes against the speed, the distance headway and the acceleration of the leading vehicles. In contrast, within this thesis, the total range of the deceleration values during a braking event was modelled against time. The outcome is the creation of deceleration profiles that describes the deceleration event and characterise comfortable braking.

One other difference lies in the fact that those studies tried to model the deceleration in a specified environment by collecting data in controlled experiments whereas the data used in this PhD are naturalistic driving data and includes different braking scenarios. Specifically, Bennett and Dunn (1995) analysed the ‘approaching a traffic light’ scenario, Ma and Andréasson (2008) studied the car-following stage and Maurya and Bokare (2012) collected the data from a 1.5 km express highway.

Chapter 5 also presented the effects of all the examined factors from the statistical analysis of the deceleration events. The appropriate statistical models, i.e. mixed effect multilevel models were applied to examine the effect of different factors on both the deceleration value and the deceleration duration. The examined factors were driver factors, trip factors, situational factors and kinematic ones and varied a bit among the different studies depending on the availability of those factors. In contrast to previous studies (Goodrich et al., 1999a; Z. Wu et al., 2009; Loeb et al., 2015) that have examined factors only from one category at the time, the work within this thesis examined all those factors simultaneously to reveal which are the most important.

7.1.1 Deceleration and driver factors

Concerning the driver factors, it was concluded that gender does not have a statistically significant effect on the deceleration, whereas age was found to affect the deceleration value for the trip-level model. Furthermore, it should be noted that regarding the deceleration duration, some driver characteristics were found to be important only in the TeleFOT dataset. Those characteristics were age, (i.e. a driver, who belongs in the 50+ age category seems to brake longer by 0.084 sec than a driver that belongs in the 31-50 category), and driving experience, (specifically a driver with more driven miles per year was found to brake in a shorter period of time, indicating more experience).

Age and gender were explored in all the datasets. Also, the driver experience, expressed in driven miles per year was studied in the OEM and TeleFOT datasets and three indexes from driver’s questionnaire and specifically the AISS and the aggressive violations index of the DBQ (DBQ_aggressive_violations) were included in the model of UDRIVE dataset. The results from all the datasets revealed that those driver factors have a statistically significant effect on neither the deceleration value nor the deceleration duration. The only exception within this work was for the variable age, which was statistically significant for the deceleration value in the OEM and UDRIVE datasets but only when a trip-level model was applied. When a driver-level model was applied, then age became statistically insignificant since its effect is included in the model structure level. The model showed that drivers, aged 18-30 and more than 50 years old brake at lower deceleration rates in the OEM study compared to drivers, aged 31-50. For the UDRIVE dataset, the drivers that belong to the younger and the middle-age category seemed to brake with lower deceleration rates than older drivers, and specifically the drivers, aged 31-50 use the lowest deceleration rates.

The results regarding driver factors seem to agree with previous studies that have explored driving characteristics. For example, Loeb et al. (2015) concluded that younger drivers have worse performance on braking, so that age is an important factor, although, this study examined only age as an influencing factor. Also, Haas et al. (2004) who tried to determine the deceleration behaviour, found that gender had no effect at all whereas age had a small effect on the deceleration behaviour, results which were similar to this work. Similarly, Xiong and Boyle (2012) supported that age is an influencing factor. However, in their study, El-Shawarby et al. (2007) found age and gender statistically significant variables. Their result demonstrates in particular that male drivers appear to have higher deceleration values than female drivers and drivers, aged 40-59 seemed to break at lower deceleration values compared to drivers in age groups under 40 years and more than 60 years. The result regarding age agrees with the outcome of the UDRIVE dataset.

7.1.2 Deceleration and trip factors

Moving on to the trip factors, it was found in the UDRIVE dataset that the model of the car influences the deceleration value. On the other hand, trip duration, trip distance and driving during day positively correlate with the deceleration duration.

Trip duration, trip distance, time of the day and car model were the trip factors examined in one or more of the datasets. It was found that only the model of the car has an impact on the deceleration value, meaning that the car characteristics affect the braking. Specifically, in the UDRIVE dataset, it was concluded that driving a premium car leads to an increase in the deceleration value. Studying the braking behaviour of different vehicle types, Maurya and Bokare (2012) also pointed out the significant effect of the driving type on braking behaviour. Although, that study was more generic since it dealt with different vehicle types, i.e. trucks, motorized three and two-wheelers and cars, it still supports the view that vehicle characteristics affect the deceleration. Moreover, the time of the day was examined by another study (Haas et al., 2004) and results revealed that time-of-day did not have a statistically significant dependency on the deceleration rate, which confirms the finding of this work.

Considering the deceleration duration more trip factors play a significant role, though the car model did not affect the deceleration duration. Trip duration and trip distance have a positive effect, meaning that when trip duration or trip distance is bigger the deceleration duration is larger too. The aforementioned effect of the trip duration and distance might be because the driver tires as the trip is longer and his braking reactions become consequently slower. In contrast with the deceleration value, deceleration duration was found to be affected by the time of the day. Specifically, in the UDRIVE dataset, which was the only dataset that time of the day (i.e. day or not) was available, 'day' variable was found to influence the deceleration duration in a way that if it is 'day', the deceleration event is shorter by 0.03-0.05 seconds. This finding shows that the driver feels more confident while braking during the day compared to the night, his/her reactions are better, and he/she needs less time to brake.

7.1.3 Deceleration and kinematic factors

Another factor category, that was examined within this work concerns the kinematic factors. The findings revealed that higher initial speed results in an increase in both the absolute value of the deceleration and the deceleration duration. Moreover, it was found that higher initial TTC results in longer duration and smaller deceleration rates (softer braking). Furthermore, the maximum steering angle had a small but significant effect on the deceleration rate, meaning that an increase in the maximum steering angle results in harder braking. Finally, the maximum jerk influences the deceleration value, in a way that a slower rate of deceleration leads to smaller deceleration values.

In general, the kinematic factors were found to have the most statistically significant effect on both the deceleration value and the deceleration duration. Regarding the initial speed of the event, it was concluded to be one of the most important factors. A 1 m/s increase in the initial speed increases the absolute value of the deceleration by 0.02-0.027m/s^2 (harder braking) for the 3 datasets, i.e. TeleFOT, OEM and their combination. For the UDRIVE dataset, the results showed that initial speed has a mixed effect which is negative similar to the other datasets, but the size of the effect varies. The importance of initial speed as an influencing factor is confirmed through the literature (Bennett and Dunn, 1995; Haas et al., 2004; Wada et al., 2008; Wu et al., 2009; Maurya and Bokare, 2012; Xiong and Boyle, 2012).

Xiong and Boyle (2012) concluded that speed is one of the factors that affect the driver's response while braking, whereas Wu et al. (2009) and Wada et al. (2008) took into consideration the velocity as a major factor to model comfortable braking in car-following scenarios. The initial speed was found to have a strong and statistically significant dependence on the deceleration value in Haas et al. (2004)'s work. Particularly, the rates of deceleration increased until the initial speed was 64 km/h but were relatively constant above that. To test if the relationship between the initial speed and the deceleration value was not linear within this work, the square of the initial speed was used as an explanatory variable, but the result could not support that hypothesis, so the linear relationship was kept. Bennett and Dunn (1995) discovered that the deceleration rate was proportional to the initial speed such that higher speed drivers decelerate harder which complies with the result of the statistical analysis of this work as well as to the results of Maurya and Bokare (2012)'s work, who supported that higher maximum initial speed leads to higher deceleration values, higher deceleration distance and higher deceleration duration.

The same effect of the increase of the initial speed to the deceleration duration was discovered in this work. In detail, a 1 m/s increase in the logarithmic of the initial speed, results in a 0.75 sec to 0.89 sec increase in the logarithmic of the deceleration duration for the different datasets. The logarithmic values were used since in all the datasets the most parsimonious models were the ones that the dependent and independent variables were in logarithmic transformations. To have a better understanding of the resulting increase in the deceleration duration, the slope coefficients with respect to the initial speed were calculated for all the models and the outcome was that if the initial speed increases by 1 m/s, the deceleration duration will be increased by 0.47-0.50 seconds.

Within the statistical analysis of the UDRIVE datasets, more kinematic factors were available and were included in the model. Those factors were TTC, THW, space headway, maximum steering angle during the deceleration event, the maximum jerk and the speed of the preceding car. The speed of the preceding car was found to be insignificant, which contradicts the results of some studies in the literature (e.g. Wada et al., 2008, 2010; Wu et al., 2009). One reason for that difference might be that those works were focused on car-following situations only whereas this PhD work examined data from many different braking scenarios. TTC and space headway were concluded to be statistically significant variables that influence the deceleration value such that an increase in the initial TTC leads to softer braking whereas an increase in the initial headway results in higher deceleration rates. The importance of those variables to the braking events was underlined by Goodrich et al., (1999a); Kazumoto et al. (2006) and Wu et al. (2009). The first study characterised the braking behaviour by the perceptual trajectory using TTC versus THW (Goodrich et al., 1999a). From the second study, it was revealed that the inverse of the TTC was the most affecting factor on a driver's judgement on when to apply the brakes (Kazumoto et al., 2006) and at the last study the braking comfort was modelled based on the space headway and the velocity of the controlled vehicle (Wu et al., 2009).

7.1.4 Deceleration and situational factors

Last but not least, different situational factors were examined. The analysis demonstrated that the reason for braking plays a statistically significant role in deceleration behaviour. The results indicate that braking due to approaching a roundabout or a junction results in softer braking (lower deceleration values) comparing to dynamic obstacles, while braking due to a pedestrian crossing leads to the highest deceleration values. Regarding the deceleration duration, the reason for braking was influencing the duration so that if the reason for braking is a dynamic obstacle, the deceleration event is shorter comparing to all the other reasons. Moreover, it was found that traffic density does not influence the braking behaviour.

By reviewing the results of the remaining situational factors in the UDRIVE dataset, it is observed that when the braking happens while following a car, it results in softer braking since the absolute deceleration value decreases by 0.08m/s^2 and the logarithm of the duration increases by 0.16 sec. This result might be because in car-following situations the driver is usually more aware and keeps a distance from the preceding car. The same effect has the existence of traffic congestion when braking. Similarly, in this situation, the driver keeps a safe distance from the other cars and the initial speed is usually not high. On the other hand, driving on a one-lane road leads to harder deceleration events, i.e. higher deceleration values and shorter duration. The nonexistence of another lane and consequently the inability to change lanes when the preceding vehicle brakes might be the reason for this result.

In terms of driver reaction variable, if the driver is looking in front (driver reaction 1) and not right/left or inside the car at the time the braking starts, it results in a decrease of the absolute deceleration value by 0.1-0.14 m/s^2 (softer braking) and to a shorter deceleration duration. The shorter duration could be explained since if the driver has his attention on the road (i.e. looking in front), his braking reaction can be faster.

By watching the videos from the TeleFOT and the OEM study, traffic density, the type of road, the existence of a traffic light when braking, the reason for braking and where the driver is looking at the beginning of the braking event were obtained and included in the analysis. Specifically, the reason for braking consists of braking due to approaching a roundabout, a cross or T-junction, pedestrian crossing or a dynamic obstacle. The reason for braking was included in the model as a categorical variable with the braking due to a dynamic obstacle category to be the reference one. Regarding the UDRIVE dataset analysis, the situational variables that were included are the type of road, the number of lanes, the speed limits of the road or the type of road, if the road is one direction road, if there is a traffic congestion at the moment of braking, if there was a following car situation at the moment of driving and if there was an intersection, a cyclist, a PTW or a pedestrian at the moment of braking.

As mentioned beforehand, traffic density was found to be statistically insignificant for both the deceleration value and the deceleration duration. The study of Xiong and Boyle (2012) concluded in the same result, i.e. that traffic density does not influence the driver's respond while braking. Although, they found also that road type and weather conditions are insignificant. Within this thesis, weather conditions were not examined but the road type, i.e. if the braking is happening in a motorway, rural or urban road resulted to be one statistically significant influencing factor for all the conducted studies. However, inconsistencies of road type effects regarding the deceleration were found across the datasets. Given the variability of the road type effect in the conducted studies, a more in-depth investigation by studying each road type separately is recommended.

Through the literature, most of the studies focused on a specific scenario and did not examine different reasons for braking or different road types (Bennett and Dunn, 1995; Haas et al., 2004; El-Shawarby et al., 2007; Wada et al., 2008, 2010). Specifically, Bennett and Dunn (1995) examined the deceleration behaviour on the motorways, Haas et al. (2004) on stop-sign controlled intersections on rural highways and El-Shawarby et al. (2007) on signalised intersections. Furthermore, within the literature when studying the braking behaviour, the car- following scenario was examined a lot, with applications on the ACC (Goodrich et al., 1999b, 1999a; Z. Wu et al., 2009; Xiong and Boyle, 2012). Moreover, in all those studies, controlled experiments on the road or simulation studies were used to collect the data whereas within this work, naturalistic driving data were used and almost all the reasons for braking and other situational factors were considered. Using naturalistic driving data ensures that the driver is constantly exposed to a natural environment and does not change his driving behaviour. For example, in the UDRIVE NDS, the drivers were monitored over a period of two years. Therefore, a more realistic picture of a daily braking behaviour can be derived. Additionally, the situational effect, which was proven to be statistically significant for the braking behaviour, was captured.

It should be noted that the situational factors, which were revealed to be statistically significant, were affecting the deceleration behaviour less than the kinematic factors. Therefore, more attention should be paid on the kinematic aspects. This is supported further by comparing the results of the statistical analysis I and II of the UDRIVE dataset. In the statistical analysis I, where more kinematic factors are included, i.e. TTC, THW, space headway, it was concluded that only the situational factor traffic congestion is statistically significant, whereas, in the corresponding statistical analysis

II, the traffic congestion, the one lane and the following a car variables were affecting the deceleration value.

Choosing the appropriate statistical model to analyse the deceleration behaviour determines the outcome of the analyses. Due to the studies' data structure, the dependences among the same driver and the same trip should be taken into consideration. Therefore, the multilevel models were employed for this study's statistical analyses which consider the similarities and differences of the deceleration event because they were executed by the same driver or during the same trip. Also, the mixed effect was investigated for all the influencing factors, since the effect of one or more variables can vary among the observations. It was also concluded that the structure of the dataset, and specifically of how many drivers the dataset consists and how many trips they have conducted, influences the selection of the most parsimonious model. In the OEM dataset, which consists of 12 drivers making around 10 trips each, the best model was the driver-level one whereas in the TeleFOT dataset, consisting of 25 drivers who have conducted 1-2 trips each, the most parsimonious model was the trip-level model. Regarding the deceleration duration, trip-level and three-level models were found to be the most parsimonious, revealing that the trip has a greater effect on the variation of the deceleration duration.

Overall, the findings discussed above demonstrate that driver deceleration cannot be effectively modelled by employing average rates and a generic braking profile since it varies a lot depending on kinematic, situational, driver and trip factors. Haas et al. (2004) found a similar result while taking only the gender and the speed into account as influencing factors. They also supported the finding that the deceleration and acceleration cannot be modelled by applying average rates and suggested the use of a statistical pool of probable values.

7.2 Comfort affecting factors

In Chapter 4, the procedure to model comfort categories was described. It was challenging to decide which variables should be taken into consideration in order to create the different comfort categories for the braking events. The literature has revealed different factors affecting the perceived comfort. Some of those factors are noise, temperature, car seat, air quality and motion (Martin and Litwhiler, 2008; Constantin et al., 2014; Elbanhawi et al., 2015). However, it was found that the way of execution of different manoeuvres affects the passenger's comfort (Scherer et al., 2015; Bellem et al., 2016, 2018). In detail, Scherer et al. (2015) concluded that acceleration and deceleration are essential parameters of the perceived comfort. Moreover, Martin and Litwhiler (2008) emphasised the importance of the control of the braking profile for the safety and comfort of the passengers in (semi)- AVs. Within this work, the braking manoeuvre was studied which can be backed up from the literature that influences the passenger's comfort.

In this work, the components that were selected to determine the level of the braking events were the deceleration value and the change of deceleration, i.e. the jerk, and both are supported by the literature as important elements of modelling comfort. Specifically, Dovgan et al. (2012) developed a two-level multi-objective optimisation algorithm for discovering comfortable driving strategies and within this algorithm, they model comfort as the change of deceleration, i.e. the jerk. To test and analyse the comfort of three different manoeuvres, i.e. lane change, acceleration and deceleration, Bellem et al. (2018) used the longitudinal and lateral jerk and the acceleration to configure the variations on those manoeuvres. In another study, Bellem et al. (2016) tried to identify the essential components for the development of comfortable highly automated driving style and they found that acceleration, jerk, quickness and headway distance are of great importance. Moreover, Wu et al. (2009) attempted to model brake comfort on car-following scenarios by categorising the braking into comfort, discomfort and dangerous situations based on the velocity, the space headway, the acceleration and the friction coefficient.

The next challenge of the comfort categories modelling was the selection of the values- limits for the deceleration and the jerk. From the literature, it was concluded that different studies used different limits and that there are no broadly-used thresholds (Hoberock, 1976; Martin and Litwhiler, 2008; Eriksson and Svensson, 2015; Powell and Palacín, 2015). Therefore, as described in Chapter 3, three different sets of thresholds were used to model the comfort categories, resulting in three classifications, with four, three and two comfort categories. Chapter 6 presented the results of the statistical analysis of the comfort categories and specifically the factors that influence the comfort level of the braking event. The appropriate statistical model, i.e. the mixed effect logit models were applied to all the classifications to discover the effect of the factors on the odds of an event to perceived as uncomfortable or comfortable. The dependent variable of the model was the comfort categories and the examined factors were kinematic, situational and driver factors. Since the change of deceleration, i.e. the jerk was used to classify the events into different comfort categories, it was not included as an influencing factor in the model.

From the results of the statistical analysis and specifically the goodness of fit of the models, it was concluded that the classification of the 4 comfort categories, i.e. very comfortable, slightly comfortable, slightly uncomfortable, very uncomfortable gave better results than the classification of the 3 comfort categories, i.e. comfortable, neutral, uncomfortable. Whereas, the classification with the 2 comfort categories gave the worst results, indicating that the existence of more categories is essential maybe because the influencing factors have a varying effect that cannot be depicted when having only the 2 categories as the dependent variable.

Moving on to the specific results from the model, it should be noted that in all the models the alternative specific constants suggest that the average effect of the unmeasured variables tend to increase the probability of a deceleration event to belong in any category but the comfortable one ('very comfortable' for classification A and 'comfortable' for classification B and C). That means that there are variables, which were not included in the model, that influence the level of comfort during a braking event by making it less comfortable. Further research is suggested to investigate other influencing factors that were not included in this thesis and which might be responsible for this effect, such as the weather conditions, the road friction.

7.2.1 Comfort level and kinematic factors

From the examined kinematic variables, THW was found to affect the comfort category the most, whereas the TTC, space headway and the initial speed were found to have an effect on the comfort categories, which was not so strong. The importance of the headway was also underlined in the literature (Brookhuis et al., 2001; Wu et al., 2009). The term of headway can be described by both the space headway and the THW. Within this work, the THW was revealed to describe the best the car-following situation and to influence the perceived comfort the most. Wu et al. (2009) supported that the available distance from the preceding vehicles (i.e. space headway) influences the comfort level of a braking situation and Brookhuis et al. (2001) mention that short headway was considered less comfortable.

Within this work, the effect of the TTC variable was clear, showing that bigger TTC results in bigger odds of the event to be in the most comfortable category. The magnitude of the effect is small. Specifically, when the TTC increases by 1 sec the odds of the event to belong in the most comfortable category are 1.02-1.035 times higher than being in other comfort categories. The exception to the clear effect of TTC is the heterogeneous effect that it was found to have on the "uncomfortable category" in the statistical analysis of Classification C (two comfort categories as dependent variable). In detail, the TTC was resulted to have 65.17% negative slopes with different values and 34.83% positive ones. By calculating the probabilities of the two comfort categories against the TTC, it was concluded that the effect of the TTC was stronger, i.e. the probability of the event to be comfortable while the TTC was increasing, was increasing rapidly till the TTC equals to 4 seconds and then there was a smoother change. This might be because the comfort perception is affected more when the preceding and the examined vehicles are too close (TTC has small values<4sec).

Regarding THW, it was found to have a strong negative effect that varies across comfort categories. The effect means that when THW increases by 1 sec the probability of a deceleration event to be anything else other than "very comfortable" for Classification A and "comfortable" for classification B and C decreases. Specifically, if THW increases by 1 second, the odds of the event to be "very comfortable" for Classification A or "comfortable" for classification B are 4.5 and 3.5 times higher than to be "very uncomfortable" or "uncomfortable" respectively. Therefore, it is revealed that THW has a stronger effect on the comfort level than TTC. Considering the mixed effect that it was found to have, the impact of THW was found to be markedly (i.e. 99%) negative. The predicted probabilities of the comfort categories against the THW revealed that probabilities for the uncomfortable categories decrease significantly as THW increases and until it reaches the value of 2.4 sec and thereafter, they still decrease but at a slower rate. Moreover, if THW is more than 3.3 seconds the probability for an event to be uncomfortable is less than

0.1. These results demonstrate that the critical values of THW are the ones smaller than 2.4 sec and that THW has a very strong negative effect on the comfort level.

Furthermore, the space headway has a positive effect on the uncomfortable categories, meaning that an increase in the space headway results in bigger odds that an event belongs to one of the uncomfortable categories. That might not be logical since someone would have expected that the increase in space headway would lead to more comfortable events. However, the effect of the space headway is not that significant since its magnitude is smaller than the magnitude of THW, which indicates that the event is affected more from THW than from space headway.

Regarding the initial speed, when THW, TTC and space headway are also considered, its increase results in smaller odds for a braking event to belong to one of the uncomfortable categories. Although, the initial speed was not found to have a strong effect on the comfort of the deceleration event. Specifically, if the initial speed is increased by 1km/h, the odds of a deceleration event to be perceived as comfortable are 1.03-1.06 more than uncomfortable. However, when the effects of THW, TTC and space headway were not included, the initial speed in statistical analysis II had a mixed effect for Classification A in that an increase at the initial speed results in bigger odds of an event to be very uncomfortable for 87% of the observations and for the rest 13% the odds got smaller. In Classification B, the increase of the initial speed leads to more probabilities for an event to belong to the “uncomfortable” category.

7.2.2 Comfort level and driver factors

The driver factors that were included in the comfort level analysis were the age of the driver (as a categorical variable with 3 age categories, i.e. 18-30, 31-50 and 51+), the gender of the driver (as a categorical variable with 2 categories, i.e. male and female), and two personality characteristics, the AISS_total and the DBQ_all_violations (violations index of the DBQ), which were continuous variables. The results of the statistical analysis acknowledged that the variables AISS_total and DBQ_all_violations do not have a statistically significant effect on the perceived comfort. This result agrees with the conclusion of the study from Bellem et al. (2018), who found that personality traits have no effect on the manoeuvre preferences. They also found that age and gender do not influence manoeuvre preferences, but this contradicts the results within this work.

Regarding the driver's gender, if the driver is a male then the probabilities of the braking event to fall into one of the comfortable categories are higher than being uncomfortable. In detail, if the gender of the driver is male and not female, it resulted in 1.12-1.40 greater odds of an event to be comfortable than uncomfortable.

On the other hand, the effect of the age of the drivers was concluded to be more complicated. Specifically, if the driver belongs in the age category 18-30, the odds of a deceleration event to fall into the most comfortable category are 1.46-1.86 times higher than falling into the most uncomfortable category compared to if the driver was in the age category 50+. This could be due to the risk tolerance that varies with age. On the other hand, if the driver belongs to the 31-50 age category, there are more probabilities of a deceleration event to fall into one of the middle categories (neutral or slightly uncomfortable) than being very comfortable compared to the drivers in the 50+ age category.

7.2.3 Comfort level and situational factors

The last category of factors that were included in the comfort modelling were the situational factors. Driving on a motorway has a negative effect on the discomfort of a braking event to all the comfort categories compared to the rural roads. Additionally, the presence of a pedestrian or an intersection results in bigger odds of an event to be uncomfortable.

The existence of a cyclist or a PTW vehicle or if the road had only one direction did not have a statistically significant effect. The traffic congestion did not have a significant effect on the most uncomfortable category, i.e. it was neither increasing nor decreasing the probabilities of an event to be perceived as very uncomfortable. Although, it affected the middle comfort categories (i.e. "slightly comfortable" for Classification A and "neutral" for classification B). Specifically, if the deceleration event takes place while there is traffic congestion, the odds of this event to be perceived as very comfortable are less than being in a medium comfort category. In detail, a deceleration event has around 1.3 more odds to be “slightly comfortable” than “very comfortable” at traffic congestion situations.

Regarding the road type, the variable motorway was concluded to have a statistically significant effect for all the analyses, whereas the variable urban was statistically significant only in the models of statistical analysis II. If the event is happening on the motorway in comparison to rural roads, its odds of falling into the most comfortable category are between 1.35 and 1.8 higher than belonging in one of the uncomfortable categories. This result might indicate that when driving on motorways, where the speed is high, the driver’s perception of comfort might change since lower values of deceleration and jerk might affect him/her. Therefore, one suggestion would be to study driving on motorways separately by applying lower values on the thresholds that determined the comfort categories. On the other hand, if the braking event takes place in an urban road and not in a rural one, the probabilities of it to be “slightly uncomfortable” or “neutral” are less than of being “very comfortable”. Although, driving on the urban road does not have a significant impact on the most uncomfortable categories.

The existence of a pedestrian was statistically significant to all the models but the one of the statistical analysis I of Classification A. Its effect can be explained as following: if there is a pedestrian presence at the moment of braking, the probabilities of the deceleration event to be in the most comfortable categories are less than being in any of the uncomfortable categories. Specifically, the odds of the event to fall into one of the uncomfortable categories are 1.24-1.6 more than to fall into the reference category. In addition, the existence of an intersection while braking, which might also be the reason for braking, has a strong positive effect on the discomfort of the deceleration event. In detail, if there is an intersection, the odds of an uncomfortable event are higher than that of a comfortable braking event. Lastly, if the deceleration event happens when driving on a one-lane road, then the probability of the event to be comfortable is higher than being uncomfortable.

Generally, by judging the goodness of fit of the best-fitted models of all the statistical analysis and classification, it is revealed that statistical analysis I gave better results. A possible reason could be because the additional variables that were included in that analysis, i.e. TTC, THW and space headway influence strongly the perceived comfort during a deceleration event. Moreover, the other important outcome of that analysis is that classifying the comfort into more categories gave better results. Therefore, the classification of the comfort categories is of great importance and can affect the results.

Overall, the findings discussed above demonstrate that comfort during braking is mostly affected by the THW, Specifically, THW has a very strong negative effect on the comfort level, which is more intense when the THW is smaller than 2.4 sec. Additionally, the situational factors that influence the braking comfort are the presence of traffic congestion, an intersection or a pedestrian. Last but not least, it was shown that driver characteristics, i.e. age and gender play a statistically significant role for the comfort level.

7.3 Recommendations for practice

The findings of this study provide some new insights regarding the deceleration behaviour of the drivers under normal driving conditions which can benefit different stakeholders to overcome some of the challenges regarding Autonomous Vehicles (see .Figure 1.1). In this section, recommendations for practice for each stakeholder will be presented in detail.

7.3.1 Car manufacturers

To recommend for practice regarding AVs, it is first important to understand the main features of an AV. Modern AVs are equipped with a variety of sensors (e.g. Ultrasonic sonars, cameras, radars, GPS, accelerometers etc.) in order to quickly and safely navigate through a road network by: 1) perceiving their position on the map (pose sensors), 2) plan, evaluate and follow a path, and 3) detect, classify and avoid the obstacles (object sensors). Sensors can be classified into proprioceptive which measure values that are internal to the car (e.g. speed, orientation) and exteroceptive which obtain information from the surroundings of the vehicle (relative distances, relative speeds, objects etc.).

Also, the control mechanism (Figure 7.1) is important in order to understand how an AV works. The sensing subsystem (sensors) is responsible for taking raw data, as well as static and dynamic urban environment measurements (Campbell et al., 2010) which are essential to navigate safely. Precise and comprehensive environment perception is necessary for safe and comfortable autonomous driving in complex traffic situations such as busy cities (Ziegler et al., 2014). As depicted in Figure 7.1 the perception subsystem is divided into two main parts: the object recognition and the localisation. The planning subsystem includes different components such as path planners, behavioural planners and route (map) planners. Finally, the trajectory control subsystem includes the actual actuators and commands to drive the car. Information for the control subsystem would come from some combination of the higher-level planning (i.e. the proposed route), and direct sensing in some emergency cases (Campbell et al., 2010).

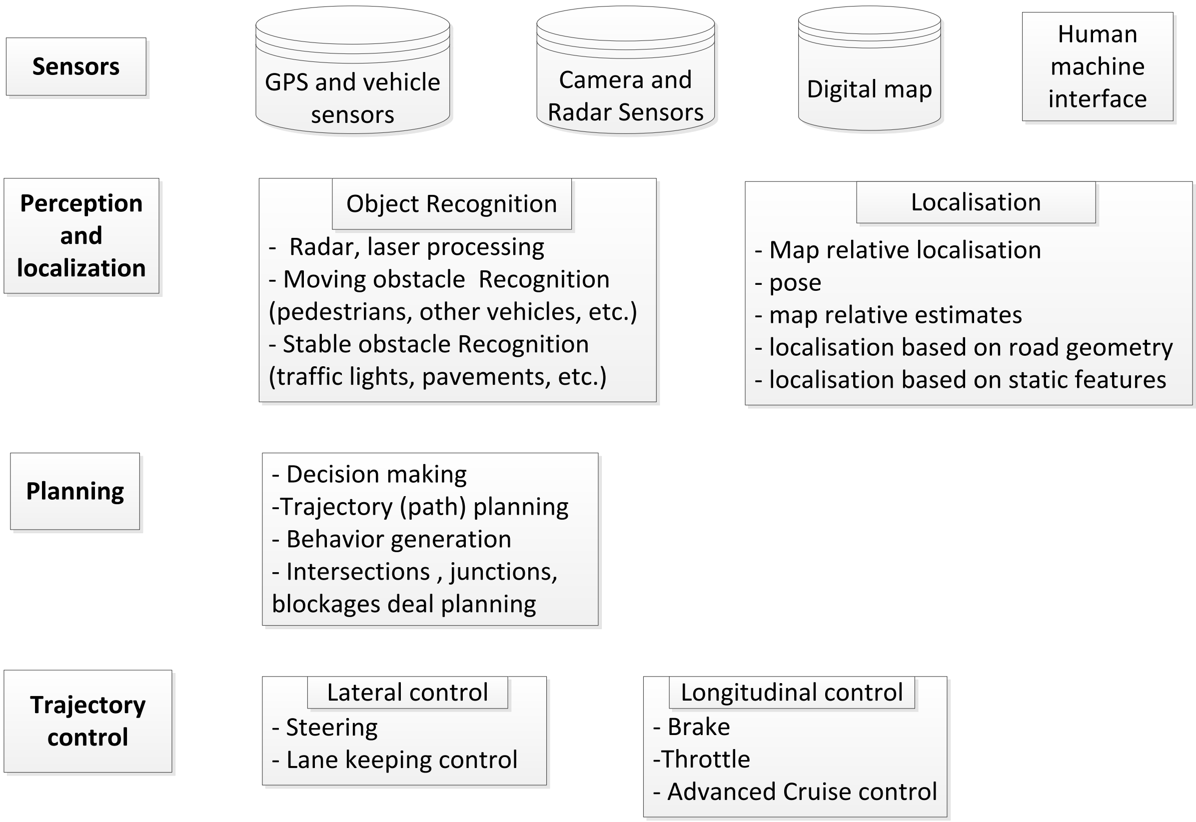


Figure 7.1: Basic Block Diagram (Forrest et al., 2007, Campbell et al., 2010, Ziegler et al., 2014, Urmson et al., 2008)

The findings of this study regarding deceleration behaviour can contribute to the system design of the AVs and specifically to the development of the trajectory control of (semi-) AVs. Moreover, the findings can benefit the braking behaviour of (semi-) AVs by generating more comfortable and safer braking events. One of the main outcomes of this study is the identification of the equations representing the deceleration profiles and the detection of the most used one. The most commonly used profile starts with smooth braking when a driver detects a reason to brake and then he/she brakes harder. The same deceleration profile can be employed by the developers of (semi-)AVs to ensure the operation of comfortable braking. This could be achieved by programming the trajectory control to generate braking that follows this deceleration profile. Also, having the situational and kinematic factors as an input from the perception and localization process (i.e. from the sensors), developers of (semi-)AVs could apply the adequate relationships resulted from this work. Furthermore, by employing these profiles the carsickness, which is common in automated driving systems and results from the conflict between the visual sensory system and the movement of the human body, could be reduced. This could also help overcome the lack of acceptance from the users (i.e. the human factor barrier).

Another recommendation is about the current technology of the Advanced Driver Assistant Systems (ADAS). AVs are considered to be the next step of the current vehicle technology and the ADAS (Elbanhawi et al., 2015). ADAS have been already studied, paying particular attention to their impact on safety, traffic flow, environment and drivers. They are low autonomy systems that assist the driver and can be used towards the development of a fully AV. The ADAS that improve the lateral and longitudinal control of the vehicle have been used and studied the most.

The lateral control consists of: 1) the Lane Departure Warning System (LDWS), whose purpose is to avoid run-off-road and sideswipe collisions, 2) the Lane Keeping Assist System, which assists the drivers to keep the vehicle in its existing lane by providing small amounts of actuation to steering and 3) the Parallel Parking Assist, which controls the steering while the driver controls the braking and acceleration in order to park successfully etc. On the other hand, the longitudinal control includes among others: 1) the Adaptive Cruise Control (ACC), which controls the speed (throttle and brake) at which the vehicle moves relative to the front vehicle in order to avoid collision and 2) the Rear Parking Assist, which helps the driver to park by controlling the brake or informing the driver that he has to brake when approaching another object (Forrest et al., 2007).

The results of this research could also be implemented on ADAS technology. Particularly, the longitudinal control ADAS, i.e. the ACC and the Rear Parking Assist could be benefited by using the deceleration profiles, since those are perceived natural by the drivers and this could increase the user's acceptance and market penetration.

One important finding was that some of the driver factors have been found to affect the comfort level of the deceleration events. These findings support the idea of developing *personalized* (semi-)AVs since each driver has different braking behaviour and braking preferences. Therefore, it is recommended for the (semi-)AVs manufacturers to develop methods that can personalize the vehicle to its passenger to ensure comfort and safety. This could deal with the human factor barrier and increase the user's trust and acceptance.

Finally, it should be noticed that the relationships of the influencing factors with the deceleration characteristics, which is the main outcome of the models that have been developed, can be key elements in the development of braking systems not only for (semi-) AVs but for conventional cars too. Specifically, the initial speed should be considered since with higher initial speed the absolute deceleration value is higher, and the duration is longer. Moreover, the situational factors play an important role. The reason for braking, road type, lighting conditions (driving during daylight) and the number of lanes affect the braking event and should be taken into consideration when developing a braking system. As a consequence, driver deceleration should not be modelled by applying average rates and all of the aforementioned factors and their effect should be well-thought-out.

7.3.2 **Researchers**

Regarding the researchers, the findings of this research can be used to face the challenges system design, human factors and modelling of impact. Specifically, the most comfortable deceleration profile that was an outcome of this study can be implemented into the algorithms which control the trajectory of the AVs. Moreover, similar profiles can be tested to study the acceleration behaviour and to reveal the most comfortable one.

The main outcome of the modelling of deceleration behaviour is the relationships of the affecting factors with the deceleration value and duration. It is strongly recommended that researchers should not apply average decelerate rates and durations when studying or modelling deceleration behaviour since many factors are affecting it. The kinematic factors, i.e. the initial speed, the TTC and the max steering angle were found to affect the deceleration event the most, so special attention should be given to those factors. Another factor category that influences the braking behaviour is the situational factors, e.g. the reason for braking, the road type etc. Thus, it is recommended to take into consideration those effects and analyse in more detail each situational factor. The developing technologies of vehicular communication (VC) that support vehicle-to-vehicle (V2V) and vehicle to infrastructure (V2I) can improve the deceleration events and provide more safe and comfortable braking. Specifically, taking into consideration the situational factors and utilizing V2I communication it can provide smooth and early decelerations.

Based on the fact that the most significant influencing factor of the comfort level during braking is THW, the car-following situations should be given special attention. Considering that a 1-second increase in THW results in 3.5-4.5 more odds for an event to be in one of the comfort categories, increasing the initial THW when the brake is applied is probably a good suggestion. Particularly, the effect was found to be more intense when the values of THW are small, i.e. lower than 2.4 seconds. The introduction of V2V communication could be very beneficial in these cases, since the leading vehicle can inform the following ones when it is about to brake and the following vehicles can perform adequately, ensuring comfortable braking events.

Furthermore, the findings revealed that braking while a pedestrian is present, leads to more uncomfortable events. Therefore, this scenario should be also studied separately, and the braking development should increase the comfort, maybe by decelerating earlier or by informing the passenger that the pedestrian has been recognized and the appropriate actions would be followed.

Modelling in simulators is a powerful tool for the researchers. It helps them plan, design and operate transportation systems. They can test numerous different scenarios, even the ones that are dangerous to be tested in real life, such as crashes and near-crashes. They can focus on a specific variable, analyse it and test for its effect in detail (SWOV Institute for Road Safety Research, Leidschendam, 2012). Regarding (semi-) AVs, modelling can test the operation of automated functions under many different scenarios and predict impacts on safety, comfort, emissions etc. (Stevens and Newman, 2013).

Based on the equations representing the deceleration profiles that were calculated in this study, traffic simulation modelling could be enhanced to depict the deceleration events more accurately. In addition, the relationships between the influencing factors and the deceleration rate and duration could be implemented into traffic simulation modelling. For example, creating different decelerations depending on the reason for braking and other situational factors. This would lead to more realistic traffic simulations. Moreover, by analysing in simulators different scenarios even near-crashes events regarding car-following situations, the braking behaviour can be studied in more detail and the impacts of possible V2V communication can be detected.

7.3.3 Drivers

Winning the trust of the drivers to give the control of the car is one of the most crucial challenges of this new technology (Kraus et al., 2010; Stevens and Newman, 2013). People are reluctant to trust an autonomous system for the uncertainty that it is not reliable and safe (Parasuraman and Riley, 1997; Lee and See, 2004). Although, feeling safe and comfortable when using a new technology increases the user's acceptance (Elbanhawi et al., 2015). Findings from this study can be used to ensure comfort and safety feeling to the user. Specifically, by implementing the most used deceleration profile and applying the adequate deceleration rates depending on the situational factors can increase the comfort level while braking. Moreover, the factors that affect the most the comfort level and contribute to the discomfort of the users were identified within this research. So, actions can be taken to prevent discomfort, such as to ensure longer THW in car-following situations, to inform the user for the detection of a dangerous situation and a need to stop with appropriate HMI, to update the road infrastructure with different signs that inform the driver for the road configuration that might lead to braking. By applying such measures, the driver can start trusting and accepting the automation and thus begin to use it in the current vehicles that are already equipped with different ADAS.

7.3.4 Regulators and legislators

The findings of this study could be considered for improving the design characteristics of future road networks. Specifically, the different deceleration characteristics that were found in this study could be beneficial into the design of different road elements such as intersection, roundabout and deceleration lane (Maurya and Bokare, 2012). Moreover, it was concluded that the initial speed affects a lot the deceleration behaviour and that higher initial speed results in harder and more uncomfortable braking. Therefore, it is suggested that the variable speed limit should be adjusted according to the situational factors and geometric characteristics. For example, where there is a turn (i.e. bigger steering angle) or there is a pedestrian crossing the speed limit should be reduced. Another recommendation is to place more signs on the road to warn when approaching road configuration that requires braking and especially in pedestrian crossings where the braking was found to be more uncomfortable. This would increase the feeling of safety and comfort of the user, especially when automation is apparent (ADAS and AVs).

To date, there is a lack of regulation and legislation regarding automation in vehicles (Lay and Saxton, 2000; Barabás et al., 2017; BSI and Catapult Transport Systems, 2017). Standardisation of the new technology could help overcome some of the barriers and specifically the lack of common standards and policy framework, the integration with existing transport systems, the cybersecurity threat and the public acceptance issues. Standard is an agreed way of doing something; “the distilled wisdom of people with expertise in their subject matter area and who collectively know the needs of the various stakeholders” (BSI and Catapult Transport Systems, 2017).

In the report by BSI and Catapult Transport Systems (2017), many existing standards regarding autonomous vehicles were found with the most used to be ISO 26262, ISO/IEC 27001 and IATF 16949 (BSI and Catapult Transport Systems, 2017). In some

US states, there have been specific automated driving legislation for vehicle deployment under certain conditions (Lay and Saxton, 2000). Although, the existing standards are too complex, and it is hard to navigate through them and there is the need for establishing an international widely used standard.

There is still the need to regulate the system design of ADAS features and (semi-) AVs as well. From the findings of this work, it can be concluded that many factors, i.e. kinematic, trip, driver and situational factors should be taking into account to design for braking and this should be ensured by regulation. Moreover, the impacts of different conditions on the automated systems should be investigated, for instance when it is raining, when the lighting conditions are bad, for different grades of friction between the tires and the road surface. Last but not least, it is recommended to regulate clearly the I2V communication and the required equipment to ensure early and comfortable braking since it was reported that communication standards were overly complex (BSI and Catapult Transport Systems, 2017).

7.4 Summary

This Chapter critically discussed the results presented in Chapters 5 and 6 of this thesis. Firstly, the deceleration profiles estimated as natural and comfortable were analysed and compared with the findings of the literature review. The main finding was that the most used profile was the one that the driver brakes smoothly at the beginning, maybe in order to evaluate the situation, followed by harder braking. Moreover, the effects of the factors on deceleration value and duration were discussed. Kinematic factors were found to mostly influence both the deceleration value and duration. Increase in the initial speed resulted in higher absolute deceleration value but longer duration, increase in the initial TTC leads to softer braking whereas an increase in the initial headway results in higher deceleration rates. THW did not affect the deceleration value but its increase leads to a longer deceleration event. One important outcome is that the driver and the trip factors do not greatly influence the deceleration event, while the situational factors and specifically the reason for braking, the driver reaction and the following a car scenario play an important role in the deceleration components. Since the deceleration events are influenced by all these factors, the deceleration behaviour cannot be effectively modelled by using average rates for all the different braking scenarios.

In this chapter, the comfort modelling and the factors affecting the comfort level while braking were also discussed. This discussion revealed the challenges of modelling the perceived comfort, in terms of which variables are most important for the perceived comfort in order to use them to model it and which thresholds used be used. The comfort modelling by employing the deceleration value and the jerk, which was used within this work, was supported by the literature and by using different classifications, i.e. different thresholds, it was concluded that having more comfort categories can result in better and more detailed results. Moreover, the factors affecting perceived comfort were reviewed, concluding that kinematic, situational and driver factors have significant effects. Specifically, THW had one of the strongest effects; when THW increases, the event has more probabilities to be comfortable. Personality traits were found to be insignificant, while gender and age affected the comfort level, supporting the idea of a personalised (semi-)AV. Some situational factors, such as intersections and pedestrian played also a significant role in comfort, underlying the importance of taking the surrounding situation into consideration while analysing or modelling the braking.

Finally, some recommendations for practice that result from this work's findings were presented regarding different stakeholders, i.e. car manufacturers, researchers, drivers and regulators/ legislators. To ensure comfort and apparent safety when a (semi-)AV decelerates, the calculated deceleration profiles and the findings regarding the influencing factors should be implemented into the development of the braking planning of (semi-)AV vehicles. Moreover, the integration of the affecting human factors into the design of the (semi-)AVs, which leads to personalized cars, is recommended. The outcomes of this study could enhance the traffic simulation modelling and the design of intersections and deceleration lanes. Finally, the need of the establishment of an international simpler standard concerning (semi-)AVs is underlying.

8 Conclusion

Vehicle automation and specifically AVs can potentially have many benefits, e.g. improvement of traffic safety by eliminating human error, extended mobility for elderly and disabled people, more efficient traffic flow and increased capacity. However, to attain the benefits of (semi-) AVs the passenger should feel safe and comfortable inside them. Therefore, comfort is of great importance for the development and acceptance of (semi-) AVs along with the analysis of vehicle dynamics. Braking has been revealed to be one of the most important factors affecting comfort. It is, therefore, necessary to fully understand the driver's braking behaviour, i.e. the braking level, the braking duration and the deceleration profiles, as well as the factors affecting this behaviour. Moreover, it is important to investigate the comfort levels of braking and the influencing factors.

Therefore, this research aims to thoroughly analyse the deceleration behaviour of drivers under normal driving conditions to ensure comfortable braking design.

It should be underlined that this research is predominantly important for the results. Specifically, the deceleration profiles that are received as natural and were calculated in this thesis are important to understand the deceleration behaviour of drivers. Moreover, within this research the influencing factors of deceleration were identified and the relationships between them and deceleration characteristics were defined. This means that the deceleration characteristics were modelled against the driver, kinematic and situational factors and the results indicate that factors from all three categories affect the deceleration behaviour. Furthermore, this PhD research identified acceptable thresholds to detect deceleration events and categorise them into different comfort categories. Finally, it examined which factors increase the likelihood of an event to become very uncomfortable and might lead to dissatisfaction and distrust of AVs.

8.1 Research objectives revisited

The aim of this research has been fulfilled by accomplishing the individual objectives:

1. To identify factors affecting the deceleration behaviour and ride comfort.

A literature review was carried out in Chapter 2 which introduces the human factors challenges regarding autonomous driving. It was found that current literature includes a number of studies about deceleration behaviour and comfort during braking, examining different affecting factors. Some studies focused on driving factors, others on kinematic ones but there is a lack of research in analysing situational factors and how they affect braking. Specifically, the kinematic factors that have been studied the most regarding ride comfort are the acceleration, the deceleration, the jerk, the TTC and the space headway. Considering the factors influencing the braking behaviour, the speed, the TTC as well as the age and gender of the driver were examined the most by the current literature. Existing analyses have employed different statistical techniques to reveal the relationship of those factors with the braking behaviour. Additionally, no research has considered all those factors in one analysis, requiring a multilevel analysis. Moreover, through the literature, there are inconsistent thresholds of how to detect a deceleration event and which deceleration events can be perceived as uncomfortable or comfortable.

2. To describe and validate data collection approaches for analysing deceleration behaviour.

An in-depth literature review on the data collection approaches that have been used to date is presented in Chapter 2. It was found that the most common methods to collect data for studying the driving behaviour are the simulators, the self-report methods such as the questionnaires, the controlled experiments, the FOTs and the naturalistic driving studies (NDS). Current literature has also used a combination of those methods. The advantages and disadvantages of the individual methods were also demonstrated. Moreover, there was extensive reporting on the two currently most used methods, i.e. the FOT and the Naturalistic driving studies (NDS). Their definition, their methodology and the most important FOT and NDS that have been conducted up to date were presented.

3. To investigate and refine the data to improve the analysis quality.

The data, used in this research were obtained from two FOTs, i.e. the TeleFOT project and the OEM project and one NDS, the UDRIVE study. The three projects provided naturalistic driving data and gave the opportunity to examine normal driving. From these projects, 35 million observations were examined obtaining from 86 different drivers and 644 different trips. The driving behaviour was monitored constantly, with the aid of different sensors such as GPS, accelerometer, radar and cameras. The variables of our interest were obtained by mining them from the time series data, by calculating them via a developed algorithm and by viewing the videos. The data had a mixture of different road elements, road users and traffic conditions. The deceleration events were obtained from the datasets using an extracting algorithm developed in this study. The algorithm uses specific thresholds and three different criteria to extract the braking events and it resulted in 21,600 events. Primarily exploratory data analysis was conducted to those events to summarise their main characteristics, detect any outliers and improve the analysis quality.

4. To develop the deceleration profiles.

An analytic description of the methodology used to estimate the deceleration profiles was presented in Chapter 4. The examined equations were visually explained and their meaning in real life was given. To correctly calculate the braking profile, a curve fitting algorithm was developed and resulted in profiles with reasonable goodness of fit (average adjusted R^2=0.85). Then, the most common profiles for the two parts of the braking event were found and presented thoroughly in Chapter 5. To explore which profiles were used in which situational scenarios, cluster analysis was applied.

5. To extract the underlying relationship between influencing factors and both, braking behaviour and comfort level.

The models that were used to extract the underlying relationship between influencing factors and both, braking behaviour and comfort level were described in detail in Chapter 4. Specifically, to examine all the influencing factors affecting the deceleration event, i.e. the deceleration value and the deceleration duration, the multilevel mixed-effect models were applied. The multilevel models were selected since all the dataset had a nested structure, i.e. the deceleration events were nested into the trips and the trips were nested into the drivers and the nested data are not statistically independent.

Multilevel models can handle this particularity by taking into consideration the correlation among the data that belong to the same group. The outcomes of the multilevel models for all datasets are interpretable and some also agree with the existing literature (as discussed in Section 7.1). The results of the multilevel mixed effect models (presented in Chapter 5) showed that the kinematic (i.e. initial speed, TTC, THW) and the situational factors (e.g. reason for braking) affect the most the deceleration variables whereas the driver or the trip factors have a small or no effect on braking. In addition, the results indicate the importance of the structure of the data; i.e. the number of the drivers in the dataset and the number of the trips each driver conducts since it affects the level of the most parsimonious model.

The relationships of the comfort level of braking events with kinematic, driver and situational factors were found by applying MMNL models (detailed description of the model in Chapter 4) since the dependent variable was categorical. The significant improvement on the goodness of fit of the models, which have 4 comfort categories compared to 3 or 2 comfort categories, revealed the importance of the classification of the data and of the selection of the appropriate thresholds for each comfort level. Also, the results underlined the importance of the car-following parameters (i.e. THW, TTC and space headway) on the braking comfort level which comes in line with the existing literature.

6. To recommend for comfortable braking design.

As discussed in Chapter 7, there are some recommendations for practice arising from the findings of this research. The coefficients of the models provided some new insight into the relationships of the influencing factors (i.e. kinematic, situational, driver and trip factors) with the deceleration event and the braking comfort level. The new information could be used for the development of more comfortable braking functions in the braking systems of conventional cars, semi or fully AVs. Moreover, the new relationships of the deceleration characteristics and their affecting factors could be helpful for the design of different road elements. The findings also supported the idea of personalised (semi-) AVs. Therefore, the acceptance and trust of the (semi-)AVs could be aggrandized leading to bigger market penetration. Moreover, the calculation of the deceleration profiles is useful to generate braking that feels familiar, safe and comfortable and could possibly be used to enhance traffic simulation modelling.

8.2 Contribution to knowledge

This work has generated new qualitative and methodological outcomes which can be used to enhance future analyses. The main contribution to knowledge of this research are:

1. <u>The establishment of an event detection methodology and the estimation of comfortable braking profiles</u>

   One of the methodological implications of this study is related to the detection of deceleration events. In the literature, there are different methods and thresholds that were applied to detect a deceleration event. However, this study presents a detection method that takes into consideration three different criteria to be more accurate. This can be widely used to detect the deceleration events in future studies and by making some small alterations to detect events from other important manoeuvres. Moreover, the precise detection of the beginning and the end of the event plays a crucial part in the estimation of the braking profiles.

   This research has calculated the equations that represent the deceleration profiles for the two parts of the braking (i.e. before the maximum deceleration and after that). Moreover, the most used deceleration profile which is assumed to be perceived as the most comfortable was estimated. The drivers at the first part of braking prefer to brake smoothly at the beginning and then proceed to harder braking. Concerning the second part, fast release of the brake was observed followed by a slower deceleration change.

2. <u>The extraction of the relationships between a range of factors and braking.</u>

   This research has examined thoroughly the relationship of the kinematic, situational, driver and trip factors with the deceleration characteristics (i.e. deceleration value and deceleration duration). The outcomes of this analysis advance the understanding of what affects the deceleration behaviour and how.

Specifically, the kinematic factors and especially the initial speed affect significantly the braking. Increase of the initial speed results to harder braking. Moreover, the situational factors influence the braking event. Particularly, the reason for braking, road type, the driver situation before the braking are statistically significant factors. On the other hand, the driver factors resulted in having no significant effect on the deceleration event.

These findings support further the event-based analysis of the manoeuvres. Within the literature, there are many studies that have analysed the braking in a specific road element such as signalised crossed intersection or roundabout. Although, those studies are missing the situational factors (i.e. the reason for braking and the road type) that actually affect the braking. This work also underlined the importance of using the appropriate statistical model to analyse naturalistic driving data. The most common structure of those data is the hierarchical structure so that each driver conducts many trips and each trip contains many events and the most suitable methodological approach is the use of multilevel modelling. The multilevel modelling can explore the effects of the influencing factors by taking into account the fact that events in the same trip or by the same driver have some dependencies.

3. The modelling of the comfort level for drivers while braking

Another methodological aspect of the deceleration behaviour analysis that has been highlighted in this work is the classification of the deceleration events into comfort level categories. Specifically, the selection of the deceleration value and the jerk (i.e. deceleration derivative) as the determinants for the classification and the appropriate thresholds to create the comfort categories are of crucial importance since there are no widely used thresholds in the literature.

From modelling the comfort level of the deceleration events applying discrete choice modelling, the relationship between the influencing factors and the comfort level was obtained. Also, the kinematic factors such as THW, the TTC and the initial speed affect significantly the comfort level. Smaller THW and TTC cause more uncomfortable deceleration events. The relationship between the reason for braking and the comfort level was that if the braking happened because of the existence of a pedestrian the comfort level was low (i.e. uncomfortable braking event). Finally, the driver characteristic and specifically the age and gender were found to affect the comfort level supporting the idea of personalised (semi-)AVs.

8.3 Limitations of the research

The research presented in this thesis is not without limitations. It includes data and methodological limitations, the most important of which are outlined below:

- **Lack of data from autonomous vehicles:** Having data from AVs would be ideal for this research. It would reveal when and why passengers of AVs feel unease. Particularly, it could be investigated, which values of deceleration and jerk make passenger uncomfortable when braking. Moreover, it could verify the results of this study concerning the relationship of the influencing factors with the comfort levels of deceleration.

- **Inaccuracies of situational factors:** The situational factors and specifically traffic density and the reason for braking (i.e. roundabout, junction, pedestrian crossing and dynamic obstacle) were obtained by watching the videos at the moment of the event for the OEM and TeleFOT datasets. This might result in some inaccuracies since there might be multiple reasons why a driver brakes which might not be captured by the video. Moreover, the estimation of traffic density was made empirically by calculating the cars on the video frame at the moment of braking and taking into consideration the road configuration, since different road configuration has different road capacity. It should be noted that for the TeleFOT dataset road type was also estimated empirically, hiding the risk of inaccuracies to this variable too.

- **Omitted variables:** The models that have been employed did not consider a number of potentially important factors affecting deceleration. Such factors are the weather, light conditions, time of the day, the friction between the tyres and the road surface (Z. Wu et al., 2009; Paleti et al., 2010; Reschka et al., 2012; Xiong and Boyle, 2012). The inclusion of these factors in the analysis could potentially describe the deceleration characteristics and the comfort level more explicitly and hence they could have improved the resulted models. Moreover, there is the risk that some of the variables that were found to be statistically significant, to be erroneously estimated.

- **Limited driver's data:** The only human factors that were accessible and were used in this study are; the age, the gender, the driver experience (only for the TeleFOT dataset) and the driver reaction before the event (obtained from the videos for the TeleFOT and the OEM datasets). However, there are many other human factors such as education level, income level, occupation and others that might affect the deceleration behaviour. Moreover, according to the literature, factors like fatigue and the sentimental state of the driver (i.e. the mood) at the time of the braking could also affect the deceleration behaviour.

- **Combination of motorways with dual carriageways:** All the roads of the Strategic Road Network in the United Kingdom include commercially and socially significant routes. However, they have different speed limits, geometry, traffic characteristics and capacity and they should be analysed separately. Although, within this study, the dual carriageways and the motorways were combined as one category since the extracted variable from the datasets was the speed limits of the travelled road and both motorways and dual carriageways have the same limit (i.e. 70 mph=112 km/h).

- **Variable selection:** For the classification of the deceleration events into the comfort categories, the deceleration value and the jerk variables were utilized. If more or different variables were added for the classification, the results might have been improved but the analyses would have been more complicated.

8.4 Further research

The work that has been presented in this research, i.e. the event-based approach and the profile calculation can be extended and can contribute to the analysis of other important manoeuvres. The method is flexible and can be easily transferred. Considering the limitations that have been previously described, there are several improvements that can be made in the future.

The statistical models and the clustering method rely on the quality of the data. Therefore, accuracy is very important to gain the correct results. In the future, image recognition and image processing techniques should be employed in order to extract the desired data from the videos. Specifically, with adequate methods such as image recognition techniques, the reason for braking, the driver reaction and the traffic density could be mined from the videos more accurate and faster. Moreover, future research should include more information about the drivers (e.g. years of driving, obedience to traffic rules, education level) and analyse the effect of these new factors on deceleration behaviour.

Future research should also investigate more factors that might influence the deceleration behaviour. The road, weather and light conditions, as well as the friction between the tyres and the road surface, are some of the factors that should be investigated. Furthermore, more accurate data for the road types should be employed to consider each road type separately since each road type has its own unique characteristics. Performing different braking analysis depending on the road type would be interesting and might reveal that each road type causes a totally different deceleration behaviour.

Regarding the comfort level of the deceleration events, a study, where passengers in an AV could report how comfortable and safe they feel at each braking, should be conducted. Another suggestion would be to measure indicators, such as heart rate, sweat, facial expression etc. that directly imply the level of discomfort. That way data that represent the comfort level can be obtained. Combining those data with the kinematic variables that were used in this study for the comfort level classification, more precise estimation of what affects the comfort level of the passengers inside an AV while braking could be achieved. In addition, more classification techniques such as Neural Networks and Naïve Bayes Classifier could be employed, and the results could be compared to reveal the best technique.

Finally, the literature supports that there are other manoeuvres apart from deceleration that play a crucial role in the comfort level of the passengers (Elbanhawi et al., 2015; Bellem et al., 2018). Acceleration and lateral lane change are two of them and the methodology that was developed within this study can be used for the detailed analysis of these manoeuvres. It would be interesting to conduct a study with fully AVs. Through this, it would be possible to confirm which manoeuvres make the passenger most uncomfortable and to focus on them in future research.

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Appendices

Appendix A

Publications related to this thesis

- Deligianni, S. P., Quddus, M., Morris, A., Anvuur, A. (2017). *Modelling Drivers' Braking Behaviour from Normal Driving*, 96th TRB Annual Meeting, Washington, USA, January 8-12.

- Deligianni, S. P., Quddus, M., Morris, A., Anvuur, A., Reed, S. (2017). *Analyzing and Modeling Drivers' Deceleration Behavior from Normal Driving*, Transportation Research Record: Journal of the Transportation Research Board, 2663:134-141.

- Deligianni, S. P., Quddus, M., Morris, A., Anvuur, A. (2018). *A normal Driving based Deceleration Behaviour Study Towards Autonomous Vehicles*, Proceedings of the 6th Humanist Conference, The Hague, Netherlands, 13-14 June.

Appendix B

Tables presenting the LR tests and the results of some other good models from multilevel modelling (Chapter 5)

<u>OEM dataset</u>

LR test for the 2-Level random intercept and random slope models of deceleration for OEM data

Model	log-likelihood	LR-TEST	Degree of freedom Difference	Chi probability	Better model	AIC	BIC
TRIP LEVEL							
random intercept model	-1200.68					2433.3	2520.2
random intercept +slope							
Initial speed	-1200.45	0.46	2	5.99	no	2434.9	2527.2
Vehicle C	-1199.88	1.606	4	9.49	no	2433.7	2526.1
Pedestrian crossing	-1200.31	0.738	6	12.59	no	2434.6	2526.9
DRIVER LEVEL							
random intercept model	-1195.69					2419.4	2495.4
random intercept +slope							
Initial speed	-1195.23	0.93	2	5.99	no	2420.4	2501.9
Urban	-1195.65	0.078	2	5.99	no	2421.3	2502.7
Pedestrian crossing	-1195.42	0.532	2	5.99	no	2420.8	2502.3
Vehicle C	-1191.73	7.912	2	5.99	yes	2413.5	2494.9

LR-test between the 3-Level and the 2-Level random intercept models for deceleration (OEM dataset)

random intercept 3-level model	log-likelihood	LR-TEST	Degree of freedom	Chi probability	Is the 3-level a better model?	AIC	BIC
3-LEVEL (driver/trip)	-1194.16					2418.3	2499.8
2-level(trip)	-1200.68	13.04	1	3.84	yes	2433.3	2520.2
2-level(driver)	-1195.69	3.06	1	3.84	no	2419.3	2495.4

Result of the 2-Level random intercept models for OEM dataset

	Trip Level			Driver Level		
Deceleration_max	**Coef.**	**z**	**P>z**	**Coef.**	**z**	**P>z**
Initial_speed	-0.0210	-7.87	0.00	-0.0200	-7.83	0.00
Vehicle A	0.1690	4.27	0.00	0.1650	5.52	0.00
Vehicle C	0.1990	5.42	0.00	0.1800	6.18	0.00
Urban	0.1000	2.87	0.00	0.1120	3.99	0.00
Roundabout	0.1630	3.61	0.00	0.1660	3.72	0.00
Junction	0.1220	3.3	0.00	0.1150	3.11	0.00
Pedestrian crossing	-0.1840	-2.17	0.03	-0.1930	-2.29	0.02
Other	0.1510	3.79	0.00	0.1550	3.92	0.00
Driver_reaction_1	0.0950	3.28	0.00	0.0980	3.36	0.00
Traffic_light	0.1350	3.55	0.00	0.1370	3.59	0.00
Car_stops	-0.1920	-6.94	0.00	-0.1920	-6.95	0.00
Age_old	0.1060	2.84	0.00			
Age_young	0.0870	2.28	0.02			
Intercept	-2.6470	-38.67	0.00	-2.5890	-39.65	0.00
Random-effects Parameters	**TripID: Identity Estimate**			**DriverID: Identity Estimate**		
Var (Intercept)	0.01			0.0089		
Var (Residual)	0.235			0.2381		
Level	**TripID**			**DriverID**		
ICC	0.041			0.036		
Obs	1689			1689		
ll(model)	-1200.68			-1195.69		
df	16			14		

LR-test for the 3-Level null model of duration for OEM dataset

3-level	log-likelihood	level	ICC	model	Log-likelihood of 2-level	LR-TEST	Degree of freedom	Chi prob.	Better model
model1 (driver-trip)	-1448.19	driver_id	0.001	model1 (driver level)	-1492.41	88.44	1	3.84	yes
		trip_id	0.126	model2 (trip level)	-1448.19	0.000	1	3.84	no
				null	-1494.5	92.61	2	5.99	yes

TeleFOT dataset

Results of the best Linear regression model of the deceleration for the TeleFOT dataset

Deceleration	Coef.	t	P>t
Initial speed	-0.025	-7.12	0.000
Traffic light	-0.104	-2.76	0.009
Roundabout	0.177	3.42	0.001
Junction	0.140	3.00	0.003
Pedestrian crossing	-0.029	-0.28	0.779
Other	0.105	2.28	0.023
Car stops	-0.227	-6.76	0.000
Driver reaction 1	0.142	3.63	0.000
Intercept	-2.244	-40.58	0.000
Adj R-squared	0.10		

LR test for the 2-Level null models of deceleration value for TeleFOT dataset

2-level	log-likelihood	ICC	LR-TEST	Degree of freedom	Chi probability	Better model
null	-455.82					
model1 (driver level)	-453.222	0.018	5.19656	1	3.84	yes
model2 (trip level)	-453.405	0.022	4.83006	1	3.84	yes

LR test for the 3-Level null models of deceleration value for TeleFOT dataset

3-level	log-likelihood	level	ICC	model	Log-likelihood of 2-level	LR-TEST	Degree of freedom	Chi probability	Better model
model1 (driver-trip)	-452.975	driver_id	0.013	model1 (driver level)	-453.22	0.49	1	3.84	no
		trip_id	0.023	model2 (trip level)	-453.41	0.86	1	3.84	no
				null	-455.82	5.69	2	5.99	no

Results of the 2-Level random intercept models for the deceleration for the TeleFOT dataset

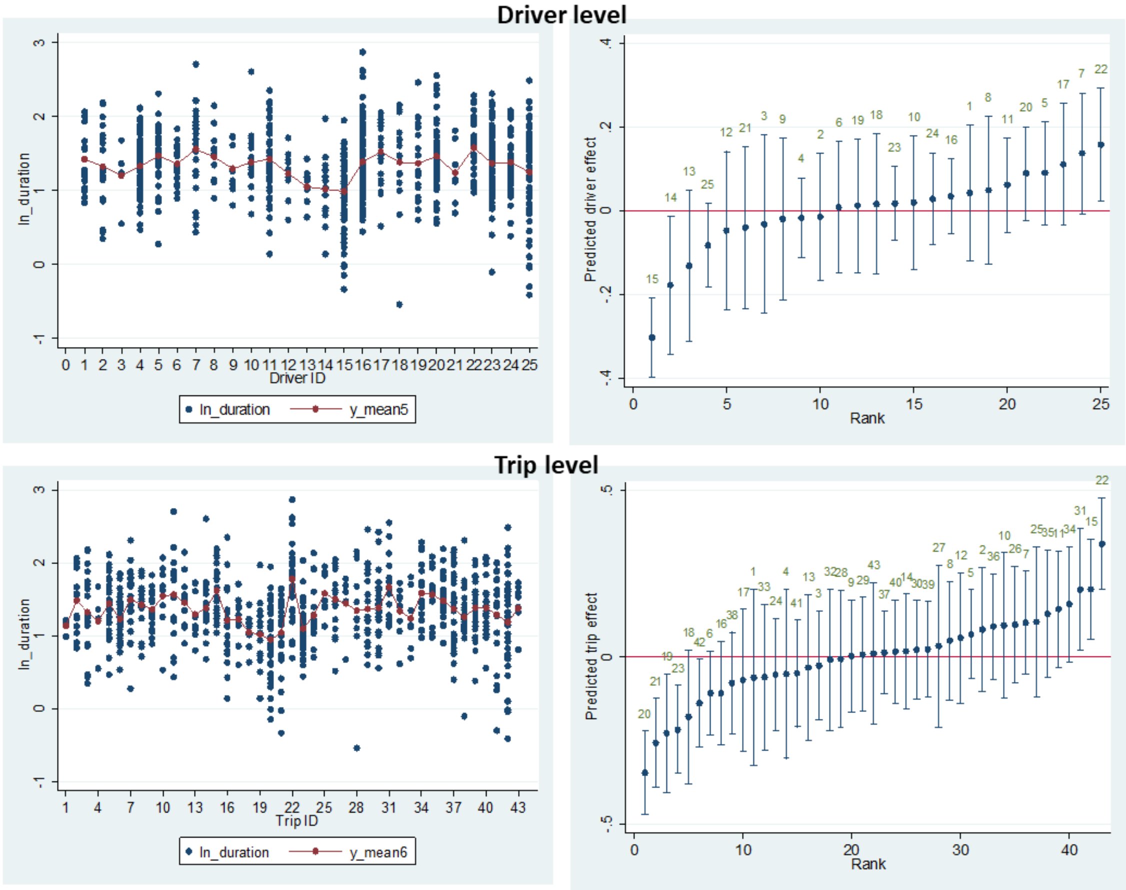
	Trip level			Driver level		
Deceleration	**Coef.**	**z**	**P>z**	**Coef.**	**z**	**P>z**
Initial speed	-0.028	-7.88	0.00	-0.027	-7.64	0.00
Traffic light	-0.090	-2.30	0.02	-0.099	-2.53	0.01
Roundabout	0.187	3.67	0.00	0.197	3.86	0.00

Junction	0.154	3.33	0.00	0.159	3.44	0.00
Pedestrian crossing	-0.024	-0.23	0.82	-0.025	-0.24	0.81
Other	0.106	2.31	0.02	0.122	2.67	0.01
Rural	0.060	2.05	0.04			
Car stops	-0.242	-7.27	0.00	-0.239	-7.21	0.00
Driver reaction 1	0.152	3.96	0.00	0.155	4.02	0.00
Intercept	-2.241	-39.51	0.00	-2.224	-38.96	0.00
Random-effects Parameters	**Estimate**			**Estimate**		
TripID: Identity						
var(Intercept)	0.007			0.006		
var(Residual)	0.146			0.148		
ICC **Obs** **ll(model)** **df**	0.046 837 -396.651 12			0.0393 837 -397.616 11		

LR test for the 2-Level random intercept and random slope models of deceleration value for TeleFOT dataset

Model	log-likelihood	LR-TEST	Degree of freedom Difference	Chi probability	Better model	AIC	BIC
TRIP LEVEL random intercept model	-396.678					815.35	867.38
random intercept +slope							
Initial speed	-393.162	7.03216	2	5.99	yes	809.49	861.51
Traffic light	-387.172	19.0105	2	5.99	yes	798.34	855.10
Junction	-396.647	0.06076	2	5.99	no	817.29	874.05
Other	-396.057	1.24074	2	5.99	no	816.11	872.87
Car stops	-392.158	9.03954	2	5.99	yes	808.32	865.07
Rural	-396.429	0.49674	2	5.99	no	816.86	873.62
Traffic light and Car stops	-385.271	22.8143	4	9.49	yes	796.54	858.03
		3.802*	2	5.99	no		
DRIVER LEVEL random intercept model	-395.142					814.28	871.04
random intercept +slope							
Traffic light	-392.784	4.717	2	5.99	no	811.64	873.05
Other	-394.331	1.62252	2	5.99	no	814.66	876.15
Rural	-395.127	0.03028	2	5.99	no	816.25	877.74
Car stops	-394.875	0.5338	2	5.99	no	815.75	877.2

* Compared with the random intercept and random slope for traffic light model



Plots representing the driver and trip effects in the duration for the 2-Level null models for TeleFOT dataset

The LR-test comparing the multi-Level null models and the single model of the duration for the TeleFOT dataset

2-level	log-likelihood	ICC		Models	LR-TEST	Degree of freedom	Chi probability	Better model
null	-574.638							
model1 (driver level)	-555.979		0.068		37.31	1	3.84	yes
model2 (trip level)	-541.225		0.112		66.82	1	3.84	yes
model1 (driver-trip)	-541.173	driver_id	0.012	model1 (driver level)	29.61	1	3.84	yes
		trip_id	0.112	model2 (trip level)	0.10	1	3.84	no
				null	66.93	2	5.99	yes

LR test for the trip-Level random intercept and random slope models of duration for TeleFOT dataset

random intercept 2-level model	log-likelihood	LR-TEST	Degree of freedom	Chi probability	Better model	AIC	BIC
2-LEVEL (trip)	-217.86					461.72	523.33
random intercept +slope							
Age_old	-215.013	5.6946	2	5.99	no	458.03	524.38
Stop_at_car_block	-217.84	0.0406	4	9.49	no	463.68	530.03
Rural	-217.433	0.8532	6	12.59	no	462.87	529.22
Driver reaction	-217.669	0.3826	6	12.59	no	463.34	529.69

Combination dataset

LR-test comparing the 2-Level random intercept against the 2-Level random intercept and random slope models for deceleration value (Combination Dataset)

Model	log-likelihood	LR-Test	Degree of freedom Difference	Chi prob.	Better model	AIC	BIC
TRIP LEVEL Random intercept model	-1699.92					3427.8	3510.5
random intercept +slope							
Trip distance	-1699.29	1.248	2	5.99	no	3428.6	3517.2
Car_stops	-1695.97	7.894	2	5.99	yes	3421.9	3510.5
Pedestrian crossing	-1697.15	5.54	2	5.99	no	3424.3	3512.9
Vehicle C	-1696.32	7.182	2	5.99	yes	3422.6	3511.3
DRIVER LEVEL Random intercept model	-1693.29					3416.5	3505.2
random intercept +slope							
Trip distance	-1691.40	3.784	2	5.99	no	3414.8	3509.3
Pedestrian crossing	-1692.58	1.398	2	5.99	no	3417.2	3511.7
Vehicle C	-1684.57	17.436	2	5.99	yes	3401.2	3495.7

Results of the best 2-Level model for deceleration (Combination dataset)

Deceleration	Coef.	z	P>z
Initial speed	-0.0004	-4.83	0.00
Traffic light	-0.0534	-2.58	0.01

Trip distance	-0.0115	-3.71	0.00
Roundabout	0.1142	3.96	0.00
Junction	0.0983	4.31	0.00
Pedestrian crossing	-0.1869	-3.02	0.00
Rural	-0.0441	-2.24	0.03
Other	0.1156	4.30	0.00
Car_stops	-0.1637	-8.41	0.00
Vehicle A	0.1375	5.26	0.00
Telefot	0.2236	6.01	0.00
Vehicle C	0.1782	4.20	0.00
Intercept	-2.5190	-72.75	0.00
Random-effects Parameters	**Estimate**		
DriverID: Independent			
var(Vehicle C)	0.012		
var(Intercept)	0.006		
var(Residual)	0.199		
ICC	0.029		
Obs	2715		
ll(model)	-1684.579		
df	16		

LR-test of the 3-Level against the 2-Level random intercept models for deceleration (Combination dataset)

random intercept 3-level model	log-likelihood	LR-TEST	Degree of freedom	Chi probability	Better model the 3-level
3-LEVEL (driver/trip)	-1685.99				
2-level(trip)	-1699.92	27.856	1	3.84	yes
2-level(driver)	-1693.29	14.610	1	3.84	yes

UDRIVE dataset

LR-test comparing the 2-Level and the 3-Level against the single-Level for deceleration (UDRIVE dataset)

Model	df	AIC	BIC	ICC	Log-Likelihood	Compa-rison	Chi prob.	L.R test	Better model
Intercept Only (1)	2	12707.3	12721.0		-6351.6				
driver_ level (2)	3	12554.8	12575.4	0.0373	-6274.4	(1 vs 2)	3.84	154.4	Yes

trip_ level (3)	3	12599.8	12620.4	0.0455	-6296.9	(1 vs 3)	3.84	109.5	Yes
three_ level (4)	4	12536.1	12563.6	ICC_{driver}= 0.0325 ICC_{trip}= 0.0184	-6262.0	(1 vs 4)	5.99	179.1	Yes
						(2 vs 4)	3.84	20.7	Yes
						(3 vs 4)	3.84	65.68	Yes

LR-test for multilevel models for Duration (UDRIVE dataset)

Model	df	AIC	BIC	ICC	logLik	Comparison	L.Ratio test	p-value
interceptOnly (1)	2	14687.2	14700.9		-7341.61			
driver_level (2)	3	14524.7	14545.3	0.037	-7259.36	1 vs 2	164.5	<.0001
trip_level (3)	3	14563.6	14584.2	0.045	-7278.82	1 vs 3	125.9	<.0001
three_level (4)	4	14496.2	14523.7	ICC_{driver} = 0.0325 ICC_{trip}= 0.0184	-7244.12	1 vs 4	194.98	<.0001
						2 vs 4	30.48	<.0001
						3 vs 4	69.4	<.0001

LR-test of the 2-Level random intercept and random slope models for duration in Statistical analysis I (UDRIVE) data

Model	df	AIC	BIC	ICC	Log-Lik.	Comparison	L.Ratio test	p-value
Linear model (1)	21	2739.1	2876.2		-1347.5			
Driver-Level random intercept model (2)	21	2716.4	2847.3	0.019	-1337.2			
Driver-Level random intercept and slope for max_jerk and car_stops variables model (3)	26	2656.9	2819.1	0.178	-1302.5	(2 vs 3)	69.44	<.0001
Trip-Level random intercept model (4)	23	2726.3	2869.8	0.031	-1340.1	(1 vs 4)	14.8	<.0001
Trip -Level random intercept and slope for max_jerk and car_stops variables model (5)	28*	2511.3	2684.9	0.224	-1227.7	(4 vs 5)	225.0	<.0001

Three-Level random intercept model (6)	22	2715.5	2852.7	0.017 &0.014	-1335.8			
Three-Level random intercept and slope model (7)	32*	2511.4	2611.0	0.065 &0.43	-1223.7	(6 vs 7)	224.0	<.0001

* Add the insignificant variables in order to have the same explanatory variables and to perform the LR test