Modelling Human-Like Deceleration Responses to Lane Change Manoeuvres on the Highway

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Modelling Human-Like Deceleration Responses to Lane Change Manoeuvres on the Highway

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Abstract

The introduction of automated vehicles (AVs) on the road causes a transition period where vehicles with different levels of automation operate alongside human road users. Modelling human driving behaviour can help to establish AVs drive predictably and according to social expectations. This research modelled the deceleration response of a rear-approaching vehicle on the target lane (i.e., the follower vehicle) when another vehicle performs a lane change manoeuvre to overtake a slower-driving vehicle on the highway. A dataset containing naturalistic vehicle trajectory information is used to model this response behaviour. Three linear regression models are developed that describe the follower vehicle's decelerating response by predicting the timing, duration and minimum acceleration based on the descriptive variables at the start of the lane change. Similar to car-following models, the follower vehicle's deceleration depends on the velocity difference and distance gap to the vehicle changing lanes. In addition, the acceleration values of the other surrounding vehicles are important predictor variables. However, much of the variance of the human response behaviour is still unexplained. This research suggests recommendations for future studies to improve the decelerating response model to lane change manoeuvres on the highway to ensure AVs drive according to human standards.

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1. Introduction

There has been a lot of enthusiasm for the introduction of automated vehicles (AVs) on the roads. Over the last decade, the field of automated driving has seen rapid technological development. Given the achievements in automated driving technology so far, their full use in future transportation systems seems inevitable (Singh & Saini, 2021). It is envisioned that AVs will have a positive environmental and social impact on urban and transport systems (Future Agenda Limited, 2020; Latham & Nattrass, 2019; Smirnov et al., 2021). A benefit of AVs is that their drivers can utilise the time spent in the vehicle by working or using the time for entertainment (Brenner & Herrmann, 2017). In addition, AVs have the potential to increase road safety, maximise traffic efficiency, reduce fuel consumption and improve access to transportation for disadvantaged persons (Domeyer et al., 2022). AVs are claimed to be safer than human drivers because AVs will not make human errors caused by distraction or tiredness (Grahn et al., 2020). However, most estimated benefits will likely be obtained when traffic consists primarily of AVs with a high level of automation or even only after full market penetration (Mahdinia et al., 2021). Although AVs can provide many benefits, there are significant challenges in their development and commercialisation to be addressed and solved before the large-scale deployment of AVs on the road.

Road traffic is unlikely to become fully automated in the near future (Markkula et al., 2021). Despite this, advancements in automation technology are leading to an increasing level of automation in vehicles. SAE International (2021) outlines five levels of automation for vehicles based on the human activity required, driver support features and automated driving features. The scale ranges from level 0 “no driving automation” where the human performs all driving tasks, to level 5 “full automation” where the vehicle performs all driving tasks under all conditions. Currently, most new vehicles are equipped with level 1 or 2 automation technology that partially assists the driver with adaptive cruise control and active lane centring. Thus, vehicles with different levels of automation are already on the market, and the level of automation in vehicles is expected to increase in the future. As a result, there is a transition period where vehicles with different levels of automation operate alongside each other and road users such as pedestrians, cyclists and other motorists (Domeyer et al., 2022; Schieben et al., 2019). AVs still have challenges to overcome when it comes to coexisting on the roads with human road users. Human road users will need to understand AVs and vice versa as they drive in the same environment. As Möller et al. (2016) mentioned, an AV “*becomes part of a complex socio-technical system and has to interact with all these actors in a socially accepted manner*” (p. 686). Interacting in a socially-compliant way is described as behaving predictably to other road users and according to social expectations (Grahn et al., 2020; Schwarting et al., 2019). Accordingly, the interaction between AVs and human road users is gaining attention in the literature because it is being acknowledged that driving is not only a mechanical performance but also a complex social activity (Grahn et al., 2020).

Currently, AVs have been developed by following mainly the architectures of robotics which focuses on driving collision-free (Xu et al., 2021). This ignores many factors contributing to human driving behaviour, such as communication, informal rules and anticipation (for example, see Brown and Laurier (2017)). In addition, AVs lack in their negotiation with human road users to coordinate a joint future motion plan (Chater et al., 2018). Ignoring these factors results in the AV driving non-human-like and overly cautious (Schieben et al., 2019). This behaviour of the AV can cause situations of uncertainty and mistrust, which could frustrate human road users and ultimately threaten road safety (Smirnov et al., 2021). To prevent this, AVs need to behave predictably and according to social expectations, to at least the extent that other road users can intuitively understand the behaviour. In other words, ensuring AVs drive according to human standards is of interest.

1. 1. Lane Change Scenarios

High to full automation levels will be first introduced for highway driving as it is relatively more tractable than urban driving (e.g., a more limited set of road user types) (Future Agenda Limited, 2020). On the highway, a lane change manoeuvre is one of the most fundamental driving behaviours (Xia et al., 2021). Inappropriate lane change manoeuvres by drivers because of miscommunication or human error can reduce road safety and increase the risk of collision (Moridpour et al., 2010). In addition, an abrupt or forced lane change can result in the rear-approaching vehicle in the target lane (i.e., the lane that the vehicle changing lanes intend to move into) needing to brake hard. Excessive decelerations can cause traffic oscillations which trigger a drop in road capacity and increase the risk of rear-end crashes (Coifman et al., 2005). Further, an AV that drives overly cautiously and does not negotiate with other drivers to change lanes can become stuck in a lane, resulting in a longer travel time or even taking the wrong route.

A lane change manoeuvre is one of the driving tasks that can comprise multiple vehicle interactions in both the longitudinal and lateral directions (Venthuruthiyil & Chunchu, 2022). A situation that particularly requires interaction between drivers is a cooperative lane change. A cooperative lane change involves interaction between a driver that wants to change lanes (i.e., the ego vehicle) and a rear-approaching vehicle on the target lane (i.e., the follower vehicle). A cooperative lane change is described as a situation where the ego vehicle requests to change lanes and, subsequently, a follower vehicle cooperates by giving way such that the driver can change lanes (Stoll et al., 2019). To participate in this kind of lane change, an AV would require to understand the other vehicle's intention, recognise the cooperative lane change situation, and know what behaviour is expected in return. If AVs are not aware of drivers requesting a lane change and do not behave cooperatively, the drivers might be more inclined to force a lane change. As a result, the AV would need to brake more abruptly, which is likely uncomfortable for the passengers (Liu et al., 2022). However, regulations on how AVs should drive are currently far from comprehensive (Bin-Nun et al., 2022). These regulations are necessary to ensure that the implementation of high automation levels on the highway does not disrupt the current traffic situation, reduce road safety, and increase the risk of collision. Modelling human driving behaviour in a lane change scenario can help in formulating these regulations.

The current literature already provides a broad range of different lane change models. The first lane change decision models were based on gap acceptance as a function of distance and speed differences, in combination with other varying parameters (e.g., Ahmed (1999) and Gipps (1986)). For instance, Gipps' model provides a framework for the driver's decision to execute a lane change based on three factors: whether it is physically safe, necessary, and desirable to change lanes. Gipps based whether it is safe to change lanes on his car-following model, which includes the relative speed and distance as well as the maximum breaking the driver is prepared to undertake. However, to completely characterise the lane change manoeuvre, it might be necessary also to include the dynamic behaviour between the lane changing vehicle and its surrounding vehicles. For example, Stoll et al. (2019) showed that drivers are willing to cooperate in lane change scenarios on the highway, such that lane change models should also account for the possibility of drivers interacting for a gap creation. Furthermore, Venthuruthiyil and Chunchu (2021) concluded that for lane change duration modelling, the follower vehicle's kinematics mainly control the lane change duration and hence stressed the importance of including the dependency between the two vehicles in lane change models.

Some more recent lane changing models do try to include the interaction between road users in lane change scenarios and can be classified into three approaches. First, search algorithms are applied to estimate the driver's lane change decisions by incorporating the limitations that the driver cannot directly observe the underlying states of other drivers (Brito et al., 2022; Ulbrich & Maurer, 2015). This is inherently part of driving, as another driver's intentions and willingness to cooperate are not directly observable. Second, learning-based models use extensive data collection to build interaction-aware prediction models or to directly derive a driving policy from sensor data (Schwarting et al., 2018). Third, game-theory models approach traffic interactions as a situation where road users pursue their own goals and reciprocally need to adapt their behaviour to the goals and behaviour of other road users (Markkula et al., 2020). Game-theory models are argued to model the interaction of drivers the most as the model is contingent on the behaviour of the other drivers, resulting in a more realistic image of driving behaviours than the other models (Ji & Levinson, 2020).

Despite game-theory models incorporating the behaviour of the follower vehicle in the decision-making process of the ego vehicle, there has been limited research that actually models the behaviour of the follower vehicle (also noted by Ali et al. (2020) and Ma et al. (2021). When and how the follower vehicle responds to the lane change request are questions that remain unanswered and motivates this study. Understanding the follower vehicle's response will improve the AV's ability to respond like humans (including the possibility of cooperation) and enhance predictions of the follower vehicle's behaviour in lane change decision models of the ego vehicle.

1. 2. Research Question

To fully comprehend the response behaviour of the follower vehicle in a lane change scenario, it is first crucial to understand the decision-making processes and interaction patterns between drivers. Currently, the literature lacks a complete overview of the interdependence between the follower and ego vehicles and how they communicate and interact during lane changes. Therefore, the first objective of this research is to develop a comprehensive flowchart that describes the decision-making processes and interaction patterns between the two vehicles in a lane change scenario.

This research continues by focussing on the specific part of the flowchart describing the response of the follower vehicle. This is particularly important as there is a lack of models characterising this behaviour in current literature. The follower vehicle's behaviour can play a crucial role in the lane change manoeuvre, especially in cooperative lane changes where it decelerates to enable the vehicle changing lanes to merge. Therefore, this study focuses on characterising the deceleration response of the follower vehicle to the lane change manoeuvre of the ego vehicle, leading to the research question:

What is the deceleration response behaviour of a rear-approaching vehicle on the target lane when a vehicle performs a lane change manoeuvre on the highway?

The decelerating response behaviour of a follower vehicle can be described by the timing, duration, and minimum acceleration (i.e., magnitude of the deceleration). Therefore, the following three sub-questions are investigated in this research:

When does a rear-approaching vehicle start decelerating in a lane change scenario?
How long does a rear-approaching vehicle decelerate in a lane change scenario?
What is the minimum acceleration of a rear-approaching vehicle in a lane change scenario?

Naturalistic vehicle trajectory data will be analysed to gain insights into human driving response behaviour. Lane change manoeuvres should be identified, and the related timing, duration, and minimum acceleration of the deceleration response of the following vehicle should be investigated. To understand of the follower vehicle's response, the important predictors of the response should be identified by analysing both the driving behaviour of the vehicles and the relationship between them in the lane change scenario. How a specific lane change scenario influences the follower vehicle's response behaviour should be modelled such that the decelerating response can be predicted. The results of this analysis should provide predictions of the human-like response behaviour of a following vehicle during a lane change manoeuvre.

1. 3. Report Outline

The research continues in Chapter 2. by providing a literature review about lane change manoeuvres with a particular interest in the interdependence and interaction between the vehicles. The Chapter ends by combining the knowledge from the literature review into a flowchart describing the decision-making process and interaction patterns between the ego and follower vehicles. Chapter 3. continues the literature review by focussing on the specific part of the flowchart that describes the response behaviour of the follower vehicle. This chapter provides the existing knowledge and models regarding the follower vehicle's response to a lane change manoeuvre. Additionally, the specific lane change scenario investigated in this study is described. Chapter 3. concludes by summarising the key findings of previous literature and stating the research hypotheses. Next, Chapter 4. explains the research method, addressing the dataset used, the descriptive parameters of the lane change scenario and the classification of the follower vehicle's behaviour. Following, Chapter 5. presents the results of the data analysis. At the end of Chapter 5. , the models describing the decelerating response behaviour of the follower vehicle are presented. This is followed by Chapter 6. , which discusses this study's results and limitations and provides recommendations for future research. Finally, Chapter 7. concludes this research by summarising the key findings.

2. Lane Change Manoeuvres

This Chapter presents a flowchart of the decision-making process and interaction patterns between the ego and follower vehicles. Literature from different aspects of driving behaviour is discussed and combined to have a comprehensive understanding of the lane change manoeuvre. Specifically, literature about general and lane change driving behaviour, as well as the formal driving rules are reviewed. Additionally, a focus is given to literature discussing traffic communication and interaction.

2. 1. General Driving Behaviour

Wilde (1976) presented a flowchart of general driving behaviour. The paper provides a model of a driver's behaviour by incorporating the role of social influences on the driver's perception, decision-making, and actions. Here, it is assumed that a driver samples information from the environment, such as the physical features of the traffic site and the informal and formal rules. In addition, the driver gathers information about the direction and speed of the surrounding vehicles. Based on this information, the driver anticipates the future environment and trajectory of the driver's vehicle and the surrounding vehicles. The intake of additional information might verify these anticipations. In turn, these anticipations (verified or not) will result in a subjectively estimated danger of the situation. The level of perceived risk determines the decision to take certain driving actions. In addition, these decisions are influenced by the driver's cognitive state and motivation, which depend on modulating factors such as experience, personality, and age. Further, a distinction has been made between long-term, short-term, and momentary decisions. Overall, Wilde (1976) provides a strong framework for defining the behaviour of drivers.

Later, Michon (1985) conceptualised driving as a hierarchically ordered structure of different behaviour levels. This so-called "Hierarchical Control Model" describes driver behaviour as a result of the traffic situation but also factors that are not entirely related to the driving process, such as intentions, personality, and preferences. The model distinguishes between strategic, tactical, and operational levels. The strategic level refers to higher-level reasoning and planning, such as route choices. While executing the strategic level decisions, tactical decisions need to be made by drivers. The tactical level includes processes that regulate safe interactions with the road environment and surrounding vehicles. This level is more concerned with the directly prevailing circumstances of the driver and short-term objectives. Examples of manoeuvres at this level are gap acceptance, obstacle avoidance and turning. The lowest decision level, the operational level, involves manipulating control outputs for driving. It refers to the car controlling processes such as following the road and managing the speed. The task of driving involves all three levels working together. For example, the decisions made on a tactical level often have to meet the criteria derived from the goals specified at the strategic level. At the same time, the outcome of behaviours at the lower level can change the criteria from the upper level. Michon (1985) stressed the importance of connecting the levels and defining the connection between them.

The Hierarchical Control Model is a well-appreciated model in literature to describe human driver behaviour (Lützenberger & Albayrak, 2014; Moridpour et al., 2010; Salvucci, 2006).

2. 2. Traffic Interaction

The driving behaviour of vehicles is dependent on other vehicles as they share the road. However, many traffic situations involving multiple vehicles can unfold without the necessity of interacting, also referred to as traffic encounters (Domeyer et al., 2022; Fabricius et al., 2022). An encounter indicates road users have the possibility of colliding where only one or neither driver adjusts their behaviour. Wilde (1976) described encounters as a unidirectional influence: *"driver A influences B without necessarily being influenced by him"* (p. 477). For example, when a vehicle approaches a slower-driving lead vehicle, there can be a collision if the approaching vehicle does not change its behaviour. In this situation, the lead vehicle will likely not change its behaviour; therefore, it is an encounter rather than an interaction. The degree of interdependence and uncertainty between drivers will determine the need for interaction behaviours (Domeyer et al., 2019).

Traffic interactions are an essential component of driving when two or more road users need to coordinate a safe joint future motion plan (Portouli et al., 2014). The drivers need to assess other drivers' intentions based on communication correctly and subsequently interact if necessary. For example, even though a driver's intended manoeuvre seems impossible at a specific time, due to interacting with other drivers and communicating one's intent, the driver might still be able to execute the manoeuvre safely. Markkula et al. (2020) concluded that all driver interaction scenarios refer to some form of negotiation to determine the order of access to some shared region of space. The authors refer to this as a space-sharing conflict:

> Space-sharing conflict: "*An observable situation from which it can be reasonably inferred that two or more road users are intending to occupy the same region of space at the same time in the near future*." (Markkula et al., 2020, p. 736)

A space-sharing conflict requires interaction as it is an ambiguous situation where road users need to determine a shared future motion plan (Rasouli & Tsotsos, 2020). If the drivers do not interact and neither changes their trajectory, the space-sharing conflict will result in a collision. The authors continue to use the concept of space-sharing conflict in defining what interactions are:

> Interaction: "*A situation where the behaviour of at least two road users can be interpreted as being influenced by a space-sharing conflict between the road users*." (Markkula et al., 2020, p. 737)

The definition suggested by the authors is cross-theoretical and brings together the four different theoretic perspectives on road traffic interactions, namely: traffic conflict and safety, game theory, sociology and linguistics (Markkula et al., 2020). In addition, several key aspects are incorporated, such as collision avoidance, order of access, coordination, and communication. However, this definition of interaction has two limitations. First, the definition inherently depends on the interpretation of the road users. In other words, the judgment of whether or not there is a space-sharing conflict and whether the situation requires negotiation is observer-dependent (Markkula et al., 2020). Each driver likely has limited information about the whole situation, allowing drivers to interpret the situation differently. Similarly, whether the space-sharing conflict is resolved depends on the driver's perspective and judgment (Markkula et al., 2020). Second, a situation is only considered to be an interaction when there is an observable difference in behaviour. However, it can occur that a driver is interacting without changing their behaviour. Nevertheless, another driver cannot know whether the driver deliberately chooses to signal an intent by not changing its behaviour or was unaware of the interaction-demanding situation. The distinction between those two driver states is irrelevant to this research as the objective behaviour of the driver is the same. Likewise, it is also impossible for road users to know this difference.

The definition of traffic interaction is closely related to Clark and Brennan's (1991) concept of joint actions (Markkula et al., 2020). Joint activity is a generalisation of joint action, and it describes situations where drivers' actions depend on each other (Domeyer et al., 2019; Fabricius et al., 2022). Effective coordination in a joint activity relies on common ground. Common ground refers to mutual understanding and anticipation toward traffic that lets drivers resolve a space-sharing conflict (Dietrich et al., 2018). Common ground is partly formed by formal regulations. However, since formal rules often involve a high degree of interpretation which is also situation-dependent, communication mainly takes place along informal rules (Latham & Nattrass, 2019; Wilde, 1976). Informal rules are based on previous experiences and social norms (Portouli et al., 2014). Consequently, informal rules are not widely shared by all road users and differ among geographical regions (Portouli et al., 2014; Wilde, 1976). Substantial differences in the common ground among road users will likely result in miscommunications. A higher rate of accidents would be expected to occur when the existing norms are inadequate, there is a completely unstructured situation, or there are contradictory or unclear informal rules (Wilde, 1976). The concept of common ground stresses the importance of shared knowledge between road users to communicate and interact successfully (Domeyer et al., 2019).

2.2.1. *Communication*

In order to interact, road users need to communicate their intent. Communication in traffic is a broad concept. Dietrich et al. (2019) state that "*once a driver's behaviour is perceivable by another one, it becomes a form of communication*" (p. 22), emphasising the importance of placing traffic behaviour in a broader context and associating it with communication. This implies that driving behaviour always shows some intent that others can interpret as communication, regardless of the driver's intention or awareness (Dietrich et al., 2019). Therefore, it is argued that one cannot not communicate, meaning that road traffic behaviour and communication are equivalent. Describing a driver's communication through its behaviour is also in line with linguistic models that use Austin's (1975) speech act theory

(Markkula et al., 2020; Portouli et al., 2014). Austin argues that to say something is to do something; verbal communication is an illocutionary act. An illocutionary act conveys a particular force to oneself or others, such as commanding, requesting, warning, or informing. Portouli et al. (2014) extend this reasoning to (nonverbal) road traffic communication. Here, communicative acts still have varying forces and cause some consequences. For example, drivers requesting to merge paths while the target lane is occupied or informing someone to pass first.

This definition of driver's communication makes it impossible to make specific distinctions. First, the definition does not allow to determine whether a driver is consciously aware of communicating and whether the driver holds a particular intention. However, this difference can also be difficult for drivers to distinguish while driving. Second, other definitions make a distinction of whether the other driver recognises this communication. Stefanov (2018) states that behaviour becomes communication if "*another person interprets the behaviour as a message and attributes meaning to it*" (p. 3). Nevertheless, drivers themselves are not capable of truly determining whether the other driver interprets and attributes meaning to the driving behaviour or not. In both cases, the actual driving behaviour will not differ. Therefore, behaviour and communication can be seen as equivalent in traffic, and further distinction is unnecessary.

A driver has various actions to communicate their intention, also referred to as communication cues (Amini et al., 2019). The communication cues can be classified into two main mechanisms, namely implicit and explicit communication (Domeyer et al., 2022; Markkula et al., 2020; Portouli et al., 2014; Schieben et al., 2019):

> Implicit communication: "*A road user behaviour which affects own movement or perception, but which can at the same time be interpreted as signalling something to or requesting something from another road user*" (Markkula et al., 2020, p. 741)
>
> Explicit communication: "*A road user behaviour which does not affect own movement or perception, but which can be interpreted as signalling something to or requesting something from another road user*" (Markkula et al., 2020, p. 742)

The purpose of the behaviour determines whether it is implicit or explicit. Explicit communication serves the exclusive purpose of conveying information with the intention to transfer one's intention directly (e.g., the turn indicator). While implicit communication is a behaviour that affects the road user's movement or perception but which can at the same time be indirectly interpreted as signalling information by other road users (e.g., accelerating or breaking lights) (Amini et al., 2019; Fabricius et al., 2022). Implicit communication also supports the notion that behaviour is equal to communication. That is, implicit communication is merely the driving behaviour without the driver's intention to communicate. Drivers' communication can also be divided into the categories of vehicle-based and driver-based (Lee et al., 2021). Vehicle-based communication is related to the motion of the vehicle and other available means of communicating through the vehicle's light and sound. Driver-based communication is the information the human driver provides, such as gestures and eye contact. Table 1 provides an overview of a driver's types of communication cues.

Table 1

Overview of possible communication cues

	Implicit	Explicit
Vehicle-based	Kinematics (e.g., position, velocity, acceleration, jerk)	Flashing headlights
		Emergency lights
	Proxemics (e.g., gap size)	Turn indicator
	Chronemics (e.g., vehicle trajectory)	Horn honking
	Braking lights	
	Engine noise	
Driver-based	Eye movement	Gesture (e.g., hand movement)
	Body language (e.g., head orientation)	Speech
		Eye contact

Note. This list is not intended to be complete but provides an overview of the literature's most analysed communication cues.

Communication cues are always interpreted in their context (Schieben et al., 2019). Drivers need to constantly analyse the communication cues in light of the driving context and past experiences, as the cues can be very ambiguous (Färber, 2016; Schieben et al., 2019). For example, headlight flashing can have multiple meanings, such as offering to yield right-of-way or indicating vehicle lights are off. The context of the situation will help interpret other drivers' communication correctly and determine their future actions.

The road environment and stereotypes can cause drivers to have different expectations that help to interpret the communication cues of drivers and interact successfully (Portouli et al., 2014). For example, the road environment (e.g., the number of lanes, traffic volume, and merging of lanes) can help a driver anticipate other vehicles will change lanes soon when their current lane is ending (Amini et al., 2019; Saifuzzaman & Zheng, 2014). Additionally, drivers form stereotypes based on previous experiences that will make a driver set specific expectations about their future actions (Dietrich et al., 2019; Schieben et al., 2019). For instance, a motorcyclist is expected to overtake fast, while a truck is likely to have lower accelerations. In addition, drivers' expectations also differ depending on the vehicle's country number plate or the specific vehicle model (Dietrich et al., 2019). The pure recognition of a vehicle will cause drivers to form an expectation about the vehicle's future motion. This strengthens the statement that drivers constantly communicate regardless of the driver's intention.

In general, the driver is inherently a crucial part of driving and consequently plays a role in traffic communication. Each diver and driving style is different, and a driver's needs and motivations will likely differ over time (Saifuzzaman & Zheng, 2014; Wilde, 1976). Saifuzzaman and Zheng (2014) presented a list of driver properties that have been shown to influence the driving style, such as socio-economic characteristics, abilities, personality, and risk threshold. These properties are essential in understanding certain behaviour differences of drivers. However, this will not be further investigated as it is not the aim of this research. It should be noted that a driver's driving style will influence the implicit vehicle-based communication cues (e.g., aggressively accelerating) and be indirectly relevant in the analyses.

2. 3. Lane Change Driving Behaviour

Literature provides different lane change models, with or without traffic interactions included. This section reviews various lane change models, which help to develop a general flowchart of the decision-making process and the interaction between the drivers. Information on the traffic rules regarding performing a lane change manoeuvre is also discussed.

2. 3. 1. *Decision-making Process*

One of the most popular lane change models is from Gipps (1986). In Gipps' model, the driver's decision to make a lane change depends on whether it is safe, necessary, or desirable to change lanes. In the case of necessary lane changes, Gipps defined three patterns of a driver's behaviour depending on the distance to the mandatory lane change manoeuvre. When the distance is large, it does not affect the driver's lane change decision, and the driver tries to keep their desired speed. When a driver is at a middle distance away, the driver wants to change lanes and ignores speed advantage opportunities. By the time the driver is close to the mandatory lane change, the driver's only interest is to reach the correct lane, and speed is unimportant. Gipps argues that a driver has multiple objectives (e.g., desired speed, correct lane, safety, and comfort) which are not necessarily consistent with each other. A driver encounters many conflicts that influence the decision to change lanes. The model of Gipps (1986) incorporates these different factors that influence drivers to change lanes.

Lane change decision models can be categorised as tactical, operational or both, but not at the strategic level (Salvucci, 2006). Moridpour et al. (2010) state that in traffic situations, "*drivers make tactical and operational decisions for their lane changing manoeuvres based on the current characteristics of the surrounding traffic and their anticipated future characteristics of the surrounding traffic*" (p. 159). Webster et al. (2007) argued that lane change models could be improved by incorporating more of the tactical decisions made by drivers. Similar to what was mentioned by Wilde (1976), decisions made by drivers are primarily based on assumptions about the behaviour of surrounding vehicles (Webster et al., 2007). Therefore, Webster et al. (2007) extended Gipps' model (1986) by implementing a driver's anticipation and manoeuvre planning behaviour.

2.3.2. *Driver Interaction*

The mentioned models are from the perspective of the driver that changes lanes. However, the interaction between drivers inherently includes the driving behaviour and decisions of two or more drivers. Therefore, Hidas (2005) developed a lane change decision model loosely based on Gipps' model (1986) with also considering the cooperation of the rear-approaching vehicle in the target lane. Hidas (2005) argues that a driver that wants to change lanes sends a request to the rear-approaching vehicle driver in the target lane. This request is evaluated by the rear-approaching vehicle driver and is either refused or accepted. The driver might refuse or accept the request depending on factors such as the vehicle's position and speed and the driver's personality. A driver who accepts the request to change lanes will reduce speed and prepares a sufficient gap for the vehicle changing lanes. Hidas (2005) summarised the cooperative lane change interaction process in three components. First, the ego vehicle indicates the desire to change lanes. Then, the rear-approaching vehicle recognises the situation, decides to cooperate, and slows down. Finally, the ego vehicle realises the rear-approaching vehicle gave way and executes the lane change manoeuvre when the distance gap is big enough.

Portouli et al. (2014) also acknowledged that it is essential to incorporate the response to a request of drivers when modelling driver interaction. Here, a linguistic model of drivers' communicative interactions is proposed. The interaction process consists of several components. First, the vehicle changing lanes communicates its intent and makes a request. Following this, the rear-approaching vehicle on the target lane perceives this act and interprets the intention of the other vehicle. This vehicle has the choice to either accept or reject this request and reacts accordingly. Next, the vehicle changing lanes perceives the act and interprets the intention. Then, the vehicle can choose to start or cancel the manoeuvre. This model allows for both successful and unsuccessful interactions, as drivers can wrongly perceive or interpret an intention.

2.3.3. *Formal Driving Rules*

Driving behaviour is influenced by formal traffic rules and informal social norms (Wilde, 1976). The Official Highway Code of the UK provides some general guidelines on how to overtake (Drivingsuccess Education, 2022). According to this highway code, a driver should check mirrors and the blind spot area to judge the speeds of surrounding vehicles and the space available. Next, when it is safe to do so, the driver should signal in plenty of time and then move out to the target lane. In addition, drivers are reminded that traffic may come up behind very quickly.

McKnight and Adams (1970) provide an extensive driver education task analysis on how to change lanes. Here, the lane change manoeuvre is divided into four steps. First, a driver decides to change lanes based on whether it is legally permissible and looks for rear-approaching traffic in the target lane. The decision to change lanes depends on the judgment of the available passing distance, the relative speed, the available passing time, and the accelerative capabilities of the vehicle. Second, a driver prepares to change lanes by signalling the intention by activating the directional signal and adjusting the car speed. Third, a driver first waits a few seconds after signalling before turning the wheels and entering the target lane. Fourth, the lane change manoeuvre is completed when the vehicle is positioned in the centre of the target lane, the directional signal is cancelled, and the speed is adjusted to the traffic flow in the new lane.

2. 4. Flowchart Lane Change Manoeuvre

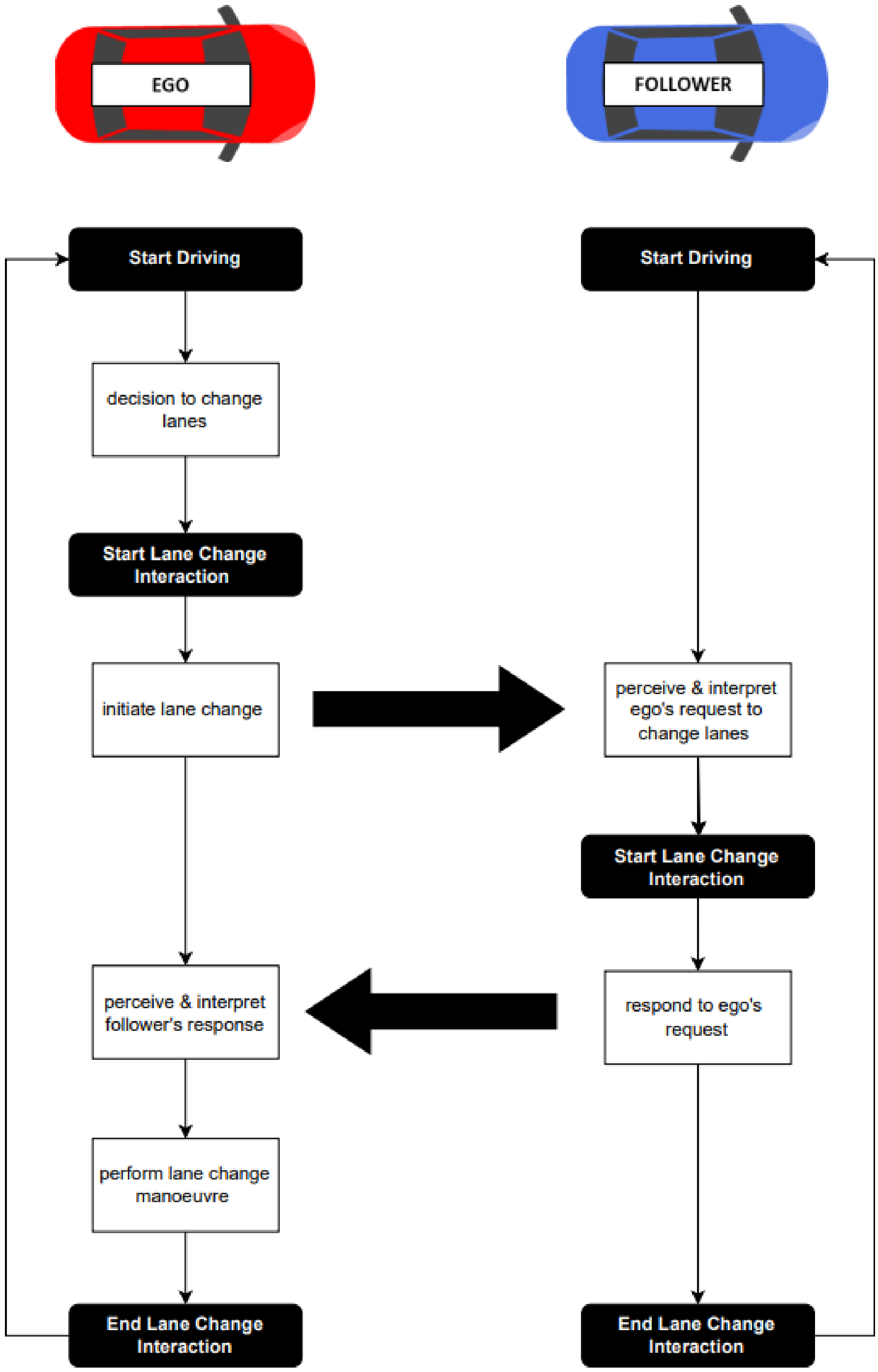
The information on the different aspects of driving, traffic interaction and communication, and the lane change manoeuvre provides a complete overview of the lane change process. This research proposes a flowchart that follows from this knowledge (see Figure A1 for the complete flowchart). Drivers might not always adhere to formal rules, such as using the turn indicator. However, the proposed flowchart assumes drivers will drive according to the formal rules. The questions posed in the flowchart are primarily subjective, such as “Can I perform the lane change manoeuvre?”. The questions are somewhat vague as they allow for differences between drivers and temporal differences within drivers. This is in line with the flowchart of Gipps (1986).

An overview of the main steps of the flowchart is shown in Figure 1. The flowchart starts with the ego vehicle scanning the surrounding vehicles (e.g., relative position, distance, and speed) and road characteristics (e.g., regulatory signs and lane markings). The process starts when the ego vehicle has the desire to change lanes. Next, the ego driver checks whether it is legally allowed to change lanes. When it is legally permissible to change lanes, the ego driver starts the lane change interaction with the follower vehicle. Similar to Hidas (2005) and Portouli et al. (2014), the interaction process is described in three phases. After the ego vehicle decides to change lanes, the driver communicates its intent. Second, the follower vehicle perceives and interprets this communication, decides to accept or reject the request, and changes behaviour accordingly. Third, the ego vehicle perceives and interprets the response of the follower vehicle and chooses to perform the lane change manoeuvre or wait.

In essence, this process of changing lanes includes the perception of the environment, its interpretation to form a decision, and an action which includes a form of communication. In other words, the flowchart follows the cycle of perception-decision-action (comparable to Markkula et al. (2018)). Saifuzzaman and Zheng (2014) also described that the process of driving “*involves perception, judgment and execution of a particular decision strategy*” (p. 390). This is also closely related to the classical approach of a sense-think-act cycle (Westhead, 1993). However, human behaviour is not constructed as a single large loop but rather as a series of small, reactive processes which work together in parallel. For example, a driver constantly perceives information, not only at a specific time point. Nevertheless, this is not incorporated in the flowchart; only the important steps are explicitly added. In the case of perception, instead of many small parallel flows, only the crucial moments in which a driver must gather perceptual information are included.

Figure 1

Overview of the decision-making process and vehicle interaction



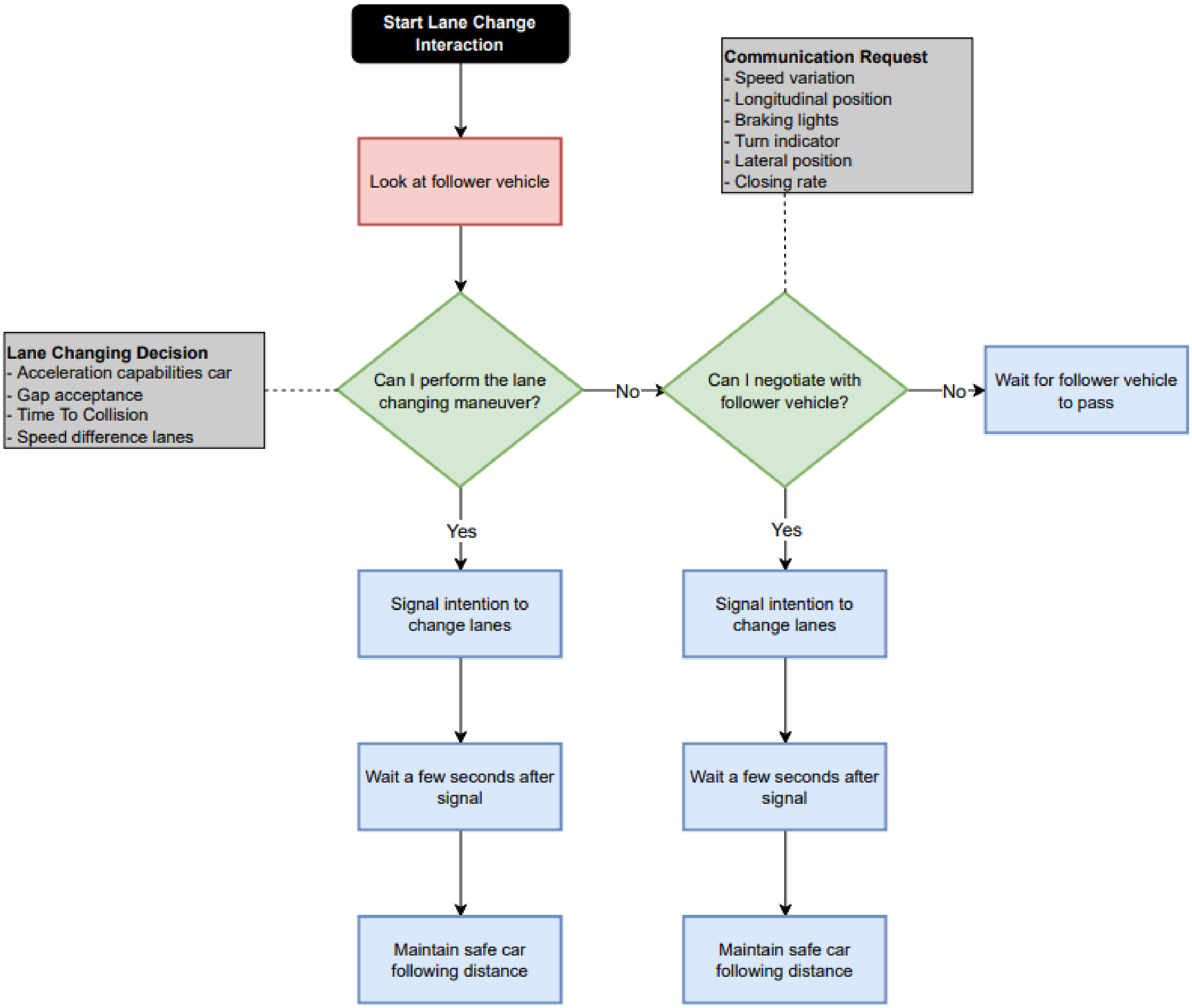
Note. The lane change interaction consists of three phases: before the arrow to the right, between the arrows, and after the arrow to the left. The arrows represent a transfer of information between the ego and follower vehicles.

2.4.1. *Phase 1: Ego Vehicle Initiates the Lane Change Manoeuvre*

The specifics of the first phase are shown in Figure 2. The ego driver needs to decide whether the lane change manoeuvre can be performed with respect to the follower vehicle. If the follower vehicle is too close to the ego vehicle, the lane change manoeuvre cannot be performed and the ego vehicle needs to wait. On the other hand, if the follower vehicle is far away, the lane change manoeuvre can be performed without the follower vehicle needing to change its behaviour. In between, the drivers must negotiate about who passes the space-sharing conflict first. The exact boundaries between those decisions are likely to differ between drivers, temporal differences within drivers, and the situation (Schwarting et al., 2019; Zhao et al., 2021).

Figure 2

Flowchart of phase 1: ego vehicle initiates the lane change



Note. This part of the flowchart is carried out by the ego vehicle. The red boxes require the driver to perceive specific information, the green boxes represent a decision the driver needs to make, the blue boxes are an action the driver performs, and the grey boxes provide extra information.

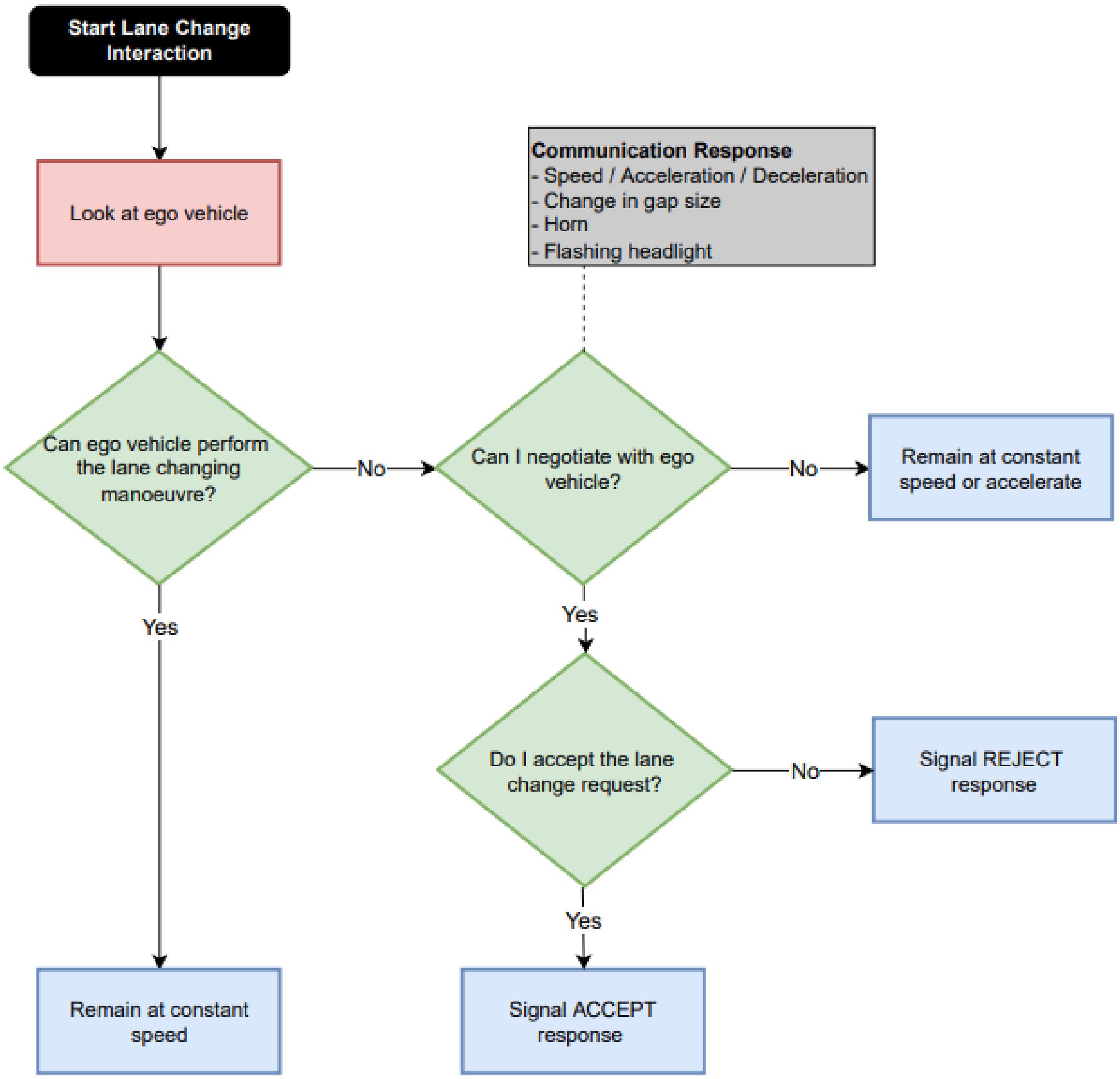
Before changing lanes, the ego vehicle signals its intent to do so. Following the formal rules (Drivingsuccess Education, 2022; McKnight & Adams, 1970), the ego vehicle should wait a few seconds after signalling and maintain a safe car-following distance before changing lanes. This signal consists of implicit and explicit vehicle-based communication cues (e.g., position, acceleration, and turn indicator). The scenario does not consider any driver-based communication cues as the scenario takes place on the highway. Driver-based communication can be of great importance to solving ambiguities between road users. However, multiple studies have shown that these cues are not used when driving on a highway at high speeds (Domeyer et al., 2019; Fabricius et al., 2022; Färber, 2016; Lee et al., 2021; Uttley et al., 2020). Lee et al. (2021) found that on roads with a 50 km/h speed limit, drivers rarely used explicit body language to communicate and relied instead on kinematic cues. In addition, Färber (2016) state that driver-based cues are limited at high speeds as there is not enough time to see inside a vehicle and evaluate the driver's eye movements.

2.4.2. *Phase 2: Follower Vehicle Perceives and Responds*

Next, the follower vehicle perceives the communication of the ego vehicle (see Figure 3). The signal of the ego vehicle is interpreted as a request to change lanes based on the common ground between the drivers (Dietrich et al., 2018). It would also be possible that there is a miscommunication between the drivers when the signal is wrongly perceived or interpreted. However, in this scenario, it is assumed that the driver correctly interprets the intention of the ego vehicle to change lanes.

Figure 3

Flowchart of phase 2: follower vehicle perceives, interprets and responds to the ego vehicle's request



Note. This part of the flowchart is carried out by the follower vehicle. The red boxes require the driver to perceive specific information, the green boxes represent a decision the driver needs to make, the blue boxes are an action the driver performs, and the grey boxes provide extra information.

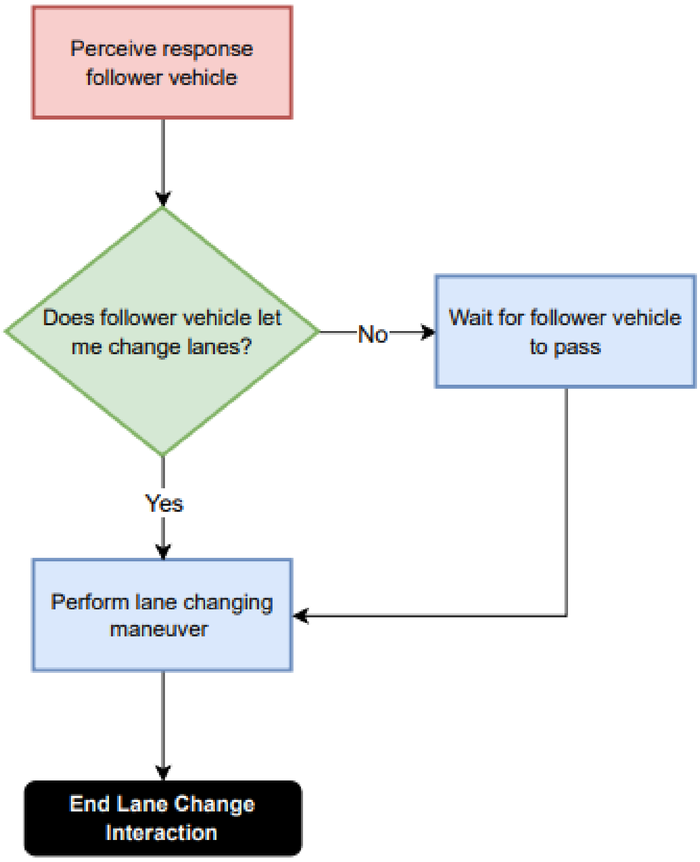
Subsequently, the driver of the follower vehicle can decide how to respond to this request. If the driver believes the distance is large enough, the driving behaviour does not have to change. Similarly, the driving behaviour does not have to change if the driver thinks the ego vehicle cannot change lanes. If there is doubt about whether a lane change manoeuvre of the ego vehicle is possible, the follower vehicle can accept or reject the request and change its behaviour accordingly. The follower vehicle uses implicit vehicle-based communication cues to signal its response. If the follower vehicle accepts the ego's request, the driver will slow down to create a larger distance gap. If not, the follower vehicle will accelerate such that the gap is too small for the ego vehicle to change lanes.

2.4.3. *Phase 3: Ego Vehicle Perceives and Responds*

Following, the ego driver perceives and interprets this response of the follower vehicle (see Figure 4). Then, based on the response, the ego vehicle decides to perform the lane change manoeuvre or wait for the follower vehicle to pass.

Figure 4

Flowchart of phase 3: ego vehicle perceives, interprets and responds to the follower vehicle's response



Note. This part of the flowchart is carried out by the ego vehicle. The red boxes require the driver to perceive specific information, the green boxes represent a decision the driver needs to make, and the blue boxes are an action the driver performs.

3. Follower Vehicle's Behaviour

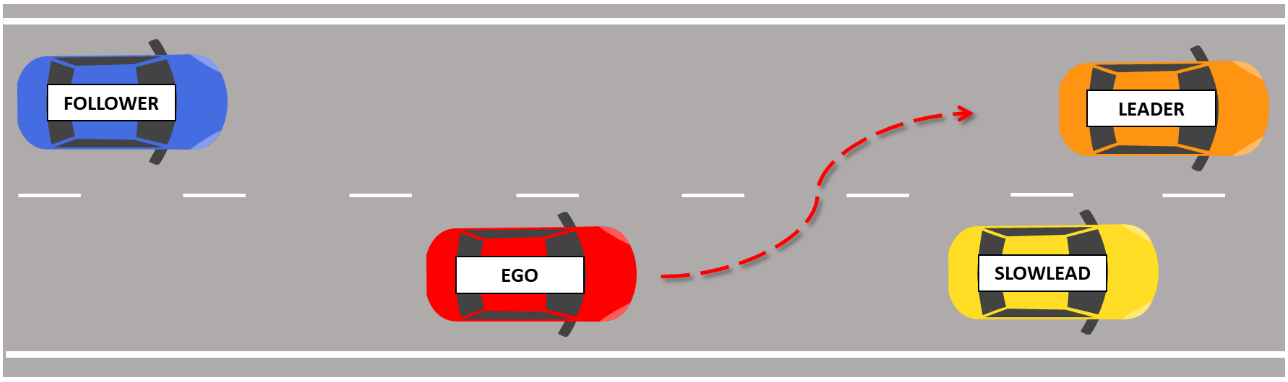
This Chapter continues by focusing on the response behaviour of the follower vehicle within the established flowchart. A specific lane change scenario is chosen to investigate as lane change interactions have been shown to be situation dependent. Furthermore, a literature review of existing knowledge and models regarding the follower vehicle's response to a lane change manoeuvre is provided. The Chapter concludes by summarising the key findings of previous literature and establishing the expectations for modelling the response behaviour of the follower vehicle.

3. 1. Lane Change Scenario

This research analyses a specific lane change scenario on highways because traffic interactions are situation-dependent and need to be understood in relation to their context (Dietrich et al., 2019; Färber, 2016; Wilde, 1976). Figure 5 illustrates this specific lane change scenario, where an ego vehicle moves from its current lane to the target lane on the left (with reference to the direction of motion) because the vehicle currently in front of it drives slower than desired (i.e., the slowlead vehicle). The ego would merge left into the gap between two vehicles travelling in the target lane: these will eventually become the ego vehicle's leader and follower vehicles at the end of the manoeuvre.

Figure 5

Illustration of the lane change scenario



A lane change manoeuvre on the highway limits the communication cues the vehicles can use to signal one's intent. That is, only vehicle-based communication cues are used (e.g., position, acceleration, and turn indicator). Even though driver-based communication can be of great importance to solving ambiguities between road users, multiple studies have shown that these cues are not used when driving on a highway at high speeds (Domeyer et al., 2019; Fabricius et al., 2022; Uttley et al., 2020). Lee et al. (2021) found that drivers rarely used explicit body language to communicate and relied instead on kinematic cues on roads with a 50 km/h speed limit. In addition, Färber (2016) state that driver-based cues are limited at high speeds as there is not enough time to see inside a vehicle and evaluate the driver's eye movements.

Lane changes to overtake a slower driving vehicle are also referred to as discretionary lane changes (Ahmed, 1999). Discretionary lane changes are made when drivers are not satisfied with the driving conditions in the current lane and desire to change lanes to gain some speed advantage. In contrast, mandatory lane changes are performed when drivers are required to leave the current lane when for example, there is an exit lane, merge of lanes or splitting of the road in different directions. The urgency (i.e., how close to the end of a lane) of mandatory lane changes influences the behaviour of drivers. That is, a higher urgency reflects the diver's willingness to brake harder and accept smaller gaps when the manoeuvre is necessary (Gipps, 1986; Schakel et al., 2012). Therefore, this research specifically focuses on discretionary lane changes.

3. 2. Follower Vehicles' Response

Previous literature discussing the behaviour of the follower vehicle in a lane change manoeuvre can be grouped into three categories. First, studies have focused on classifying the lane change scenario to understand its influence on the behaviour of the follower vehicle. Second, other studies have analysed the follower vehicle's behaviour irrespective of the lane change scenario classification. Third, some studies have specifically examined the drivers' willingness to cooperate and methods to encourage cooperation. These three categories will be discussed in further detail in the following sections.

3. 2. 1. *Lane Change Classifications*

Hidas (2005) analysed lane change manoeuvres and concluded that the manoeuvres could be classified into free, forced, and cooperative lane changes. Hidas' (2005) classification of the lane change manoeuvre is based on the relative gaps between the leader and follower vehicle. A free lane change is when there is no noticeable change in the relative gap between the leader and follower. This indicates there is no interference or interaction between the ego and follower vehicles. A forced lane change is indicated by a distinct change in gap size before and after the ego vehicle merges into the target lane. The gap size gets larger after the ego vehicle enters the target lane, indicating that the follower vehicle was forced to slow down. A cooperative lane change is characterised by an increasing gap before the ego vehicle enters the target lane and a decreasing gap afterwards. Here, the follower vehicle allows the ego vehicle to change lanes. In other words, a cooperate lane change manoeuvre is referred to as the specific case where the ego vehicle interacts with the follower vehicle and consequently, the follower vehicle facilitates a lane change for the ego vehicle.

In cooperative lane change manoeuvres, the interaction process between the ego and follower vehicle can be described in three phases (Hidas, 2005; Portouli et al., 2014). First, the ego vehicle communicates its intent to change lanes. Second, the follower vehicle perceives and interprets the intention of the ego vehicle. Subsequently, the follower vehicle decides to either accept the request by decelerating or reject the request by accelerating or keeping a constant velocity. Third, the ego vehicle perceives and interprets the response of the follower vehicle and chooses to perform the lane change manoeuvre or wait for the follower vehicle to pass. This lane change may take several seconds, during which the vehicles must communicate and coordinate their actions.

Hidas (2005) developed a lane change model based on his lane change classifications. The model determines the vehicle's trajectory by incorporating explicit modelling of vehicle interactions. The ego vehicle can change lanes if the distance gaps in front and behind the vehicle on the target lane are not less than some minimum acceptable distance at the end of the manoeuvre. In a free lane change, the distance gaps are at least equal to the desired distance gaps. In cooperative lane change manoeuvres, the lane change is feasible if the deceleration required for the follower vehicle to create a safe distance gap is acceptable. The maximum deceleration the follower vehicle is willing to use depends on an aggressivity parameter, where a more aggressive driver will select a lower speed decrease. In forced lane change manoeuvres, the ego vehicle makes assumptions about the maximum deceleration which the follower vehicle will use. Then, if the manoeuvre is feasible with the assumed values, the ego vehicle will force the follower vehicle to reduce speed and provide a safe distance gap.

Sun and Elefteriadou (2014) extended the model of Hidas by incorporating the probability of occurrence of either a free, forced or cooperative lane change manoeuvre. The decision framework of the ego vehicle is based on the initial gap on the target lane and the personality of the ego vehicle's driver. Sun and Elefteriadou (2014) also divided cooperative lane changes into cooperative and competitive behaviour based on the follower's decision to accept or reject the request, respectively. This decision framework of the follower vehicle is based on (1) the existing distance gap between the vehicles, (2) the distance travelled with a specific deceleration (based on the driver's personality) during the lane change of the ego vehicle, (3) the distance travelled by the ego vehicle during the lane change, and (4) the minimum safe distance gap. If the follower vehicle accepted the lane change request, the vehicle would decelerate. The resulting change in velocity of the follower vehicle is then calculated based on a car-following model. When rejecting, the follower vehicle would maintain speed or accelerate depending on the driver's aggressiveness. If the follower vehicle maintained its speed, the ego vehicle could choose to make a forced lane change.

The proposed classification based on the change in gap size by Hidas (2005) was reviewed by Chauhan et al. (2022). Chauhan et al. (2022) investigated the response of the follower vehicle and found that Hidas' classification of free, cooperative, and forced lane changes does not closely replicate real-world driving. The study found misclassifications when also considering the velocity change of the follower vehicle. For example, the misclassification of a cooperative lane change manoeuvre was when the gap increased before the ego vehicle entered the target lane and then decreased, which was not caused by the follower vehicle decreasing its speed initially and increasing its speed afterwards. Therefore, Chauhan et al. (2022) proposed that the response of the follower vehicle should be classified into free, fully-constraint or partially-constraint lane changes based on the impact on the vehicle's velocity before and after the ego vehicle merges into the target lane. The results of Chauhan et al. (2022) imply that it is best to characterise the response behaviour of the follower vehicle based on the follower vehicle's change in acceleration rather than the distance gap between the follower and ego vehicles.

3.2.2. *Impact on Follower Vehicle*

Irrespective of the lane change classification and whether the follower vehicle's behaviour is cooperative, a few studies have investigated how the lane change manoeuvre of the ego vehicle impacts the follower vehicle's velocity using naturalistic driving datasets.

Yang et al. (2019) proposed the so-called "speed change rate" to characterise the degree of the follower's response. Here, the velocity of the follower vehicle at the moment when the ego vehicle initiates the lane change and stabilises on the target lane are compared. In most cases, the lane changes have a limited influence on the follower vehicle such that there would be a constant velocity or only a small deceleration. However, this speed change rate differs depending on the road type and motivation (i.e., mandatory versus discretionary lane change). Mandatory lane changes trigger larger responses from the follower vehicle than discretionary lane changes. Occasionally, follower vehicles would accelerate in an attempt to close the gap in order to prevent the lane change but fail. Wang et al. (2019) found that in lane change scenarios, the follower vehicle's deceleration mostly ranged from -2 m/s^2 to 0 m/s^2. The maximum deceleration observed was as high as -6 m/s^2, which likely has a high discomfort for the follower vehicle.

Liu et al. (2022) also analysed the follower vehicle's behaviour in a lane change scenario. In the study, hierarchical multi-level linear models are developed to characterise the follower vehicle's maximum deceleration, time to release the acceleration pedal and time of braking. The linear regression models include the follower vehicle's velocity, velocity difference, and distance gap between the follower and ego vehicles. Additionally, the linear regression models are tested to be different depending on the direction of the lane change, the traffic density, road type and the use of the turn indicator. Here, one of the key findings is that the turn indicator usage significantly affects the timing of the follower vehicle's response but not the minimum acceleration. In addition, Liu et al. (2022) highlighted the importance of incorporating a non-linear relationship between the follower's response and the velocity difference between the ego and follower vehicles. Namely, if the ego vehicle merges into the follower's lane at a much lower speed, the increase in velocity difference causes an increase in the breaking intensity of the follower vehicle; if the vehicles drive about the same velocity or the ego vehicle drives faster, the velocity difference will have little effect, or there will be no response. However, it is noteworthy that the model of Liu et al. (2022) only considers the minimum acceleration of the ego vehicle after reaching the lane marking, ignoring the possibility of cooperation from the follower vehicle before.

Yang et al. (2019) and Liu et al. (2022) both use a maximum longitudinal distance between the follower vehicle and ego vehicle to determine whether the vehicles influence each other, respectively 75 and 55 meters. Yang et al. (2019) found that 44.0% brake before and 14.1% after the ego vehicle crosses the line, and in the resulting 41.9%, the follower vehicle did not break at all. Liu et al. (2022) found that on the freeway, follower vehicles in 24.8% would not release the acceleration pedal, 43.4% would release the acceleration pedal but not use the brake pedal, and 31.8% would use the brake pedal after the ego vehicles reached the lane marking. The studies indicate that in many cases, there is only a small velocity change and little impact on the follower vehicle.

3. 2. 1. *Driver's Willingness to Cooperate*

Several studies have specifically investigated the predictors that influence the willingness of the follower vehicle to accept the lane change request and drive cooperatively. Individual modulating factors such as personality traits (e.g., selfish or altruistic), driving experience or motivational states (e.g., short-term time pressure) have been shown to cause different reactions from drivers in the same situation (Wilde, 1976). Sun and Elefteriadou (2011) found that there are four driver types, ranging from drivers that would not change lanes in most situations to drivers that would always try to get a better position or speed advantage without thinking about other drivers. Several lane change models try to account for this influence. Some models include the desired speed and headway drivers want to return to in the long term (e.g., Schakel et al. (2012)). However, Sultan et al. (2002) concluded that these desired predictors do not result in a better fit of the model compared to only using predictors about the driving conditions at the time of the lane change manoeuvre. Furthermore, among others, Hidas (2005) incorporated the driver's aggressiveness. However, this is tested in a simulation where a different aggressivity parameter is assigned to each vehicle. In real-world driving, a driver's personality is often unknown at a specific time. Additionally, in game-theory-based lane change models, the use of a so-called "Social Value Orientation" (SVO) matric is used to categorise the driver's behaviour as altruistic, pro-social, egoistic or competitive (Schwarting et al., 2019). This value is based on the comparison between the vehicle's trajectory and a predicted future motion with a specific SVO value. Nevertheless, lane change scenarios are often a single interaction between vehicles where drivers cannot base the other driver's personality on past interactions or long trajectory information. Overall, predictors related to the driver's personality have shown to be challenging to include in lane change model.

Zimmermann et al. (2018) showed that time pressure is a reason for the uncooperative behaviour of the follower vehicle and concluded that drivers behave rationally and egoistically for their individual advances in traffic. To increase the willingness of drivers to cooperate in lane change scenarios, studies have proposed interaction concepts using game theory or vehicle-to-vehicle (V2V) communication to motivate the driver (Ali et al., 2020; Zheng et al., 2022). For example, Ali et al. (2020) showed that drivers more often cooperated when the driver received messages through V2V of the lane change request compared to only the indicator light. These motivation concepts demonstrate that the driver is a key element in the willingness to cooperate.

Furthermore, it has been shown that the driving situation also influences the follower vehicle's willingness to accept the lane change request and drive cooperatively. Stoll et al. (2019) examined human driver behaviour and communication cues in potentially cooperative lane change situations to understand the behaviour and expectations of drivers. The willingness of the follower vehicle to cooperate was dependent on several conditions. First, in cases where the ego vehicle used the indicator lights, the follower vehicle was more inclined to cooperate compared to using no indicator lights. Similarly, the earlier the ego vehicle would indicate its intention using the indicator light, the more cooperative it was perceived by the follower vehicle (Kauffmann et al., 2018). Second, when the time-to-collision (TTC) (i.e., the time it would take for vehicles to collide if the following vehicle's behaviour does not change) between the follower and ego vehicle was larger, the follower vehicle would more often decelerate compared to situations with a smaller TTC. It is reasoned that this is because the cost of cooperating for the follower is lower with a higher TTC. Third, the follower vehicle preferred a lane change to the left over decelerating when there was a third lane available. Fourth, less cooperative behaviour was shown when the TTC between the ego and slowlead vehicle was large. In other words, the follower vehicle would cooperate in situations where the criticality to cooperate was higher. Overall, Stoll et al. (2019) have shown that the surrounding traffic situation and the use of the ego vehicle's explicit and implicit communication cues are relevant predictors in the follower vehicle's decision to cooperate.

3.3. Conclusion

The literature reviews indicate that only limited research has tried to model the follower vehicle's decelerating response. Further analysis of naturalistic vehicle trajectory data is necessary to understand when, for how long and with which deceleration value a follower vehicle responds. Previous studies suggest that multiple factors influence the response of the follower vehicle in a lane change scenario. But taken together, the response of the follower vehicle is essentially a reaction to the lane change manoeuvre of the ego vehicle and traffic conditions. Therefore, the response behaviour of the follower vehicle in a lane change scenario can be described using stimulus-response models.

The use of a stimulus-response model is also a common approach in car-following models and can be reasoned to be also of relevance for the follower vehicle's response to a lane change. That is, car-following models describe how a follower vehicle needs to adjust its behaviour depending on that of its leading vehicle. This is related to a follower vehicle changing its behaviour to another vehicle changing lanes in front of the follower vehicle. This link to car-following models is also seen in lane change models such as Sun & Elefteriadou (2014), which calculate the change in velocity based on car-following behaviour after classifying the follower vehicle cooperates in that particular situation. Classical car-following models are the Gazis-Herman-Rothery (GHR) model (Gazis et al., 1961), Gipps' model (Gipps, 1981), and Intelligent Driver Model (IDM) (Treiber et al., 2000). Although the car-following logic is somewhat different between the models and each model includes different predictor variables (Zhang et al., 2021), two overarching conclusions can be important when modelling the follower vehicle's response behaviour. The car-following models include the velocity difference and distance gap between the follower and its leading vehicle to describe the change in velocity of the follower vehicle. Additionally, Gipps' model and the IDM include the transition between situations where the follower vehicle is car-following and driving freely.

Nevertheless, these models are developed explicitly for car-following scenarios and may not be suitable to apply to lane change scenarios directly. The merge of the ego vehicle onto the lane causes the follower vehicle in car-following models to break heavily when the gap size is small. However, vehicles are often closer to each other in lane change scenarios than based on car-following relationships. There will be a so-called "relaxation period", where the ego and follower vehicles are willing to accept smaller gap sizes for a while, and the follower vehicle will only apply small decelerations (Ali et al., 2020; Hidas, 2005; Schakel et al., 2012). Fu et al. (2019) developed a human-like car-following model specifically for cut-in situations and found that the maximum deceleration was smaller compared to the car-following models such as IDM. The authors comment that the IDM model would result in a deceleration higher than 3 m/s^2, which will seriously impair the comfort of the passenger.

Multiple linear regression models are a type stimulus-response model used to describe the relationship between the variable of interest and two or more predictors. One of the strengths of a linear regression model is to identify the most important predictors based on a set of descriptive variables of the lane change scenario that influence the follower vehicle's response. Several studies have used linear regression models to describe the behaviour of the follower and ego vehicles in a lane change scenario. For instance, Liu et al. (2022) used a multi-level linear regression model to predict the minimum acceleration and timing of the follower vehicle from the moment the ego vehicle reached the lane marking. Moreover, Venthuruthiyil and Chunchu (2021) used a log-linear function to model the duration of a lane change. In addition, Yang et al. (2019) used a multi-level linear regression model to determine the gap size between the ego and follower vehicles. Taken together, a linear regression model seems a suitable method to predict the decelerating response of a follower vehicle to the lane change manoeuvre of the ego vehicle.

3.3.1. *Hypotheses*

The literature review provides some suggestions on how the lane change scenario influences the response behaviour of the follower vehicle. First, the timing of the follower vehicle is expected to be closely related to whether the vehicle cooperates or not. In a cooperative lane change, a follower vehicle will respond before the ego vehicle starts merging into the lane. Previous studies indicate that a follower vehicle is more inclined to cooperate when the costs to do so are low (i.e., the TTC between the follower and ego vehicles is high) and the urgency of the ego vehicle to change lanes is high (i.e., the TTC between the ego and slowlead vehicles is low). Consequently, it is expected that the timing of the follower vehicle is related to these variables. Second, car-following models predicting the deceleration of a follower vehicle responding to the vehicle in front are often a function of the velocity difference and distance gap, among other parameters. Therefore, it is expected that also the minimum acceleration of the follower vehicle's response is most dependent on the velocity difference and distance gap between the follower and ego vehicles. That is, a higher velocity difference and a smaller distance gap will result in a lower minimum acceleration. Third, previous literature does not explicitly discuss the duration of a follower vehicle's response. Nevertheless, it can be reasoned that a higher velocity difference between the follower and ego vehicles requires a larger change in the follower vehicle's velocity, and as such, a longer response is expected. In addition, when the distance gap between the follower and ego vehicles is larger, the follower vehicle has more time to decelerate before reaching a critical distance gap. Therefore, it is expected that at higher distance gaps, the duration of the response is longer.

Overall, it is also likely that the timing, duration, and minimum acceleration are related to each other. For example, it can be assumed that drivers do not prefer harsh decelerations as they are uncomfortable, and such prefer small decelerations for a longer period of time to reach the same change in velocity, which also implies an earlier response. That drivers do not abruptly decrease speed is also seen in models incorporating a maximum deceleration threshold for vehicles (e.g., Schakel et al. (2012)). This is also in line with cooperative lane changes, as a follower vehicle is more inclined to cooperate (i.e., respond early) when the minimum acceleration is small. Therefore, it is expected that the response variables are correlated, and the models have similar predictor variables.

4. Method

This Chapter outlines the methodology used to characterise the timing, duration, and minimum acceleration of the follower vehicle's deceleration response in a lane change scenario. The dataset and the selection procedure to extract the lane changes are discussed. In addition, the (relative) descriptive variables used to characterise the response are provided. Following, the method to determine the start of the lane change is described. The longitudinal behaviour of the follower vehicle is analysed to identify the lane changes in which the follower vehicle started to decelerate. The Chapter concludes by describing the statistical analyses used to develop the linear regression models of the follower vehicle's decelerating response.

4. 1. Dataset

Real-world traffic data is essential to analyse, describe and model human-like responses to a lane change manoeuvre. The highD dataset contains naturalistic vehicle trajectory information and is the best available dataset for this research (*HighD*, n.d.). In the dataset, traffic was recorded at German highways using unmanned aerial vehicles that are hardly visible to passing vehicles for the highD dataset. This is an unobtrusive data-gathering method which results in uninfluenced human behaviour. Siebinga et al. (2022) also stressed the importance of selecting a naturalistic dataset to develop and validate driver models. The highD dataset is a diverse and large-scale dataset including 110500 vehicles with 440 driven hours and 13901 lane changes at six recording locations and is of high quality, with a typical precision error smaller than 10 cm (Krajewski et al., 2018). Other available data sources at TNO, such as naturalistic driving studies or simulated driving tests, are less satisfactory for this research. Aside from those data gathering methods being obtrusive, these methods have limitations on the visibility of the behaviour of other road users (e.g., blind spots because of sensor placement).

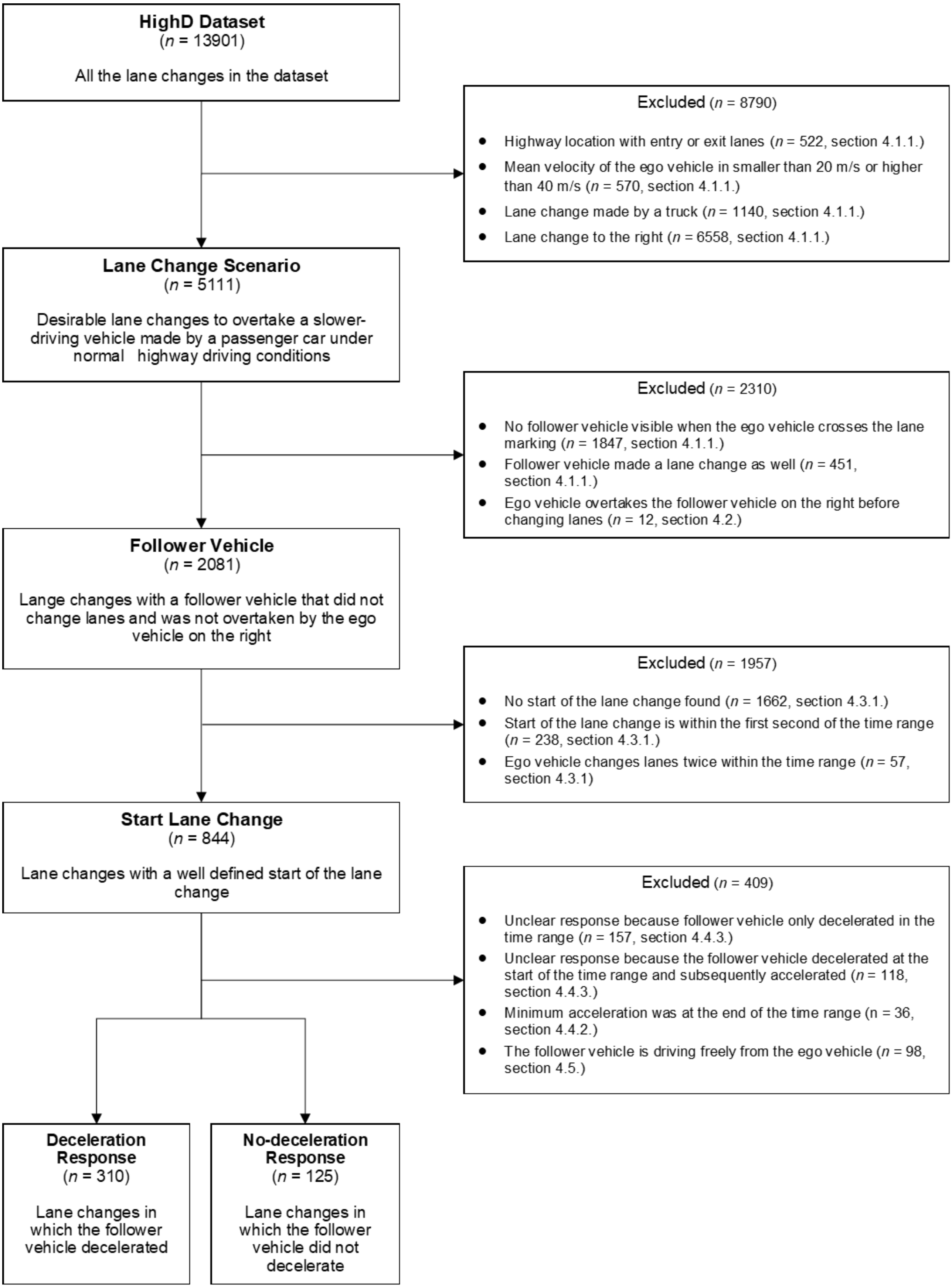
The trajectories from the vehicles in the highD dataset were extracted using computer vision algorithms and detected and localised in every frame using neural networks (Krajewski et al., 2018). Subsequently, the vehicles were tracked over time, and their movement was smoothed using Bayesian smoothing. This research project used this resulting smoothed trajectory information. In addition, the dataset provides pre-extracted information, such as the surrounding vehicles and which vehicles performed a lane change.

4. 1. 1. *Lane Change Extraction*

The lane change scenario illustrated in Figure 5 was selected from the highD dataset using specific selection criteria. Figure 6 provides an overview of these selection criteria and a reference to the corresponding section for their in-depth explanation.

Figure 6

Overview of the selection process of the lane change cases



In this research, only desirable lane changes to overtake a slower-driving vehicle made by a passenger car under normal highway conditions were considered. The scenario was also filtered based on the availability of information on the follower vehicle and whether the follower vehicle did not make a lane change. The reasoning behind these criteria was as follows.

The dataset recordings from locations with highway entry lanes were excluded (*n* = 522). Merging on the highway is a mandatory lane change that needs to be performed before the end of the lane, which can result in different driving behaviour (Gipps, 1986; Schakel et al., 2012). The filtered dataset consisted of over 107600 vehicles recorded with 429 driven hours across two- and three-lane highway locations. There was a speed limit the vehicles needed to adhere to of 120 km/h or 130 km/h, or there was no speed limit. However, the dataset also includes recordings of traffic jam situations. Therefore, the mean velocity of the vehicle that changed lanes should be at least higher than 20 m/s. In addition, extremely high velocities above 40 m/s are disregarded (*n* = 570).

Lane changes made by trucks were excluded as this research only focuses on passenger cars changing lanes (*n* = 1140). Trucks have different motion characteristics due to their size and weight, such as lower maximum speed and acceleration (Schieben et al., 2019). Previous studies have taken into account these physical differences related to the vehicle type in lane change models (e.g., Hidas (2005) and Schakel et al. (2012)). Because of a truck's speed and acceleration limitations, the impact on the follower vehicle is likely higher when a truck changes lanes. To eliminate this bias, this research only analysed lane changes made by passenger cars.

This research focuses on investigating the response of the follower vehicle when the ego vehicle made a desirable lane change to overtake a slower-driving lead vehicle. Accordingly, lane changes from the left to the right lane were excluded (*n* = 6558). Left and right lane change manoeuvres have also been shown to have different durations and driving behaviour, as left lane changes are more likely to be influenced by the follower vehicle (Li et al., 2015; Sultan et al., 2002). As Venthuruthiyil and Chunchu (2021) concluded, the duration of a lane change is mainly controlled by the follower vehicle's kinematics.

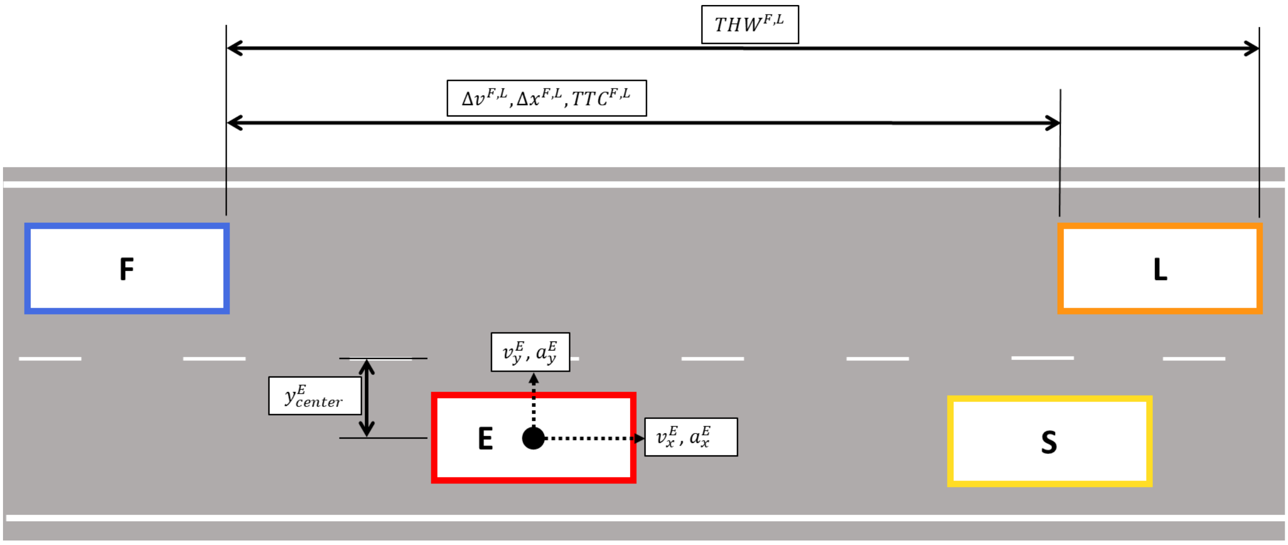
The lane changes were further filtered on the presence of a follower vehicle as this research analyses the behaviour of the follower vehicle. Lane changes were excluded in which the trajectory information of a follower vehicle was not available at the moment the centre of the ego vehicle was at the lane marking (i.e., the white lines that indicate the centre between two lanes) (*n* = 1847). Additionally, the follower vehicles that made a lane change as well in the recorded time frame were disregarded, as the interaction in those cases was likely different (*n* = 451). For example, the behaviour of the follower vehicle was not influenced by the ego vehicle's lane change when the follower vehicle changed lanes to the right before the ego vehicle changed lanes. Furthermore, Stoll et al. (2019) showed that follower vehicles prefer a lane change to the left when possible over decelerating when cooperating. In these cases, the response on the follower vehicle is different compared to vehicles that cannot change lanes and need to decelerate. Simultaneously, excluding follower vehicles that changed lanes allows for the analysis of the follower vehicle's behaviour on both two- and three-lane highways.

4. 2. Descriptive Variables

The behaviour of the vehicles in the lane change scenario was analysed in the time range in which both the trajectory information of the follower and ego vehicle were available. That is, the start time is the first moment in which both vehicles are tracked until the end time, which is the last moment where both vehicles are tracked. Figure 7 shows the basic descriptors of the driving scenario analysed during this time range. The highD dataset provides pre-extracted information on the top left position of the vehicle and the velocity and acceleration in both the lateral and longitudinal directions (i.e., v_y^E, a_y^E, v_x^E and a_x^E). The width of the vehicle is as well provided and used to define the center position of the ego vehicle with respect to the lane marking (y_{center}^E).

Figure 7

Illustration of the driving scenario and its basic nomenclature



Note. The ego vehicle is indicated by "E", the slowlead vehicle by "S", the follower vehicle by "F", and the leader vehicle by "L".

The relation between the ego vehicle and other vehicles in the scenario is described through the velocity difference, distance gap, time headway (THW) and Time-To-Collision (TTC), which are calculated as follows:

$$\Delta v_x^{F,E}(t) = v_x^F(t) - v_x^E(t) \tag{1}$$

$$\Delta x^{F,E}(t) = x_{back}^E(t) - x_{front}^F(t) \tag{2}$$

$$THW^{F,E}(t) = \frac{x^{E}_{front}(t) - x^{F}_{front}(t)}{v^{F}_{x}(t)} \tag{3}$$

$$TTC^{F,E}(t) = \frac{\Delta x^{F,E}(t)}{\Delta v^{F,E}_{x}(t)} \tag{4}$$

where $\Delta v^{F,E}_{x}(t) > 0$ and $\Delta x^{F,E}(t) > 0$

The TTC variable describes the time it would take for the vehicles to collide if their driving behaviour remained unchanged. However, if the vehicles are not in the same lane, a collision will not occur. Despite this, the relational variables are calculated as if the vehicles were in the same lane (i.e., as if ego vehicle maintained the x^{E}_{back} value but the y^{E}_{top} position was shifted to the left lane). The TTC variable can cause extreme outliers when the velocity difference between the vehicles is close to zero. In addition, the requirements of the follower vehicle to drive faster than the ego vehicle results in fewer observations. Therefore, the ratio of velocity difference and distance gap (also referred to as velocity-distance ratio) is calculated without this requirement as follows:

$$ratio^{F,E}_{\Delta v,\Delta x}(t) = \frac{\Delta v^{F,E}_{x}(t)}{\Delta x^{F,E}(t)} \tag{5}$$

where $\Delta x^{F,E}(t) > 0$

The relational variables, as shown in Equations 1 to 5, are calculated between the follower and ego vehicle. Similarly, the relational variables are calculated between the follower and leader vehicles (i.e., $\Delta v^{F,L}_{x}(t)$, $\Delta x^{F,L}(t)$, $THW^{F,L}(t)$, $TTC^{F,L}(t)$, and $ratio^{F,L}_{\Delta v,\Delta x}(t)$), the ego and slowlead vehicles (i.e., $\Delta v^{E,S}_{x}(t)$, $\Delta x^{E,S}(t)$, $THW^{E,S}(t)$, $TTC^{E,S}(t)$, and $ratio^{E,S}_{\Delta v,\Delta x}(t)$), and the ego and leader vehicles (i.e., $\Delta v^{E,L}_{x}(t)$, $\Delta x^{E,L}(t)$, $THW^{E,L}(t)$, $TTC^{E,L}(t)$, and $ratio^{E,L}_{\Delta v,\Delta x}(t)$). In the time range, the leader vehicle can pass the ego vehicle before the lane change. Therefore, the relative variables between the ego and leader vehicles were only considered after the start of the lane change. Furthermore, the distance gap between the ego and follower vehicles should never be negative, as the follower vehicle will always be behind the ego vehicle. However, in some cases, the ego vehicle has overtaken the follower vehicle on the right before making a left lane change manoeuvre. This is a specific manoeuvre that is excluded from the analysis (*n* = 12).

4. 3. Start Lane Change Ego Vehicle

The real beginning of a lane change, being the decision to make the lane change, is difficult to measure and impossible with unobtrusive data-gathering methods (Thiemann et al., 2008). Different methods exist to determine the beginning of a lane change using the ego vehicle's lateral position, steering angle, or lateral speed. The choice of method can significantly impact the lane change analysis (Chauhan et al., 2022). In this research, the start of the lane change ($t_{startLC}$) was the moment where the lateral speed of the vehicle was zero before reaching a maximum when crossing the lane marking. (similar to Venthuruthiyil & Chunchu (2021) and Weber et al. (2021)). Figure 8 illustrates the typical behaviour of the ego vehicle changing lanes and the corresponding starting time definition. The start of the lane change was automatically defined using the timing of the lane crossing and the lateral velocity as follows:

$$t_{linecrossing} \text{ is the } t\,\epsilon[0,\ t_{end}] \text{ such that } y^E_{center}(t) = 0 \tag{6}$$

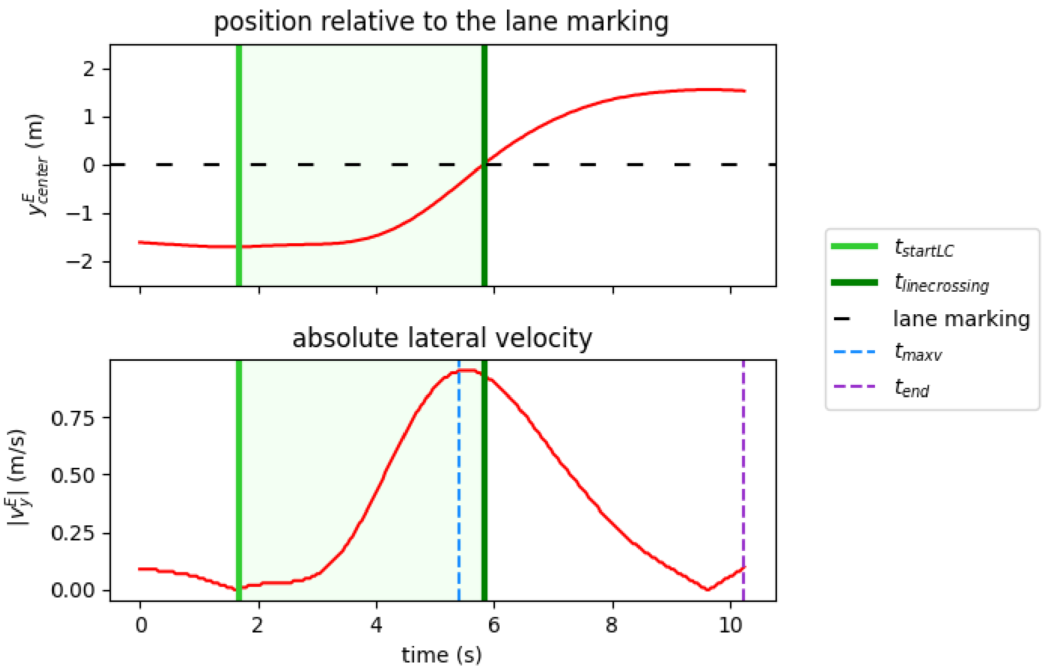
$$t_{\max v} = \arg\max\left(\left|\, v^E_y \,\right|(t)\right), \text{ where } t\,\epsilon\left[0,\ t_{linecrossing}\right] \tag{7}$$

$$t_{startLC} = \max(t) \text{ such that } \left|\, v^E_y \,\right|(t) = 0, \text{ where } t\,\epsilon[0,\ t_{\max v}] \tag{8}$$

$$\Delta t_{linecrossing} = t_{linecrossing} - t_{startLC} \tag{9}$$

Figure 8

Relationship among timing definitions related to the lateral behaviour of the ego



Note. $\Delta t_{linecrossing}$ is indicated by the light-green highlighted area between $t_{startLC}$ and $t_{linecrossing}$.

4.3.1. *Additional Filtering*

The start of the lane change was not found for all vehicles because the start was outside the video recording. These cases were excluded from further analysis (*n* = 1662). In addition, lane changes were not considered when the start of the lane change was within the first second (*n* = 238). In those cases, there was not enough vehicle trajectory information of the follower vehicle before the start of the lane change. Moreover, the start of the lane change was not correctly defined in some instances because the vehicle would change lanes twice shortly after each other (*n* = 57). For example, a vehicle would change lanes to the left lane before completing a lane change to the right lane or perform two left lane changes in one continuous lateral movement. The ego vehicles that changed lanes twice in the time frame are specific cases that are disregarded from further analysis.

4. 4. Response Categories Follower Vehicle

The longitudinal velocity and longitudinal acceleration of the follower vehicle were investigated to characterise the follower vehicle's response to the ego vehicle changing lanes. The use of velocity and acceleration has shown to be a better descriptor of the follower vehicle behaviour than the change in gap size (Chauhan et al., 2022). The lateral behaviour of the follower vehicle (e.g., changing lanes to allow the ego vehicle to change lanes) is in this research not considered. The longitudinal behaviour of the follower vehicle is categorised as a no-deceleration, deceleration, or unclear response.

4. 4. 1. *No-deceleration Response*

The first category included cases where the follower vehicle did not decelerate in the longitudinal direction. In other words, response category 1 represents the lane change cases where the minimum acceleration was either zero or higher than zero. The minimum acceleration value (${a^F_x}_{min}$) and the timing of this minimum acceleration ($t_{\min a}$) of the follower vehicle were calculated as follows:

$$ {a^F_x}_{min} = \min\left(a^F_x(t)\right), \text{ where } t \in [0, t_{end}] \tag{10} $$

$$ t_{\min a} = \min\left(\arg\min\left(a^F_x(t)\right)\right), \text{ where } t \in [0, t_{end}] \tag{11} $$

4. 4. 2. *Deceleration Response*

In the second category, the follower vehicle has a clear decelerating response. That is, response category 2 is characterised by first a constant or increasing velocity, followed by a decrease in velocity due to decelerating. A visualisation of such a response of the follower vehicle is shown in Figure 9. The timing of the response ($t_{response}$) of the follower vehicle to the ego vehicle was considered to be the moment where the vehicle started to decelerate, and it was calculated as follows:

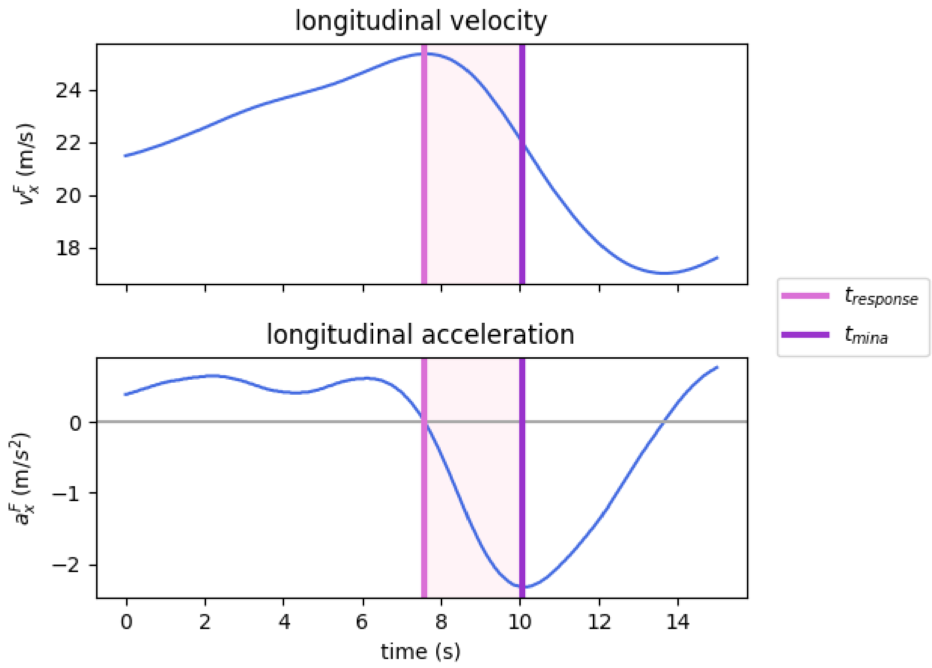
$$ t_{response} = \max(t) \text{ such that } a^F_y(t) = 0 \text{ and } \frac{d}{dt}\left(a^F_y(t)\right) < 0, \text{ where } t \in [0, t_{\min a}] \tag{12} $$

$$ \Delta t_{response} = t_{\min a} - t_{response} \tag{13} $$

In the specific cases when the follower vehicle fluctuated between positive and negative acceleration, the response time was the first time the acceleration value crossed zero before the minimum acceleration. The cases where the response time is equal to the end time are excluded from further analysis as it is unknown what the actual maximum deceleration was and when it was reached (*n* = 36). In the analysis of the follower's response, the response time is always relative to the start of the lane change, where a negative value indicates a response before the start.

Figure 9

Relationship among timing definitions related to the longitudinal behaviour of the follower vehicle



Note. $\Delta t_{response}$ is indicated by the pink highlighted area between the $t_{response}$ and $t_{\min a}$.

Response category 2 is characterised by a decelerating response of the follower vehicle. Therefore, negligible fluctuations in the follower vehicle's velocity should not be considered in this category. Hence, the change in velocity from the start of the lane change to the minimum acceleration should be at least 0.5 km/h to be considered a response. Assuming the typical response behaviour as illustrated in Figure 9, the total velocity change should be 1 km/h or more. It can be argued that in the cases with a lower velocity change of 0.5 km/h, the follower vehicle did not respond to the ego vehicle and was categorised as a response category 1.

4.4.3. *Unclear Response*

There are also lane change cases in the dataset in which there is not a clear no-deceleration response or deceleration response, respectively response categories 1 and 2. In some cases, the follower vehicle only decelerated during the investigated time range (i.e., the maximum acceleration is below zero) (*n* = 157). The maximum acceleration value ($a_{x\,max}^F$) was calculated as follows:

$$a_{x\,max}^F = \max\left(a_x^F(t)\right), \text{ where } t \in [0, t_{end}] \qquad (14)$$

The response timing could also not be defined in cases where the follower vehicle was already decelerating at the start of the time range followed by an accelerating till the end of the time range (*n* = 118). Here, either the response timing was before the recorded trajectory information, or there was not a decelerating response as the follower vehicle's velocity could accelerate. In both cases, the timing of the response cannot be determined and were therefore excluded from further analysis.

4. 5. Situations Within the Scenario

The follower vehicle was expected to be influenced by the ego vehicle's lane change manoeuvre, as depicted in Figure 5. Simultaneously, a leader vehicle that decelerated could also have influenced the follower vehicle. However, with large distances between vehicles, the influence would be minimal. Therefore, within the scenario, there was made a distinction between whether the follower vehicle could be considered driving freely with respect to the ego and leader vehicles. Liu et al. (2022) and Yang et al. (2019) classified vehicles as influencing each other's behaviour if they are within 55 and 75 meters, respectively. However, this definition of a boundary is limited as it does not consider the velocity and whether the ego vehicle drives faster. Therefore, the classification of freely driving vehicles is based on the definition of Weber et al. (2021). That is, driving freely is defined as when the THW between the follower and ego vehicles is more than 3.5 seconds, or more than 2 seconds if the ego vehicle is driving faster than the follower vehicle.

The lane change of the ego vehicle will likely not influence the behaviour of the follower vehicle if the follower vehicle is driving freely with respect to the ego vehicle, and as such are not further analysed (n = 98). The resulting lane changes are further categorised based on whether the follower vehicle is driving freely or not with respect to the leader vehicle. When the follower vehicle drives freely from the leader vehicle, the scenario is classified as situation A; when not, it is classified as situation B. The categorisation of vehicles driving freely from each other is limited to the influence on the follower vehicle, as the research aims to model the follower vehicle's response.

4. 6. Statistical Analysis

The filtering of the lane changes in the highD dataset resulted in a total of 435 lane change scenarios (as shown in Figure 6). Several analyses are conducted to eventually predict the timing, duration, and minimum acceleration of the decelerating response behaviour of the follower vehicle using linear regression models.

It is tested whether the proportion of no-deceleration or deceleration responses differs depending on whether or not the follower vehicle is driving freely from the leader vehicle. Namely, if no difference is found, it can be argued that it is irrelevant whether the follower vehicle is driving freely with respect to the leader vehicle. A Chi-Square Test of Independence was performed to assess the relationship between the response and the scenario. The assumptions of the Chi-Square Test are met as the lane change cases are independent, the categories are mutually exclusive, and no category has less than 5 cases.

Furthermore, it is tested what the differences are between the lane change scenario for cases where the follower vehicle did or did not decelerate (without differentiating between situation categories). The results can suggest which descriptive variables of the scenario influence the follower vehicle's need to decelerate. Two-sample *t*-tests are performed to determine the significant differences between the mean values of the descriptive variables at the start of the lane change between response categories 1 and 2. Table 2 presents an overview of all the analysed descriptive variables of the lane change scenario. The *t*-tests assume that the sampling distribution of means follows a normal distribution. This assumption is always met in this research as the central limits theorem applies (i.e., the sample sizes of the groups compared are larger than 30). The second assumption of the *t*-test is that there should be homogeneity of variance between the groups. This assumption may not always hold as the sample sizes of the groups compared are unequal. A corrected *t*-test (Welch-Satterthwaite) was used when the Levene's test indicated no homogeneity of variance between the groups.

The decelerating responses are further analysed after determining how these lane change scenarios differ from those of no-decelerating responses. Before the analyses, extreme outliers on the timing, duration and minimum acceleration of the follower vehicle's response were identified and removed. An extreme outlier is considered a data point that is more than four times the interquartile range (IQR) above the 75^{th} percentile of the boxplot or has a standardised score above four. It is first of interest to determine if and how the three dependent variables are related to each other. The linear correlation between the timing, duration and minimum acceleration of the follower vehicle's decelerating response are calculated using the Pearson correlation coefficient. Additionally, the lane change scenarios with a decelerating response were then compared between situation categories A and B to test how the scenarios differ besides the follower vehicle driving freely from the leader vehicle. The differences in mean values of the descriptive variables at the start of the lane change (see Table 2) between situation categories A and B are investigated using two-sample *t*-tests.

4.6.1. *Linear Regression Models*

The linear regression models for the timing, duration and minimum acceleration of the follower vehicle's decelerating response are developed using several steps.

1. The linear regression model's assumption of linearity was checked, and non-linearity was solved by transforming the variables as needed.
2. The Pearson correlation coefficients between the response variable and descriptive variables were analysed to identify which variables are related to the response variable.
3. A backward stepwise linear regression was used to point out the most significant predictors for the linear regression model as an exploratory approach. At each step, variables were removed based on the highest *p*-value, and the procedure stopped when no variables satisfied the elimination criteria of a *p*-value above 0.05.
4. The significance of the descriptive variables related to the follower and ego vehicle in the linear regression model was examined, including the investigation of interaction effects.

Table 2

All analysed descriptive variables at the start of the lane change manoeuvre

Variable ($t_{startLC}$)	Abbreviation	Unit
Velocity ego vehicle	v_x^E	m/s
Velocity follower vehicle	v_x^F	m/s
Velocity leader vehicle	v_x^L	m/s
Velocity slowlead vehicle	v_x^S	m/s
Acceleration ego vehicle	a_x^E	m/s²
Acceleration follower vehicle	a_x^F	m/s²
Acceleration leader vehicle	a_x^L	m/s²
Acceleration slowlead vehicle	a_x^S	m/s²
Lateral position ego vehicle relative to lane marking	y_{centre}^E	m
Lateral acceleration ego vehicle	a_y^E	m/s²
Velocity difference follower and ego vehicles	$\Delta v_x^{F,E}$	m/s
Velocity difference leader and ego vehicles	$\Delta v_x^{E,L}$	m/s
Velocity difference slowlead and ego vehicles	$\Delta v_x^{E,S}$	m/s
Velocity difference leader and follower vehicles	$\Delta v_x^{F,L}$	m/s
Distance gap follower and ego vehicles	$\Delta x^{F,E}$	m
Distance gap leader and ego vehicles	$\Delta x^{E,L}$	m
Distance gap slowlead and ego vehicles	$\Delta x^{E,S}$	m
Distance gap leader and follower vehicles	$\Delta x^{F,L}$	m
THW follower and ego vehicles	$THW^{F,E}$	s
THW leader and ego vehicles	$THW^{E,L}$	s
THW slowlead and ego vehicles	$THW^{E,S}$	s
THW leader and follower vehicles	$THW^{F,L}$	s
TTC follower and ego vehicles	$TTC^{F,E}$	s
TTC leader and ego vehicles	$TTC^{E,L}$	s
TTC slowlead and ego vehicles	$TTC^{E,S}$	s
TTC leader and follower vehicles	$TTC^{F,L}$	s
Ratio of velocity difference and distance gap follower and ego vehicle	$ratio_{\Delta v,\Delta x}^{F,E}$	1/s
Ratio of velocity difference and distance gap leader and ego vehicle	$ratio_{\Delta v,\Delta x}^{E,L}$	1/s
Ratio of velocity difference and distance gap slowlead and ego vehicle	$ratio_{\Delta v,\Delta x}^{E,S}$	1/s
Ratio of velocity difference and distance gap leader and follower vehicle	$ratio_{\Delta v,\Delta x}^{F,L}$	1/s

Note. The variables are used in the analysis as possible important predictor variables in the linear regression models of the follower vehicle's response timing, duration, and minimum acceleration.

5. The impact of adding variables related to the leader vehicle to the linear regression model was analysed, including the use of a multilevel linear regression analysis and dummy variables to represent the different scenario categories.
6. The impact of the descriptive variables related to the slowlead vehicle on the linear regression model was investigated.
7. The possibility of nested groups in the dataset was tested. The number of lanes on the highway and whether the ego vehicle changed lanes from the right or middle lane were considered possible nested groups.

The assumptions of the linear regression model were tested by checking the estimated errors of the predictions of the multiple linear regression model (i.e., the residuals). The residuals should be normally distributed, have a constant variance, and be random and independent. The multi-collinearity of the explanatory variables was checked using the Variable Inflation Factor (VIF), with the rule of thumb of individual VIF values below 10 and average VIF below 2.5 to avoid redundant variables (O'Brien, 2007). The linear regression models were validated using cross-correlation between the actual and predicted value. The model was trained on 80% of the dataset and validated on the remaining 20%.

5. Results

This Chapter presents the results of the analyses. The differences between the lane change scenarios where the follower did or did not decelerate are compared. Subsequently, the focus is analysing the lane change cases where the follower vehicle decelerates. The correlations between the timing, duration and minimum acceleration of the follower vehicle's decelerating response are analysed. Additionally, it is tested whether the follower vehicle's response is different depending on whether the follower vehicle is driving freely from the leader vehicle. The Chapter concludes by providing the best linear regression models of the follower vehicle's response timing, duration, and minimum acceleration using descriptive variables at the start of the lane change.

5. 1. Response and Situation Categories

Table 3**Table** *3* presents an overview of the number of lane change cases where there is a no-deceleration or deceleration response (i.e., response categories 1 and 2, respectively) and situation categories A and B. A chi-square test of independence was conducted to assess whether the proportion of no-deceleration or deceleration responses differ depending on whether or not the follower vehicle is driving freely from the leader vehicle. There was a significant relationship between the two variables, $X^2(1, 435) = 46.95$, $p < .001$, indicating that situation A is less likely to have a decelerating response than situation B. This shows that the presence of a leader vehicle also influences the need for the follower vehicle to decelerate and should be considered in the models.

Table 3

Number of lane change cases categorised over scenario and response

Situation	Response		Total
	1 No-decelerating response	2 Decelerating response	
A Influence ego vehicle	90	111	201
B Influence ego and leader vehicles	35	199	234
Total	125	310	435

5. 1. 1. *Differences in Response Categories 1 and 2*

The follower vehicle's response is categorised based on whether or not there was a deceleration. To understand the differences between the lane change scenarios of the two response categories, the descriptive variables of the lane change scenario (as listed in Table 2) are compared. Car-following models like Gipps' model and IDM differentiate between whether or not the follower vehicle is influenced by its leading vehicle on mainly the velocity difference and distance gap between the vehicles. Similarly, in this research, it is expected that when the velocity difference is small and the distance gap is large, the follower vehicle will not be influenced by the ego vehicle and therefore will not need to decelerate. That is, the lane change scenario is expected to differ between response categories 1 and 2 in terms of the velocity difference and distance gap between the follower and ego vehicles.

A complete overview of the *t*-test results testing the differences in descriptive variables between the two response categories can be found in Table B1. These differences help to identify when the follower vehicle needs to respond by decelerating. Overall, the significant differences between response categories 1 and 2 show that a smaller THW and higher velocity difference between the follower and ego vehicles are related to a decelerating response of the follower vehicle. It is noteworthy that the distance gap between the vehicles was not significant. The results also show that the presence of a leader vehicle that is closer to the follower vehicle and has a lower velocity than the follower vehicle influences the need for the follower vehicle to decelerate. Moreover, in lane change scenarios in which the follower vehicle did not decelerate, the average acceleration value for the ego and leader vehicles was around 0.22 m/s^2. This shows that the vehicles could accelerate, including the follower vehicle with an average value of 0.21 m/s.

5. 2. Decelerating Response

The aim of this research is to characterise the deceleration response behaviour of the follower vehicle in a lane change scenario. Therefore, the timing, duration and minimum acceleration of the deceleration response (i.e., response category 2) are analysed in detail. Prior to conducting the analyses, two extreme outliers were identified on the dependent variables (i.e., timing, duration and minimum acceleration of the follower vehicle's response). The first outlier had a minimum acceleration value of -3.61 m/s^2. This low minimum acceleration value was caused by a harsh deceleration of all vehicles due to the road situation and not specifically due to the lane change manoeuvre of the ego vehicle. The second outlier has a response duration of 11.08 seconds, during which the follower vehicle only slightly decelerated with a maximum acceleration of 0.01 m/s^2. This lane change should be classified as an unclear response where the follower vehicle only decelerates. Accordingly, the two outliers were removed from the analysis. The descriptive statistics of the timing, duration and maximum deceleration of the response are presented in Table 4.

Table 4

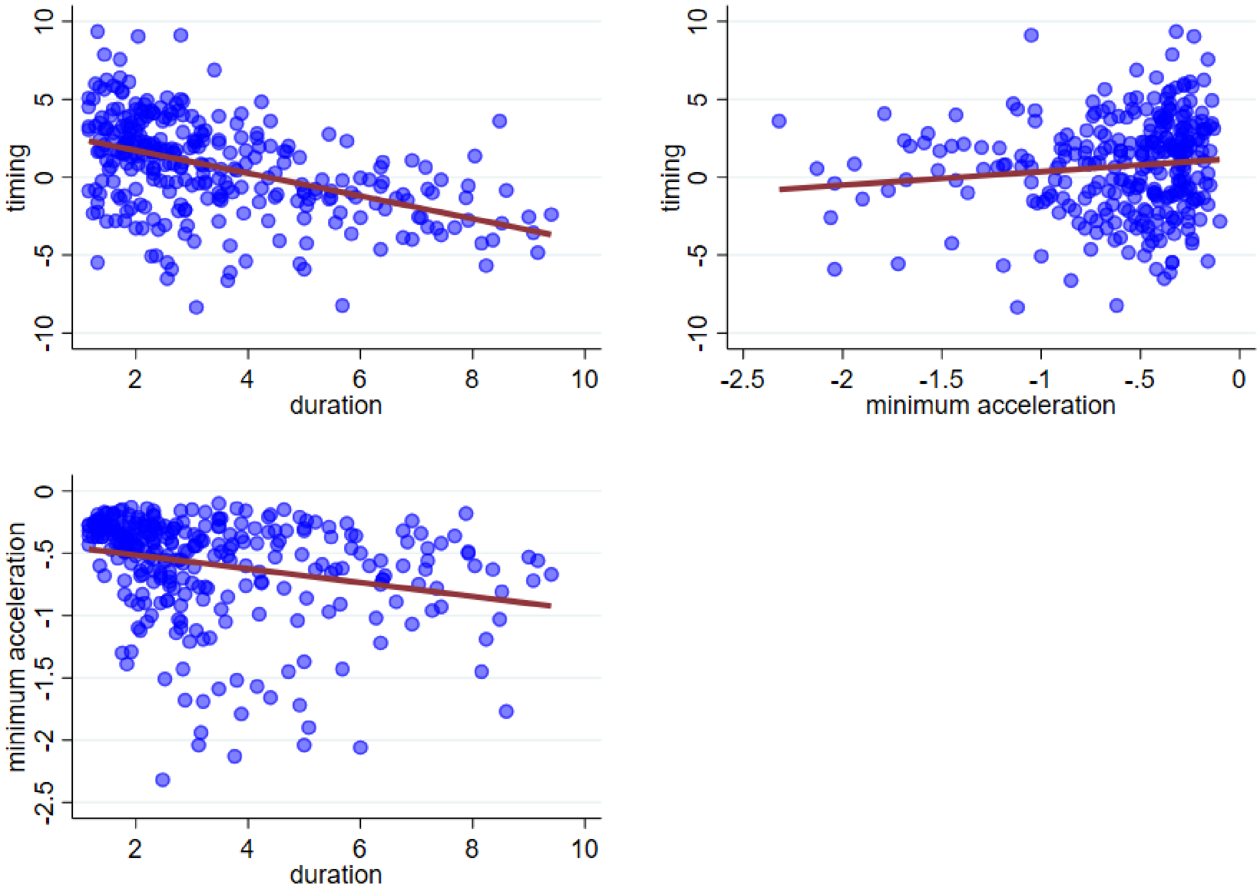
Descriptive statistics of the follower vehicle's response

Response Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Timing	308	0.71	3.09	-8.36	9.36
Duration	308	3.38	1.94	1.16	9.4
Minimum acceleration	308	-0.59	0.42	-2.32	-0.1

It was expected that these response variables are related to each other as they together reflect the decelerating behaviour of the follower vehicle. For instance, it can be expected that a lower minimum acceleration takes more time to reach. Moreover, in cooperative lane changes where the follower vehicle responds early, a higher minimum acceleration is expected as people are more inclined to cooperate when the costs to do so are low (Stoll et al., 2019). The results show that there are indeed significant correlations between the duration, timing, and minimum acceleration of the follower vehicle's response. The significant correlations are visualised in Figure 10. The response duration is negatively correlated with both the minimum acceleration ($r(308) = -.26$, $p < .001$) and response timing ($r(308) = -.46$, $p < .001$). This indicates that the longer the response, the lower the minimum acceleration and the earlier the response timing. Additionally, contrary to expected, the minimum acceleration was positively correlated with the response timing ($r(308) = .12$, $p = .041$), suggesting that an early response is related to a lower minimum acceleration. However, the strength of the correlation between the minimum acceleration and response timing is only weak.

Figure 10

Relationships between the timing, duration, and minimum acceleration of the follower vehicle's response



Note. The blue dots are the lane change observations, and the red line is the linear fitted line illustrating the relationship between the variables.

In this research, linear regression models are developed to predict the timing, duration, and minimum acceleration of the follower vehicle's decelerating response. In essence, this deceleration of the follower vehicle is a response to the lane change manoeuvre of the ego vehicle. Consequently, the differences in the lateral behaviour of the ego vehicle should also be considered as potential predictors of the response behaviour of the follower vehicle. The descriptive statistics of the lane change manoeuvre of the ego vehicle can be seen in Table 5 and highlight the variations in the lateral behaviour of the ego vehicle. For example, the time taken to cross the lane marking from the start of the lane change ranges from 2.3 to 9.3 seconds.

Table 5

Descriptive statistics of the ego vehicle's lane change manoeuvre

Response Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
$\Delta t_{linecrossing}$	308	4.15	1.34	2.32	9.28
$y^{E}_{center}(t_{startLC})$	308	-1.86	0.34	-2.83	-1.08
$a^{E}_{y}(t_{startLC})$	308	0.15	0.08	0.01	0.43

5. 2. 1. *Differences in Situation Categories A and B*

The findings indicate that a follower vehicle is more likely to decelerate when not driving freely from the leader vehicle. In addition, the analysis of lane change scenarios between non-decelerating and decelerating responses showed that a leading vehicle that is closer to the follower vehicle with a slower velocity influences the need for the follower vehicle to decelerate. This influence of the leader vehicle on the decelerating response is further analysed by comparing the timing, duration, and minimum acceleration response variables between situations A and B. The results are presented in Table 6, with a graphical representation in Figure 11. The results indicate that there is a significant difference in the duration and minimum acceleration of the follower vehicle's response between situations A and B. Specifically, in situation B, the response duration is longer and the minimum acceleration is lower compared to situation A. However, the timing of the response is not found to be significantly different between the two situations.

Table 6

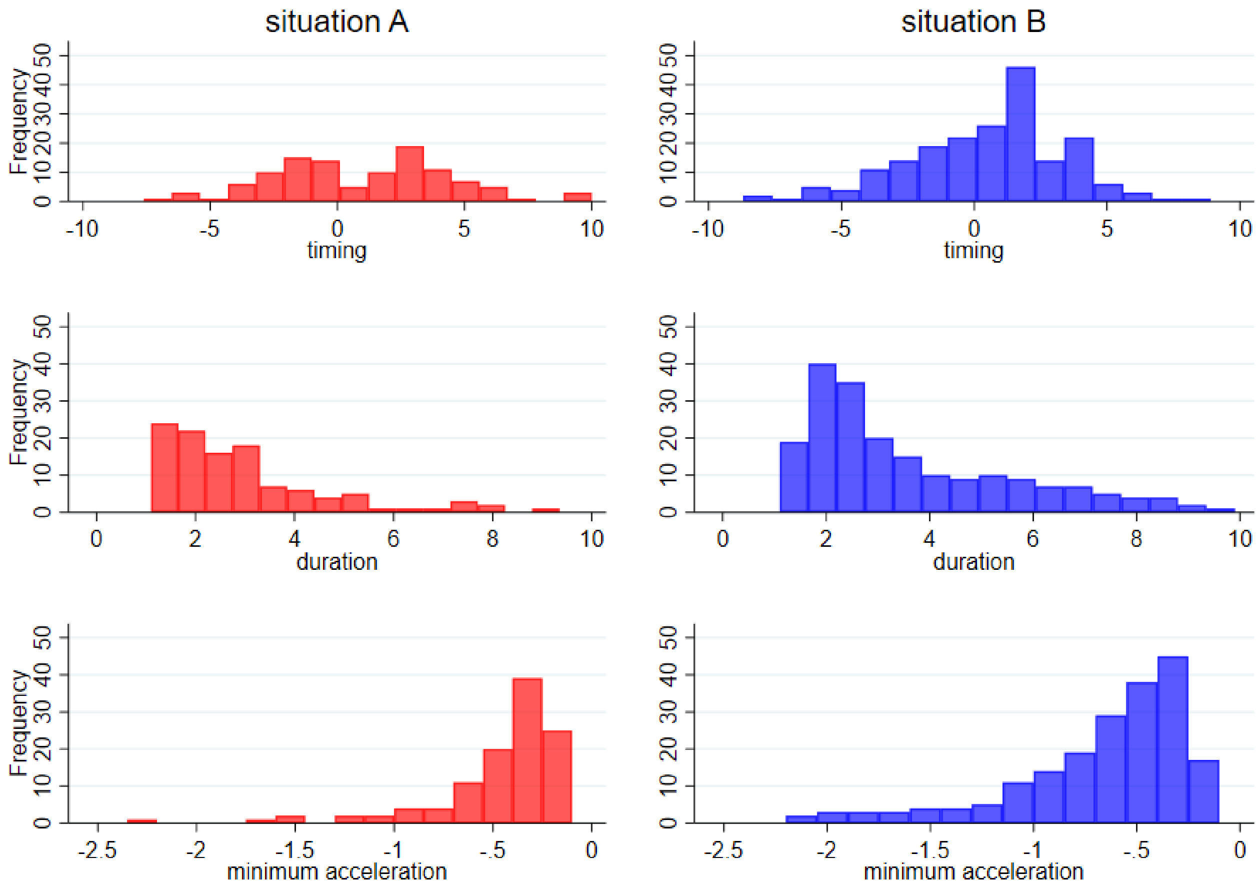
Differences between situation categories A and B in the response variables

	Situation A Influence ego vehicle			Situation B Influence ego and leader vehicles				
Response Variable	*N*	*M*	*SD*	*N*	*M*	*SD*	*t*	*p*
Timing	111	1.03	3.34	197	0.53	2.94	1.31*	.192
Duration	111	2.98	1.72	197	3.61	2.02	-2.91*	.004
Minimum acceleration	111	-0.46	0.35	197	-0.66	0.44	4.39*	< .001

Note. * indicates the use of the Welch's *t*-test because of unequal variances between the categories.

Figure 11

Distribution of the response variables values compared between situation categories A and B



Note. The red visualisations on the left represent situation A and the blue visualisations on the right represent situation B.

Furthermore, *t*-tests are performed to compare the mean values of the descriptive variables at the start of the lane change between situations A and B. This is to determine if the lane change scenarios between situations A and B differ beyond the selection criteria of the follower vehicle driving independently from the leading vehicle. An overview of the *t*-test results can be found in Table B2. The results reveal that there are differences in the lane change scenario other than the category selection of whether the follower vehicle is driving freely from the leader vehicle. Namely, the vehicles are closer to each other and display more interdependent driving behaviours in situation B than in A. Specifically, the distance gap is smaller, and the velocity difference is higher between the follower and ego vehicles in situation B compared to A.

The findings from comparing non-deceleration and deceleration responses, as well as the situations in which the follower vehicle is driving freely from the leader vehicle provide several insights. Overall, the key finding is that the follower is more likely to decelerate, with on average a higher minimum acceleration and longer duration when the follower vehicle is not driving freely from the leader vehicle. This is also related to a smaller distance gap and higher velocity difference between the follower and ego vehicles. The findings imply that the distance gap and velocity difference are likely significant predictors in the linear regression models. Additionally, the findings show the importance of considering the leader vehicle's influence when developing the linear regression models.

5. 3. Timing Response Model

This section outlines the steps taken to develop the best linear regression model for predicting the timing of the follower vehicle's response in a lane change scenario using the descriptive variables at the start of the lane change. The process includes examining the relationships between response timing and the variables through visualisations and correlation analysis. The findings are used to develop the best possible linear regression model.

In the linear regression model of the timing of the response, as well as the duration and minimum acceleration, the follower vehicle's acceleration value at the start of the lane change is not considered a possible predictor variable. This is because the research focuses on characterising the decelerating response of the follower vehicle, which is directly related to the acceleration value and can be inferred from it. For example, suppose the response timing (i.e., the follower vehicle starts to decelerate) is before the start of the lane change. In that case, the follower vehicle's acceleration will be negative at the start of the lane change. Therefore, the follower vehicle's acceleration at the start of the lane change will not be included as a predictor in the linear regression models. This research aims to understand the influence of the other descriptive variables on the decelerating response of the follower vehicle.

5. 3. 1. *Relationships Between Response Timing and Descriptive Variables*

The linearity of the relationships between the response timing of the follower vehicle and descriptive variables are investigated using visualisations (see Figures C1 to C6). The results do not indicate clear non-linear relationships; therefore, no transformations are required to develop the linear regression model. However, the visualisations also reveal a wide distribution of response timing values, suggesting that the descriptive variables may not fully explain the response timing.

The visualisations also highlight key observations about the descriptive variables in general. The majority (59.7%) of the lane changes start when the distance gap between the ego and leader vehicles is negative, meaning that the leader vehicle's rear bumper is not further than the ego vehicle's front bumper. This results in fewer observations of the TTC between the ego and leader vehicle, as the distance gap is negative and the leader vehicle's velocity is often higher. Similarly, the velocity difference between the leader and follower vehicle is often negative, which also results in few TTC observations. Besides, the TTC value can have extreme outliers when the velocity difference between the vehicles is close to zero. The ratio of the velocity difference and the distance gap includes cases with a negative velocity difference and has less extreme outliers. Therefore, the velocity-distance ratio between the vehicles is a more informative variable to use in the analyses.

In addition, the correlations between the response timing and all descriptive variables at the start of the lane change are analysed. A complete overview of the Pearson correlation coefficients can be found in Table C1. The results confirm the lack of strong linear correlations, with the highest correlation coefficient being 0.25. The key findings are discussed but should be interpreted cautiously as the correlations' strength is only weak. First, the results show that the response timing is negatively correlated with the acceleration of the ego ($r(308) = .21$, $p < .001$), leader ($r(300) = .25$, $p < .001$), and slowlead ($r(307) = .21$, $p < .001$) vehicles at the start of the lane change. This suggests that the acceleration of other vehicles influences the response timing of the follower vehicle, such that the follower vehicle will need to respond earlier if the other vehicles are decelerating. Conversely, the follower vehicle can respond later when the other vehicles accelerate. Second, the correlation between the response timing and the velocity difference between the follower and ego vehicles is negative ($r(308) = -.15$, $p = .010$), as well as for the follower and leader vehicles ($r(300) = -.13$, $p = .025$). The results suggest that a larger velocity difference leads to an earlier response. Third, the negative correlation between the lateral acceleration of the ego vehicle at the start of the lane change and the response timing of the follower vehicle suggests that the response is earlier when the ego vehicle starts the lane change with high lateral acceleration ($r(308) = -0.19$, $p < .001$).

5.3.2. *Linear Regression Model*

The linear regression model was developed through a series of steps applied to the training dataset, which comprised 80% of the total number of observations. The expectations from previous literature and the significant correlations found provide indications of the descriptive variables that are important predictor variables of the follower vehicle's response timing. The significant predictor variables were identified and added to the model, taking into account possible interaction effects. In addition, the effect of the situation category was analysed using multilevel analysis. Detailed information about the steps and intermediate results can be found in Appendix C. 2 The final best regression model using the descriptive variables at the start of the lane change is shown in Table 7. The multiple linear regression to predict the timing of the response was as follows ($F(4, 233) = 14.01$, $p < .001$, $R^2 = 0.19$):

$$t_{response} = 1.95 + \left(2.99 - 0.42\,\Delta v_x^{F,E}\right) a_x^E + 2.00\,a_x^L - 9.21\,a_y^E \tag{15}$$

Table 7

The linear regression model of the follower vehicle's response timing

Variable ($t_{startLC}$)	Coefficient	Standard Error	*t*	*p*	[95% confidence interval]
a_x^E	2.99	0.83	3.61	< .001	1.36, 4.62
$a_x^E * \Delta v_x^{F,E}$	-0.42	0.16	-2.57	.011	-0.75, -0.10
a_x^L	2.00	0.56	3.57	< .001	0.89, 3.10
a_y^E	-9.21	2.26	-4.08	< .001	-13.66, -4.76
(constant)	1.95	0.40	4.90	< .001	1.17, 2.74

The final linear regression model has four predictors. A positive coefficient was found for the acceleration of both the ego and leader vehicle. This means that when the acceleration of the vehicles is higher, the need for the follower vehicle to decelerate occurs later. On the other hand, when the vehicles are decelerating, the follower vehicle will respond earlier. Additionally, there is an interaction between the ego vehicle's acceleration and the velocity difference between the follower and ego vehicles, such that the effect of the ego vehicle's acceleration decreases for higher velocities. This means that when the ego vehicle accelerates, the effect of a later response is weaker for higher velocity differences. Similarly, the effect of an early response is weaker for higher velocity differences when the ego vehicle decelerates. Furthermore, the lateral acceleration of the leader vehicle has a positive coefficient, resulting in a later response timing for the follower vehicle during acceleration and an earlier response during deceleration. Lastly, the model found that as the lateral velocity of the ego vehicle increases, the follower vehicle responds earlier. The impact a predictor has on the follower vehicle's response timing can be assessed by considering the size of the coefficient relative to the range of values the predictor can take. For instance, although the coefficient for the lateral acceleration of the ego vehicle is larger, it has a smaller range of values than the longitudinal acceleration of the ego vehicle, which has a smaller coefficient.

The assumptions of a linear regression model of the follower vehicle's response timing were evaluated using the standardised residuals. The Shapiro-Wilk test for normality showed that the residuals were not normally distributed (W = 0.98, p = .011). However, a W-value of 0.98 suggests that the distribution is not very different from a normal distribution. The Breusch-Pegan test for heteroskedasticity showed there was a constant variance in the residuals ($X^2(1)$ = 2.19, p = .129). In addition, the correlations between the predictor variables of the model were analysed. The VIF values have an average of 1.75 and no individuals above 10, showing no multicollinearity problem. The linear regression model was validated using the cross-correlation value between the predicted and actual response timing on the test data. The results show a cross-correlation value of 0.001, which is tremendously lower than the original R^2-value of 0.19. The results indicate that the model does not cross-correlate well.

5. 4. Response Duration Model

This section outlines the results of the linear regression model of the follower vehicle's response duration. The relationships between the response duration and the descriptive variables at the start of the lane change are investigated visually and through correlation analysis. Following this, the best possible linear regression model is developed.

5. 4. 1. *Relationships Between Response Duration and Descriptive Variables*

The relationships between the duration of the response and the descriptive variables at the start of the lane change are visualised in Figures D1 to D6. The visualisations do not show any obvious non-linear relationships between the variables, and no transformations were necessary for developing the linear regression model. However, the relationship between the response duration and the distance-related variables for the follower and leader vehicles and the ego and leader vehicles seem less linear. Here, the response duration can vary widely within short distances, while there are only brief responses at the highest distances (i.e., more than 150 meters). Nevertheless, this effect is only weak as there are limited data points in the high distance range and there is a substantial concentration in the low distance range. Therefore, transforming these distance-related variables did not enhance the linear relationship.

Next, the correlations between the duration of the follower vehicle's response and the descriptive variables are analysed. The key results are discussed, and a complete overview of all the Pearson correlation coefficients can be found in Table D1. Similar to the correlation coefficients of the response timing, the relationship between the response duration and the descriptive variables are only weak to moderate. The strongest correlation is with the leader vehicle's acceleration ($r(300) = -.36$, $p < .001$), where a shorter response duration is observed when the leader vehicle accelerates at the start of the lane change. The correlation between the response duration and the acceleration of the ego ($r(308) = -.26$, $p < .001$) and slowlead ($r(307) = -.23$, $p < .001$) vehicles show a similar pattern, but with a lower correlation coefficient. Furthermore, the velocity difference between the follower and ego vehicles ($r(308) = .14$, $p = .011$) and the follower and leader vehicles ($r(300) = .16$, $p = .006$) showed a positive correlation with the response duration. This indicates that the larger the velocity difference between the vehicles, the longer the follower vehicle responded. However, the correlation coefficient shows there is only a weak relationship.

5. 4. 2. *Linear Regression Model*

Through several steps, the linear regression model was created on the training dataset (i.e., 80% of the total number of observations). Indicators of the key descriptive variables that influence the follower vehicle's response timing were determined based on previous literature and the significant correlations. The predictor variables were then incorporated into the model, including any potential interaction effects. The impact of the situation category was also analysed through multilevel analysis. Further details on the process and intermediate results are available in Appendix D. 2 The final linear regression model to predict the follower vehicle's response duration using the descriptive variables at the start of the lane change is as follows (F(4, 237) = 13.85, $p < .001$, $R^2 = 0.19$) (see Table 8):

$$\Delta t_{response} = 3.78 + \left(-0.02 + 0.002\, \Delta v_x^{F,E}\right) \Delta x^{F,E} - 1.95\, a_x^L - 0.94\, a_x^S \quad (16)$$

Table 8

The linear regression model of the follower vehicle's response duration

Variable ($t_{startLC}$)	Coefficient	Standard Error	t	p	[95% confidence interval]
$\Delta x^{F,E}$	-0.02	0.01	-2.05	.042	-0.03, -0.001
$\Delta x^{F,E} * \Delta v_x^{F,E}$	0.002	0.001	2.44	.015	0.0003, 0.003
a_x^L	-1.95	0.34	-5.78	< .001	-2.62, -1.29
a_x^S	-0.94	0.42	-2.23	.027	-1.76, -0.11
(constant)	3.78	0.31	12.27	< .001	3.17, 4.39

The linear regression model that predicts the duration of the follower vehicle's response in a lane change scenario has four predictors. The distance gap between the follower and ego vehicles has a negative coefficient, meaning that a larger distance gap results in a shorter response. Additionally, this relationship is moderated by the velocity difference between the vehicles. Specifically, higher velocity differences lead to longer response durations even with a large distance gap. If the velocity difference is negative between the follower and ego vehicles, the effect of a short response duration at large distances is even stronger. Moreover, the negative coefficient for the leader and slowlead vehicles' acceleration indicates that a deceleration of the vehicles results in a longer response duration from the follower vehicle.

The assumptions and validity of the linear regression model of the response duration of the follower vehicle were assessed. The normality of residuals was assessed using the Shapiro-Wilk test, and it was found that the residuals were not normally distributed ($W = 0.92$, $p < .001$). The Breusch-Pegan test for heteroskedasticity showed there is no constant variance in the residuals ($X^2(1) = 13.05$, $p < .001$). The findings suggest that the linear regression model lacks an important predictor that is not included in the descriptive variables at the start of the lane change. Additionally, the predictor variables were analysed for multicollinearity. The results show there is no problem with multicollinearity, as the average VIF value is 1.83 and no individual variable has a value above 10. Finally, the model was validated using the cross-correlation value between the predicted and actual response timing values on the test dataset. The results show a cross-correlation value of 0.12, which is a decrease of 37% from the original fit of the model (i.e., R^2-value of 0.19).

5. 5. Response Minimum Acceleration Model

This section describes the third linear regression model to predict the minimum acceleration of the follower vehicle's response. The initial examination of the relationships between the response duration and various descriptive variables at the start of the lane change was conducted through visual analysis and correlation analysis. Next, the linear regression model of the follower vehicle's response minimum acceleration is developed.

5. 5. 1. *Relationships Between Response Minimum Acceleration and Descriptive Variables*

The relationships between the minimum acceleration of the follower vehicle's response and the other descriptive variables at the start of the lane change are investigated (see Figures E1 to E6). The analysis revealed that the relationships are not overly non-linear, with the exception of the TTC values between the follower and ego vehicles. However, as discussed before, the velocity-distance ratio is a better predictor variable to consider in general, and this variable was found to be linear.

Furthermore, the correlations between the minimum acceleration of the follower vehicle's response and the descriptive variables at the start of the lane change are analysed. Table E1 provides a complete overview of all the Pearson correlation coefficients. The most important findings of the analysis are discussed. A positive correlation is found between the minimum acceleration and the acceleration of the ego ($r(308) = .28$, $p < .001$), leader ($r(300) = .37$, $p < .001$), and slowlead ($r(307) = .22$, $p < .001$) vehicles, with the strongest correlation found for the leader vehicle. Thus, as the acceleration value of other vehicles is lower, the minimum acceleration of the follower vehicle is as well lower. Furthermore, a negative correlation is found between the velocity difference of the follower and ego vehicles ($r(308) = -.26$, $p < .001$), as well as the follower and leader vehicles ($r(300) = -.17$, $p = .003$). As the velocity difference increases, the minimum acceleration of the follower vehicle decreases. In addition, the follower vehicle's velocity has a negative correlation with the minimum acceleration ($r(308) = -.20$, $p < .001$), meaning that as the follower vehicle's velocity increases, its minimum acceleration decreases. Despite no strong correlations overall, the results indicate that the best predictors of the minimum acceleration of the follower vehicle are the acceleration values of the other vehicles and the velocity difference between the follower and ego vehicles (similar to the response duration).

5. 5. 2. *Linear Regression Model*

The process of creating the linear regression model for predicting the minimum acceleration of the follower vehicle's response involved several steps. The key descriptive variables influencing the minimum acceleration of the follower vehicle's response were identified based on previous research and the significant correlations. The significant predictor variables, including possible interaction effects, were then incorporated into the model. The influence of the situation category was also analysed through multilevel analysis. The full details and intermediate results of this process can be found in Appendix E. 2 The final linear regression model is shown in Table 9 (F(3, 237) = 20.06, p < .001, R^2 = 0.30) and as follows:

$$a^F_{x\,min} = -0.64 + (-0.07 + 0.04\, a^E_x)\, \Delta v^{F,E}_x + 0.01\, \Delta x^{F,E} + 0.30\, a^L_x + 0.17\, a^S_x \tag{17}$$

Table 9

The linear regression model of the follower vehicle's response minimum acceleration

Variable ($t_{startLC}$)	Coefficient	Standard Error	*t*	*p*	[95% confidence interval]
$\Delta v^{F,E}_x$	-0.07	0.01	-6.51	< .001	-0.09, -0.05
$a^E_x * \Delta v^{F,E}_x$	0.04	0.01	2.84	.005	0.01, 0.07
$\Delta x^{F,E}$	0.01	0.001	5.16	< .001	0.003, 0.01
a^L_x	0.30	0.07	4.30	< .001	0.16, 0.43
a^S_x	0.17	0.08	2.00	0.046	0.003, 0.33
(constant)	-0.64	0.05	-11.66	< .001	-0.75, -0.53

The linear regression model to predict the minimum acceleration of the follower vehicle's response has five predictors. The velocity difference between the follower and ego vehicles has a negative coefficient. This means that the higher the velocity difference, the lower the minimum acceleration. Additionality, there was an interaction effect between this velocity difference and the acceleration of the ego vehicle. That is, if the ego vehicle accelerates, the impact of the velocity difference on the follower vehicle's minimum acceleration is reduced, resulting in a smaller minimum acceleration compared to when the ego vehicle does not accelerate. Furthermore, a positive coefficient was found for the distance gap, meaning that as the distance between the follower and ego vehicles increases, the minimum acceleration value will also increase. Besides, a positive coefficient was found for the acceleration of the leader and slowlead vehicles, indicating that if the vehicles decelerate, the minimum acceleration of the follower vehicle will also decrease.

The assumptions and validity of the linear regression model were tested. The Shapiro-Wilk test indicated that the residuals were not normally distributed (*W* = 0.83, *p* < .001). In addition, the Breusch-Pegan test showed there was no constant variance in the residuals ($X^2(1)$ = 9.62, *p* = .002). The results imply that the linear regression model misses an important predictor that is not covered by the descriptive variables at the start of the lane change. There was no issue with multicollinearity as the VIF values had an average of 1.33, with none above 10. The model was validated using the cross-correlation of the predicted versus the actual minimum acceleration values on the test dataset. The cross-correlation value is 0.45, which is an increase of 50% of the original fit of the model.

6. Discussion

This Chapter presents an evaluation of the research results, highlights key findings, and discusses their significance and implications. It starts with a summary of the key results, followed by an interpretation of the findings in the context of previous literature. The Chapter then discusses the implications of the research and acknowledges its limitations before providing recommendations for future studies.

6. 1. Key Research Findings

The introduction of AVs on the road causes a transition period where vehicles with different levels of automation coexist with human road users. Therefore, it is of interest to ensure that AVs drive according to human standards. Modelling human driving behaviour can help to establish AVs drive predictably and according to social expectations. This research specifically focuses on modelling the deceleration response of a rear-approaching vehicle, known as the follower vehicle, on a target lane during a lane change manoeuvre by another vehicle on the highway. The lane change manoeuvres were extracted from a dataset containing real-world vehicle trajectory information, selected based on specific criteria. The lane change scenarios where the follower vehicle either started to decelerate or did not decelerate at all were further analysed.

The comparison between the two categories showed that a higher velocity difference and a smaller THW between the follower and ego vehicles led to a decelerating response by the follower vehicle. The decelerating response is further characterised by its timing, duration, and minimum acceleration. These three variables were also interrelated: a longer response correlated with a lower minimum acceleration and an earlier response timing, while an early response was related to a lower minimum acceleration. Additionally, the differences between lane changes performed with and without a leader vehicle were evaluated. The results show that if there is a leader vehicle, all vehicles have a shorter relative distance and seem more influenced by the driving behaviour of the other vehicles. Consequently, the follower vehicle had a lower minimum acceleration and a longer response duration when a lead vehicle was present. Three linear regression models were created to predict the timing, duration, and minimum acceleration of the follower vehicle's decelerating response and determine the most important predictor variables. The analysis of the follower vehicle's decelerating response resulted in the following linear regression models:

$$t_{response} = 1.95 + \left(2.99 - 0.42\ \Delta v_x^{F,E}\right) a_x^E + 2.00\ a_x^L - 9.21\ a_y^E \tag{15}$$

$$\Delta t_{response} = 3.78 + \left(-0.02 + 0.002\ \Delta v_x^{F,E}\right) \Delta x^{F,E} - 1.95\ a_x^L - 0.94\ a_x^S \tag{16}$$

$$a_{x_{min}}^F = -0.64 + (-0.07 + 0.04\ a_x^E)\ \Delta v_x^{F,E}\ + 0.01\ \Delta x^{F,E} + 0.30\ a_x^L + 0.17\ a_x^S \tag{17}$$

6. 2. Interpretation Results

The differences between the response categories (i.e., deceleration or no-deceleration) and the situation categories (i.e., presence or absence of a leader vehicle) were analysed before characterising the follower vehicle's decelerating response. Three observations were made from comparing the lane changes where the follower vehicle did or did not decelerate. First, the results show that the follower vehicle was more likely to decelerate when there was a shorter THW and higher velocity difference between the follower and ego vehicles. In car-following models, the distance gap and velocity difference are the most used predictors to determine an acceleration value based on the behaviour of a leading vehicle (Saifuzzaman & Zheng, 2014; Zhang et al., 2021). However, the results showed that the THW, rather than the distance gap, was statistically different between the response categories. This suggests that the decelerating response is more influenced by the velocity of the follower vehicle and velocity differences between the vehicles.

Second, in lane change scenarios where the follower vehicle did not decelerate, the average acceleration value for the ego and leader vehicles was around 0.22 m/s^2. This shows that the vehicles could accelerate, and as such, the follower vehicle also accelerated with an average value of 0.21 m/s. In these cases, using the gap size between the follower and ego vehicles, as proposed by Hidas (2005), would result in misclassifications similar to those shown by Chauhan et al. (2022). For example, Hidas (2005) classified a cooperative lane change as a situation where the distance gap increases before the ego vehicle crosses the lane marking and subsequently decreases. This pattern of change in the distance gap can occur due to a change in the ego vehicle's behaviour while the follower vehicle continues to accelerate.

Third, the study found that the leader vehicle plays a significant role in the follower vehicle's behaviour. The results show a smaller distance gap and higher velocity difference between the follower and lead vehicles increases the likelihood of a decelerating response from the follower vehicle. Additionally, in the situation where the follower vehicle does not decelerate, the leader vehicle on average drives faster than the follower vehicle. The opposite holds for the situations of a decelerating response (i.e., the leader vehicle drives slower than the follower vehicle).

The impact of the leader vehicle on the decelerating response of the follower vehicle was further examined by comparing situations where the follower vehicle is driving freely from the leader vehicle or not (i.e., situation A and B, respectively). The velocity difference between the follower and ego vehicles is significantly higher in situation B, and the distance gap is smaller. This results in a stronger deceleration response of the follower vehicle, as in situation B, the response duration of the follower vehicle is longer, and the minimum acceleration is lower. This is in line with car-following models predicting a higher deceleration for higher velocity differences and smaller distance gaps (Zhang et al., 2021).

6.2.1. *Linear Regression Models*

The decelerating response of the follower vehicle is characterised by linear regression models of the timing, duration and minimum acceleration. A correlation analysis showed that these three response variables are related to each other. A longer response was related to a lower minimum acceleration and an earlier response timing. It is reasonable to expect the follower vehicle to respond with a higher deceleration that consequently takes longer to avoid a collision when the ego vehicle cuts in with a lower velocity. In addition, an early response correlated with a lower minimum acceleration. This is opposite to expected from cooperative lane changes as the follower vehicle is more inclined to cooperate when the cost to do so are lower (i.e., small decelerations) (Stoll et al., 2019). In other words, it was expected that an early response of the follower vehicle to cooperate was related to a higher minimum acceleration. The results show the opposite pattern, which suggests that the follower vehicles did not cooperate or only did in the minority of lane change cases. The three response variables of the follower vehicle's response were expected to be described by some of the same descriptive variables as the variables correlate and together characterise the decelerating response of the follower vehicle. The results show that indeed the linear regression models have overlapping predictor variables.

The linear regression models for the response variables of the follower vehicle's deceleration all include the acceleration of the leader vehicle. This emphasizes the impact of the leader vehicle on the follower vehicle's behaviour. This result also aligns with the observed differences between the response and situation categories. Previous research on the follower vehicle's behaviour often ignores this influence and does not include this in the models (e.g., Chauhan et al. (2022) and Liu et al. (2022)). The results highlight the importance of including the car-following properties between the follower and leader vehicles when modelling the response to the ego vehicle's lane change manoeuvre. For instance, Fu et al. (2019) suggested a car-following model for cut-in scenarios that considers the car-following state prior to the cut-in event.

The velocity difference between the follower and ego vehicles is an important predictor in all three linear regression models, but its influence on the response variable differs. First, in the response timing model, there is an interaction between the velocity difference and the ego vehicle's acceleration. Here, the effect of the ego vehicle's acceleration is weaker for larger velocity differences. Second, in the response duration model, there is an interaction between the velocity difference and the distance gap between the follower and ego vehicles. The response duration is generally shorter at large distances, but the effect is weaker at higher velocity differences. Third, in the minimum acceleration model, the velocity difference interacts with the ego vehicle's acceleration and is also a predictor on its own. A lower minimum acceleration is seen at higher velocity differences, and even a stronger effect is seen when the ego vehicle decelerates. These results emphasize the crucial role of the velocity difference in the linear regression models and its interaction effects with other variables.

The linear regression models of the duration and minimum acceleration of the follower vehicle's response are most similar. Following the pattern of typical car-following models, both values depend on the distance gap and velocity difference between the follower and ego vehicles. In addition, in both the duration and minimum acceleration models, the acceleration of the slowlead vehicle is a significant predictor. This was not expected as the follower vehicle is not in the same lane as the slowlead vehicle. This may indicate that the slowlead vehicle's acceleration is a strong indicator of overall deceleration or that there is another correlation between the slowlead vehicle's acceleration and a different descriptive variable that influences the follower vehicle's response. However, as this research only explored correlations, the reason for the slowlead vehicle's acceleration being a significant predictor cannot be determined.

The findings of Liu et al. (2022) regarding the relationship between the follower vehicle's minimum acceleration and the velocity difference between the ego and follower vehicles were different from this research. Liu et al. (2022) found a non-linear relationship, while this research found a linear relationship and did not transform the variables. This could be due to the different range of minimum acceleration values studied and the number of observations studied where the ego vehicle was driving faster than the follower vehicle. In this research, only negative minimum acceleration values (i.e., representing a decelerating response) were investigated, while Liu et al. (2022) also included positive values. This resulted in a non-linear relationship due to the region where the ego vehicle was driving faster and the minimum acceleration was small to positive. However, as this range was not studied in this research, a linear relationship was found.

The linear regression model of the follower vehicle's response timing includes the lateral velocity of the ego vehicle. The model shows that as the lateral velocity of the ego vehicle increases, the response timing of the follower vehicle decreases. This finding is unique, as the lateral acceleration of the ego vehicle has not been considered in previous studies and models. It can be reasoned that a higher lateral acceleration is a clearer communication to the follower vehicle, and as such, the follower vehicle perceives and responds to the lane change earlier. However, it is important to note that this research only establishes correlations and not causality. It could also be the case that an earlier response from the follower vehicle results in a higher lateral acceleration during the lane change by the ego vehicle. The model also reveals that the response timing is influenced by the acceleration of the ego vehicle, which is moderated by the velocity difference. As the ego vehicle accelerates, the follower vehicle's response timing is expected to be later, but the effect is weaker when the velocity difference is high. It makes sense that the response timing of the follower vehicle is later when the ego vehicle accelerates. This is because an accelerating ego vehicle increases the time it takes for the follower vehicle to close the gap, providing the follower vehicle to decelerate later. On the other hand, when the ego vehicle decelerates, the response timing is not as intuitive as the follower vehicle does not need to respond as early with lower velocity differences. The model's low cross-correlation value ($R^2 = 0.001$) suggests that the linear regression model is not accurate in predicting the response timing. Further investigation is needed to identify the true predictor variables that influence the response timing of the follower vehicle.

The response timing of the follower vehicle was expected to depend on whether or not the follower vehicle cooperated. Literature indicates that a follower vehicle is more inclined to cooperative when the costs of the follower vehicle to do so are low (i.e., low velocity-distance ratio between follower and ego vehicles), and the criticality of the ego vehicle to change lanes is high (i.e., high velocity-distance ratio between slowlead and ego vehicles) (Stoll et al., 2019). The results show that both variables are not significant predictors of the follower vehicle's response timing linear regression. However, the correlation analysis does show that a higher ratio of the velocity difference and distance gap between the ego and slowlead vehicles correlated with an earlier response from the follower vehicle. The correlation pattern between the velocity-distance ratio between the follower and ego vehicles and the follower vehicle's response did not match the expectations based on previous research. The results show that a higher velocity-distance ratio between the follower and ego vehicles is related to an earlier response of the follower vehicle. Still, in 41.6% of the analysed lane changes, the follower vehicle started to decelerate before the ego vehicle's lateral movement, suggesting cooperative behaviour. However, it is challenging to make claims on whether or not the follower vehicle deliberately cooperated based on this research's analysis of natural vehicle trajectories without information on turn indicator usage. It can be possible that the expected relationship does hold specifically for cooperative lane change cases, but a different relationship may exist for non-cooperative responses. The lack of distinction between these responses can be a reason that the overall prediction of the response timing is uncertain.

In this research, the lane changes of both two-lane and three-lane highways are analysed. Consequently, there are lane changes where the ego vehicle changed lanes to the left lane from the right or middle lane. Therefore, a multilevel linear regression analysis was performed to determine if differences in lane changes influenced the response of the follower vehicle (similar to the approach of Yang et al. (2019) and Liu et al. (2022)). The results showed that these are no nested groups, suggesting that the same linear regression model applies to all lane changes. This implies combining data from two-lane and three-lane highways in future studies is possible.

6.2.2. *Fit of the Models*

The fit of the linear regression models predicting the timing, duration and minimum acceleration are relatively low (i.e., an R^2 value of 0.19, 0.19, and 0.30, respectively). The linear regression models cannot explain 81, 81, and 70% of the variance in the observed response behaviour. A large proportion of the follower vehicle's deceleration response is not explained by the linear regression models with these predictor variables. Three possible reasons are discussed.

First, the linear regression model can benefit from considering driver-related predictors. For instance, a driver's abilities, personality and risk threshold are expected to influence the driving style (Saifuzzaman & Zheng, 2014). Moreover, temporal differences between drivers can influence the response behaviour, such as whether the driver is in a hurry or pays attention to the ego vehicle. However, previous studies have already shown that a driver's personality is difficult to include in lane change models and often unknown to other drivers (e.g., Hidas (2005) and Sultan et al. (2002)). In general, predicting human behaviour is inherently difficult, and it is expected to have large portions of unexplained variances. Research modelling human behaviour often encounters low R^2 values as it is difficult for a single model to capture all the factors that predict human behaviour at a specific time (Ozili, 2023). Therefore, it is also argued that a low R^2 is not a particular problem when the predictor variables are significant.

Second, the linear regression models are limited in that they are based on a single moment in time (i.e., the start of the lane change). However, the ego vehicle's lane change manoeuvre, the follower vehicle's response, and the possible interaction between the drivers are not instantaneous events. The behaviour of the vehicles after the start of the lane change can influence the follower vehicle's response. For instance, the ego vehicle can slightly decelerate when approaching the slowlead vehicle at the start of the lane change and accelerates after initiating the lane change. Then, the ego vehicle increases speed, and the velocity difference between the follower vehicles becomes lower, so the follower vehicles can decelerate less. However, the values at the start of the lane change suggested that the ego vehicle was decelerating, resulting in a prediction of a higher deceleration. Additionally, there is a correlation between the timing, duration and minimum acceleration of the follower vehicle. That is, the timing of the response of the follower vehicle also influences the duration and minimum acceleration of the follower vehicle's response. Thus, considering only the start of the lane change to determine the response might be limited, resulting in more unexplained variance.

Third, linear regression models may not be the best method for predicting the follower vehicle's deceleration response. More complex stimulus-response models might better describe the follower vehicle's response. For example, the popular car-following models are non-linear (e.g., the GHR model and Gipps' model) (Zhang et al., 2021). Moreover, it can be reasoned that a good response model should as well include the transition from a response behaviour to car-following behaviour, similar to how car-following models incorporate a transition between free-flow and car-following states (e.g., IDM model (Treiber et al., 2000)).

6.3. Limitations

This study has several limitations that are acknowledged and reflected in the following sections. The generalisability of the results, the restrictions of the dataset used, and the method of characterising the response behaviour are discussed.

6.3.1. *Generalisability*

The results of the study have limited generalisability due to specific methodological choices. The scenario analysed includes a desirable lane change on the highway where the ego vehicle has a mean velocity ranging between 20 to 40 m/s and may not apply to other traffic scenarios. Previous literature has shown that the driving behaviour differs in other lane change scenarios. For example, in urban traffic scenarios, drivers have also been shown to rely on driver-based communication cues as the vehicles' velocities are lower (Domeyer et al., 2019; Lee et al., 2021). Moreover, a mandatory lane change (e.g., merging on the highway) can influence the behaviour of drivers because there is an urgency to change lanes (Gipps, 1986; Schakel et al., 2012). In addition, Dietrich et al. (2019) demonstrated that drivers would show more cooperative behaviour in congested traffic.

Moreover, the results of the study only apply to passenger cars changing lanes, as lane changes made by trucks were disregarded. This is because the motion characteristics of trucks differ from those of passenger cars, such as lower maximum velocity and acceleration capabilities (Schieben et al., 2019). It is expected a lane change of a truck has a higher impact on the follower vehicle, and as such, the response behaviour is different. However, it was out of the scope of this research to investigate this effect. Therefore, the results apply specifically to passenger cars changing lanes and might not be generalisable to lane changes made by a truck.

Lastly, this study only analysed decelerating responses and did not account for the possibility of the follower vehicle changing lanes in response to the ego vehicle's lane change. Stoll et al. (2019) showed that in cooperative situations, the follower vehicle preferred a lane change to the left instead of decelerating when there was a third lane available. Because the situations in which the follower vehicle cooperates by changing to the left lane were beyond the scope of this research, the results are less generalisable. However, these research findings of a decelerating response of the follower vehicle do apply to normal highway conditions without entry, exit or ending lanes. In addition, the findings of the study also apply to cut-in or forced lane changes, as the research did not make a distinction between these types of lane changes.

6.3.2. *HighD Dataset*

The highD dataset (a naturalistic dataset recorded with an unmanned aerial vehicle) constrains the analyses in three ways. First, the dataset does not provide turn indicator or brake light information as this is not visible from a top view. The use of an indicator light has been shown to be an important communication cue when changing lanes. Research showed that in cases where the ego vehicle used the indicator lights, the follower vehicle was more inclined to cooperate compared to no indicator lights (Stoll et al., 2019). Similarly, the earlier the ego vehicle would indicate its intention using the indicator light, the more cooperative it was perceived by the follower vehicle (Kauffmann et al., 2018). The turn indicator likely influences the decelerating response of the follower vehicle. Liu et al. (2022) showed that the turn indicator influenced the timing of the follower vehicle to release the acceleration pedal.

However, the ego vehicle's use of the turn indicator did not affect the follower vehicle's minimum acceleration (Liu et al., 2022). Here, the turn indicator is a redundant variable when descriptive variables are considered. The turn indicator is often used when the ego vehicle drives slower than the follower vehicle or when traffic density is high. In this research, the descriptive variables are used to characterise the response behaviour of the follower vehicle and might have limited the influence of missing the turn indicator information. Nevertheless, this research cannot make any claims about the response behaviour relative to the indicator light.

Second, the results may be influenced by the absence of trajectory information for motorcyclists in the highD dataset. This absence can lead to biased results, as the presence of motorcyclists in between vehicles may be overlooked, giving the appearance of a larger distance gap between vehicles. The impact of this constraint on the results is unknown.

Third, the length of the highway section recorded is 420 meters resulting in vehicles being, on average, 11.3 seconds recorded (ranging between 7.3 and 17.8 seconds). This time range is limited compared to other studies using drivers with long-term observations. This research focused on recording the start of the lane change until the moment of crossing the lane marking, but not necessarily the end of the lane change (i.e., when the ego vehicle stabilises on the new lane). This means that the response of the follower vehicle may have occurred outside of the recorded time range or before it became visible on the recording. In principle, these cases were classified as unclear responses and were disregarded from further analysis. However, this could have led to classifying lane changes as a no-deceleration response, while in reality, there was a response outside the recording.

Overall, the highD dataset used in this research has some limitations that might have influenced the research findings. Despite this, the highD dataset was an appropriate dataset for developing a human-like response model of the follower vehicle in a lane change scenario. The dataset was collected using an unobtrusive method, has a precision error of less than 10 cm, can locate all surrounding vehicles, and contains a total of 13379 lane change manoeuvres. Other available data sources at TNO would not have provided this research with this extensive large-scale and precise naturalistic vehicle trajectory information.

6.3.3. *Characterisation Response Behaviour*

The classification of the follower vehicle's response behaviour is limited by the time frame within which both vehicles are visible in the recording. This can lead to missed responses, as the recorded time frame is relatively short. In addition, this causes there to be no consistent time range before and after the ego vehicle starts the lane change manoeuvre in which the follower vehicle's response behaviour is investigated. That is, the time before and after the start of the lane change depends on when the ego vehicle started the lane change in the time range. Previous literature has used different time ranges to analyse the follower vehicle's response. For example, Yang et al. (2019) analysed the impact on the follower vehicle from the start of the lane change until the vehicle stabilises in the new lane. Liu et al. (2022) used as starting time the moment the ego vehicle reached the lane marking and measured the response after this moment. Both studies do not consider that the follower vehicle could respond before the lateral movement of the ego vehicle and overlook the possibility of the follower vehicle anticipating the lane change, cooperating, or responding to the turn indicator used before the lateral movement. Furthermore, Chauhan et al. (2022) investigated the follower vehicle's response over two time ranges: 5 seconds before the start of the lane change and during the lane change. The 5 seconds before the start of the lane change is considerably longer compared to the 1 second before the start of the lane change used in this study. Nevertheless, there are also many lane changes with more than 5 seconds before the start of the lane change due to the inconstant time range before and after the start of the lane change.

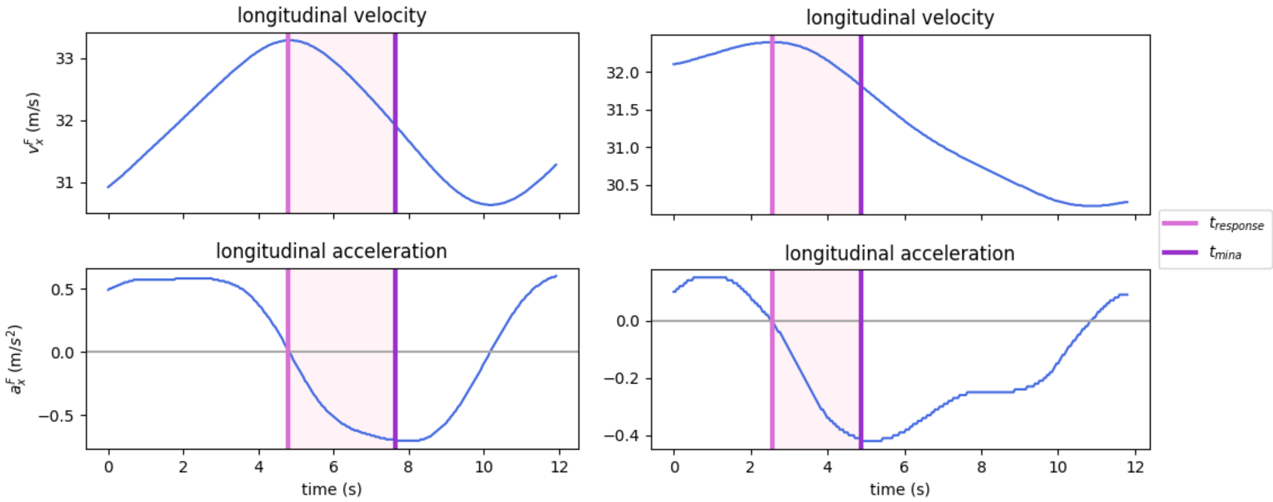
In the definitions of the time range to determine the response behaviour, the start of the lane change is the central element. However, literature presents different approaches to define the start of the lane change. The definition is most often related to the follower vehicle's lateral speed (Chauhan et al., 2022) or position (Liu et al., 2022). However, these definitions fail to consider that the follower vehicle can respond to the use of a turn indicator by the ego vehicle. It can be argued that in cooperative lane changes, the lane change interaction starts before the ego vehicle's lateral movement, as the follower vehicle can also respond to the turn indicator. This suggests the need for a consistent definition of the start time of the lane change that considers both the physical movement and the communication cues of the ego vehicle. However, as information on the turn indicator was not available in the used dataset, this was not explored.

In this research, the response behaviour of the follower vehicle was classified based on a velocity difference of at least 0.5 km/h between the start of the response and the timing of the minimum acceleration. The velocity change value was used as this includes both the minimum acceleration and response duration. That is, a vehicle with a small minimum acceleration for a long time can change in velocity as much as another vehicle with a lower minimum acceleration for a short time. The threshold was chosen after visually inspecting the behaviour of the follower vehicles and determining that decelerations below this value were negligible fluctuations and not considered a response to the lane change manoeuvre of the ego vehicle. While this classification method may seem reasonable, alternative methods could have been used to better differentiate between actual responses and random fluctuations in velocity.

Drivers will respond to a lane change manoeuvre by decelerating and subsequently return to a constant speed after reaching the desired car-following distance. This research used the maximum deceleration to quantify the response intensity (similar to Liu et al. (2022)). This is different from the approach of Yang et al. (2019), who only looked at the change in the follower vehicle's velocity during the lane change manoeuvre of the ego vehicle. However, it is important to note that this method may not capture the entire response intensity and duration, as the entire response could start before the lane change manoeuvre and last longer than it. In this study, the minimum acceleration and the time it took to reach that value were used to characterise the decelerating response. It is assumed that people will decelerate and return to a constant speed (or start to accelerate) at a similar rate. However, the analysis showed that this does not hold for all decelerating responses of the follower vehicles, as shown in Figure 12.

Figure 12

Comparison of two decelerating responses of follower vehicle's



Note. The example on the left illustrates a deceleration response where the follower vehicle returns to a constant value is roughly the same time as reaching the minimum acceleration. The right example shows where the time to return to a constant velocity is more than twice as long.

The deceleration pattern observed on the right of Figure 12 might be due to the so-called relaxation phenomenon. Here, follower vehicles tend to accept smaller gap sizes and largely apply small decelerations over time in lane change scenarios (Schakel et al., 2012). It can be reasoned that drivers might first apply a strong deceleration to avoid a critical gap size and continue to decelerate with smaller values to reach a desired car-following distance eventually. This suggests that the most comprehensive method might have been to track the start of deceleration until the returning point to a constant speed. However, this was not possible to investigate in this research due to the limited time range.

6.4. Future Work

This research aimed to characterise the decelerating response of the follower vehicle in a lane change scenario on the highway. The findings provide valuable perspectives that could be explored in potential future research. Several future research directions are suggested.

Future research could address the need to clearly define the interested time range and start of the lane change to determine the follower vehicle's response to the lane change manoeuvre of the ego vehicle.

Simultaneously, from this time range definition, it should be recognised whether the entire response can be captured with a recording of a specific highway section or requires tracking one vehicle. Additionally, it should be critically analysed when a follower vehicle responds to the ego vehicle's lane change manoeuvre such that random fluctuations in velocity should not be recognised as a decelerating response. Moreover, this research has shown that the acceleration of the leader vehicle plays a role in the decelerating behaviour of the follower vehicle. It is suggested to investigate which behaviour of the follower vehicle is specifically a response to the ego vehicle's lane change manoeuvre and how this could be incorporated into existing car-following models.

This research did not examine the influence of the ego vehicle using the turn indicator because this information could not be extracted from the used dataset. Future research should evaluate the influence of the turn signal in the follower vehicle's decelerating response as it is expected to be an important predictor. In addition, it should be analysed whether the use of the turn indicator should be incorporated in the definition of the start of the lane change. Investigation of the use of turn indicators in lane change scenarios can help to better differentiate cooperative lane change from all the decelerating responses, allowing for more accurate conclusions about the timing and manner of cooperation by the follower vehicle.

This study could be further extended by incorporating the scenario of the following vehicle changing lanes to the left. Stoll et al. (2019) found that drivers are more likely to change lanes when possible than to decelerate in cooperative lane changes. The current research only applies to scenarios where the following vehicle needs to decelerate. In addition, the linear regression models predicting the response timing, duration and minimum acceleration are not applicable when the following vehicle does not need to decelerate. Currently, the models will always make predictions, including negative durations and positive minimum acceleration values. A more comprehensive characterization of the following vehicle's behaviour would consider situations where there is a no-decelerating response, a decelerating response, or a response by changing lanes. Similarly, this research presents three separate linear regression models characterising the response behaviour, but future research could focus on combining these models into a single model.

7. Conclusion

This Chapter will conclude this research by summarising the key research findings. The research findings are discussed in relation to the research questions. In addition, the value of the results is discussed with respect to the findings of other studies.

The introduction of AVs on the road caused a transition period where vehicles with different levels of automation operate alongside human road users. Therefore, it is of interest to ensure that AVs drive according to human standards. Modelling human driving behaviour can help to establish AVs drive predictably and according to social expectations. Specifically, this research focuses on examining the interdependence and interaction between a vehicle changing lanes and the rear-approaching vehicle on the target lane during highway lane changes. While previous literature mainly focused on the behaviour of the vehicle changing lanes, limited research has modelled the behaviour of the follower vehicle. Nevertheless, the follower vehicle's behaviour can play a crucial role in the lane change manoeuvre, especially in cooperative lane changes where it decelerates to enable the vehicle changing lanes to merge. Therefore, this research aimed to model the decelerating response of the follower vehicle.

A naturalistic vehicle trajectory information dataset was analysed to model human-like behaviour. The lane changes in which the follower vehicle decelerated in relation to another vehicle's lane change manoeuvre were characterised. The central questions for this research were to predict when, for how long, and with which minimum acceleration value the follower vehicle responds. These questions were answered by developing three linear regression models that predict the timing, duration and minimum acceleration of the follower vehicle's decelerating response based on the descriptive variables at ego vehicle's start of the lane change.

The three linear regression models are different from each other but have overlapping predictor variables. In all models, the leader vehicle's acceleration is an important variable influencing the follower vehicle's response behaviour. That is, if the leader vehicle decelerates, the follower vehicle response is earlier, takes longer and with a lower minimum acceleration than when the leader vehicle accelerates. In addition, the duration and minimum acceleration models include the slowlead vehicle's acceleration. This was not expected as the slowlead vehicle is not in the same lane as the follower vehicle. Together, the results indicate the importance of including the general driving situations when explaining the response behaviour of the follower vehicle. This finding suggests that other models describing the follower vehicle's response are limited as they do not account for the influence of other vehicles (e.g., Chauhan et al., 2022; Hidas, 2005; Liu et al., 2022).

The cross-correlation value of the linear regression model predicting the timing of the response is extremely low, which questions the prediction of the model. Additionally, the duration and minimum acceleration models are more similar, which was expected because the three models characterise the response behaviour together. Therefore, it seems that a linear regression model using descriptive variables at the start of the lane change cannot accurately predict the timing of the response. It was expected that the timing of the response was related to whether or not the follower vehicle cooperated. It is possible that without distinguishing between cooperative and non-cooperative lane changes, the overall prediction of the response timing is uncertain.

The linear regression models of the duration and minimum acceleration both include the velocity difference and distance gap between the follower and ego vehicles. However, the contribution of the variables is slightly different. The follower vehicle's response duration was shorter if the distance gap was smaller, but this effect was weaker when the velocity difference was high. In the linear regression model predicting the minimum acceleration, a smaller distance gap results in a lower minimum acceleration. Additionally, the minimum acceleration was lower for a higher velocity difference, and this effect was more prominent when the ego vehicle decelerated. The significant influence of the velocity difference and distance gap was expected because of car-following models and Liu et al. (2022) also used these variables to describe the minimum acceleration. The findings suggest that the response behaviour is closely related to car-following behaviour.

Overall, this research characterised the follower vehicle's response timing, duration and minimum acceleration to a lane change manoeuvre on the highway by developing three linear regression models. However, the three linear regression models do not explain about 75% of the variance in the follower vehicle's response behaviour. This is considerably high and implies that future research is needed to predict the response behaviour better. Still, the results provide some interesting insights that guide the development of a human-like response model with the goal of ensuring AVs drive according to human standards.

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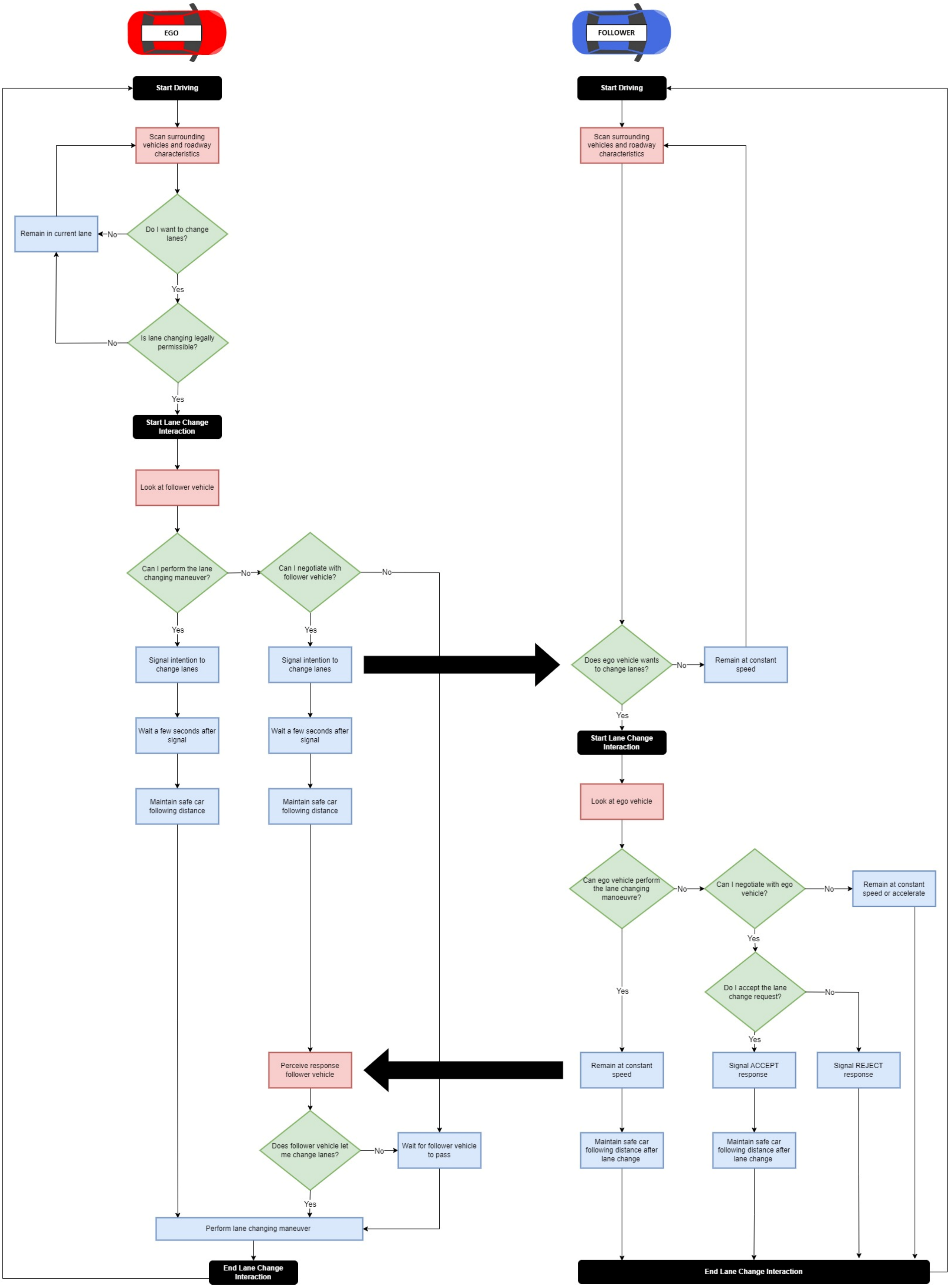
Appendix A.
Entire Flowchart

Figure A1

Flowchart of the process of a lane change manoeuvre



Note. The red boxes require the driver to perceive specific information, the green boxes represent a decision the driver needs to make, and the blue boxes are an action the driver performs.

Appendix B.
Results *t*-tests

Table B1

Differences between response categories 1 and 2 in the descriptive variables

Variable ($t_{startLC}$)	Response 1 No-decelerating response			Response 2 Decelerating response				
	N	*M*	*SD*	*N*	*M*	*SD*	*t*	*p*
v_x^E	125	29.55	3.99	310	28.96	3.89	1.42	.157
v_x^F	125	32.07	4.02	310	32.89	4.34	-1.81	.071
v_x^L	119	32.45	3.87	302	32.19	4.04	0.59	.555
v_x^S	123	26.42	3.32	309	25.80	2.97	1.93	.055
a_x^E	125	0.23	0.33	310	0.04	0.35	5.26	< .001
a_x^F	125	0.21	0.17	310	0.04	0.34	6.83*	< .001
a_x^L	119	0.22	0.27	302	0.01	0.36	6.55*	< .001
a_x^S	123	0.07	0.23	309	-0.04	0.29	3.70	< .001
y_{centre}^E	125	-1.84	0.36	310	-187	0.35	0.60	.550
a_y^E	125	0.15	0.08	310	0.15	0.08	-0.14	.887
$\Delta v_x^{F,E}$	125	2.53	2.30	310	3.93	2.79	-5.41*	< .001
$\Delta v_x^{E,L}$	119	-3.05	3.15	302	-3.31	3.08	0.80	.424
$\Delta v_x^{E,S}$	123	3.09	2.57	309	3.14	3.08	-0.17	.866
$\Delta v_x^{F,L}$	119	-0.54	2.80	302	0.62	2.61	-4.03	< .001
$THW^{F,E}$	125	2.05	0.76	310	1.82	0.72	2.88	.004
$THW^{E,L}$	119	1.12	1.31	302	0.88	1.43	1.63	.105
$THW^{E,S}$	123	1.63	0.99	309	1.70	1.05	-0.59	.557
$THW^{F,L}$	119	3.11	1.30	302	2.62	1.48	3.15	.002
$\Delta x^{F,E}$	125	61.15	26.78	310	55.98	27.07	1.81	.071
$\Delta x^{E,L}$	119	30.11	43.05	302	22.41	45.78	1.58	.115
$\Delta x^{E,S}$	132	43.96	32.36	309	43.92	1.87	0.01	.990
$\Delta x^{F,L}$	119	95.79	48.60	302	82.69	54.16	2.30	.022
$TTC^{F,E}$	110	112.8	727.97	294	32.08	133.94	1.16*	.250
$TTC^{E,L}$	17	81.68	100.60	37	137.37	312.62	-0.71	.478
$TTC^{E,S}$	115	18.20	12.73	283	28.21	74021	-2.19*	.029
$TTC^{F,L}$	40	410.33	1716.6	168	95.01	207.10	1.16*	.253
$ratio_{\Delta v,\Delta x}^{F,E}$	125	.04	.05	310	0.07	0.05	-6.66	< .001
$ratio_{\Delta v,\Delta x}^{E,L}$	83	-0.74	4.34	176	-0.83	2.81	0.21	.832
$ratio_{\Delta v,\Delta x}^{E,S}$	123	0.07	0.05	309	0.07	0.06	-0.50	.618
$ratio_{\Delta v,\Delta x}^{F,L}$	119	-0.01	0.03	302	0.00	0.03	-4.76	< .001

Note. * indicates the use of the Welch's *t*-test because of unequal variances between the categories.

Table B2

Differences between situation categories A and B in the descriptive variables

Variable ($t_{startLC}$)	Situation A Influence ego vehicle			Situation B Influence ego and leader vehicles				
	N	*M*	*SD*	*N*	*M*	*SD*	*t*	*p*
v_x^E	111	29.70	4.38	197	28.58	3.52	2.30*	.023
v_x^F	111	33.10	4.98	197	32.82	3.92	0.54	.592
v_x^L	103	32.59	4.69	197	32.03	3.64	1.14	.255
v_x^S	111	25.85	3.32	196	25.80	2.74	0.16	.872
a_x^E	111	0.06	0.38	197	0.02	0.34	1.06	.291
a_x^F	111	0.02	0.32	197	0.05	0.35	-0.56	.577
a_x^L	103	0.01	0.43	197	0.00	0.32	0.27*	.791
a_x^S	111	-0.04	0.32	196	-0.04	0.27	-0.06	.955
y_{centre}^E	111	-1.85	0.35	197	-1.87	0.34	0.66	.507
a_y^E	111	0.14	0.08	197	0.16	0.08	-2.65	.009
$\Delta v_x^{F,E}$	111	3.40	2.78	197	4.24	2.76	-2.56	.011
$\Delta v_x^{E,L}$	103	-3.07	3.51	197	-3.45	2.84	0.95*	.345
$\Delta v_x^{E,S}$	111	3.84	3.59	196	2.74	2.69	2.82*	.005
$\Delta v_x^{F,L}$	103	0.30	3.43	197	0.80	2.05	-1.37*	.174
$THW^{F,E}$	111	2.18	0.76	197	1.63	0.63	6.53*	< .001
$THW^{E,L}$	103	1.96	1.89	197	0.32	0.59	8.62*	< .001
$THW^{E,S}$	111	1.84	1.09	196	1.60	1.00	2.00	.046
$THW^{F,L}$	103	3.98	1.68	197	1.93	0.66	11.91*	< .001
$\Delta x^{F,E}$	111	67.76	28.92	197	49.50	23.71	5.67*	< .001
$\Delta x^{E,L}$	103	56.38	61.63	197	4.94	17.87	8.29*	< .001
$\Delta x^{E,S}$	111	50.21	36.69	196	40.05	30.10	2.48*	.014
$\Delta x^{F,L}$	103	128.55	64.76	197	59.16	25.28	10.46*	< .001
$TTC^{F,E}$	102	55.20	209.08	190	19.64	63.25	1.68*	.096
$TTC^{E,L}$	17	205.52	395.68	20	79.43	213.7	1.23	.226
$TTC^{E,S}$	105	27.47	80.69	176	28.36	70.55	-0.10	.923
$TTC^{F,L}$	35	97.90	129.29	132	93.04	223.9	0.12	.902
$ratio_{\Delta v,\Delta x}^{F,E}$	111	0.05	0.05	197	0.08	0.04	-6.95	< .001
$ratio_{\Delta v,\Delta x}^{E,L}$	85	-0.56	2.37	91	-1.09	3.15	1.24	.217
$ratio_{\Delta v,\Delta x}^{E,S}$	111	0.08	0.05	196	0.07	0.06	0.86	.391
$ratio_{\Delta v,\Delta x}^{F,L}$	103	-0.01	0.02	197	0.01	0.04	-3.48*	< .001

Note. * indicates the use of the Welch's *t*-test because of unequal variances between the categories.

Appendix C. Response Timing

This Appendix provides supplementary information on the analyses of the follower vehicle's response timing. First, the relationships between the descriptive variables and the response timing are examined through visualisation (see Figures C1 to C6) and the Pearson correlation coefficient (see Table C1). Second, the development and intermediate results of the linear regression model are described.

C. 1. Relationships Between Response Timing and Descriptive Variables

Figure C1

Response timing versus the behaviour of the ego vehicle at the start of the lane change

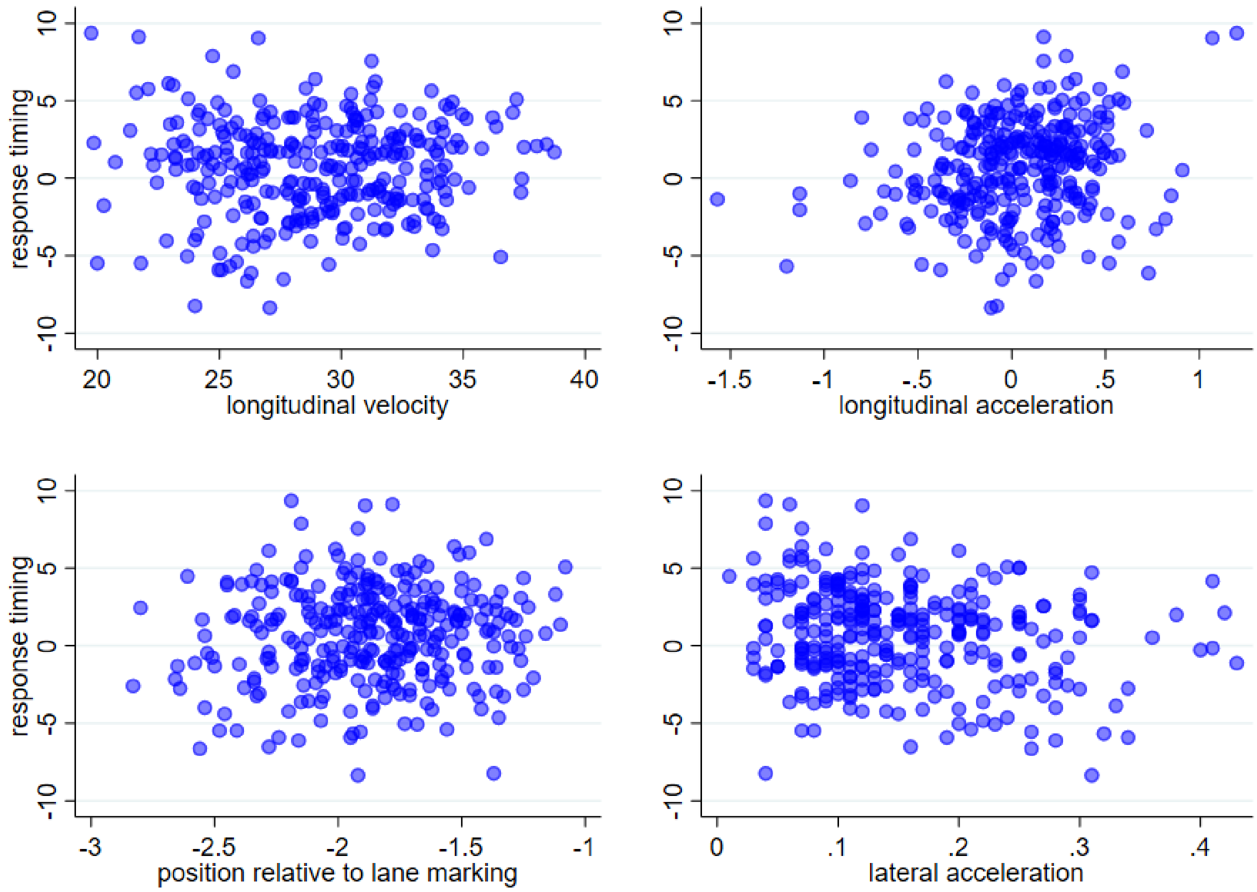


Figure C2

Response timing versus the longitudinal behaviour of the follower, leader and slowlead vehicles at the start of the lane change

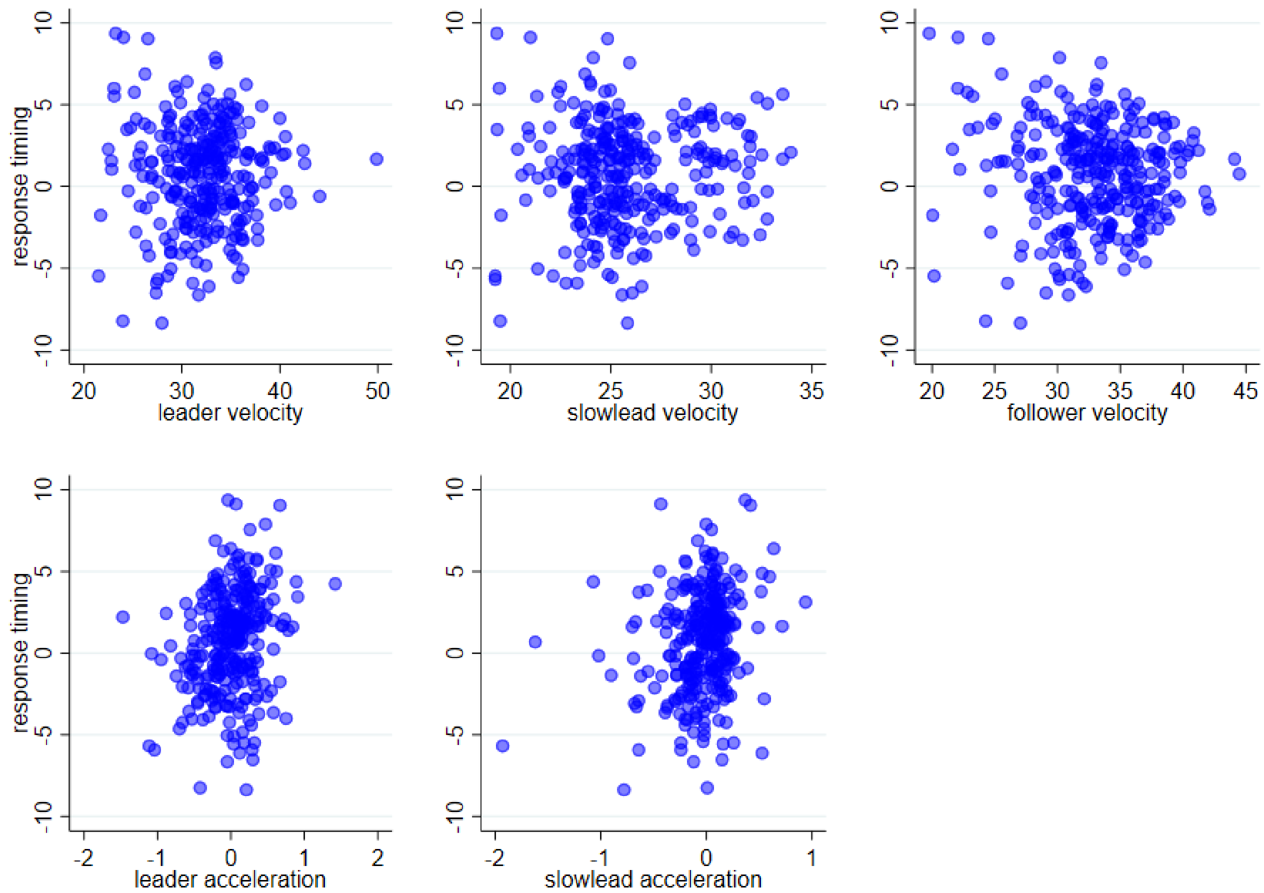
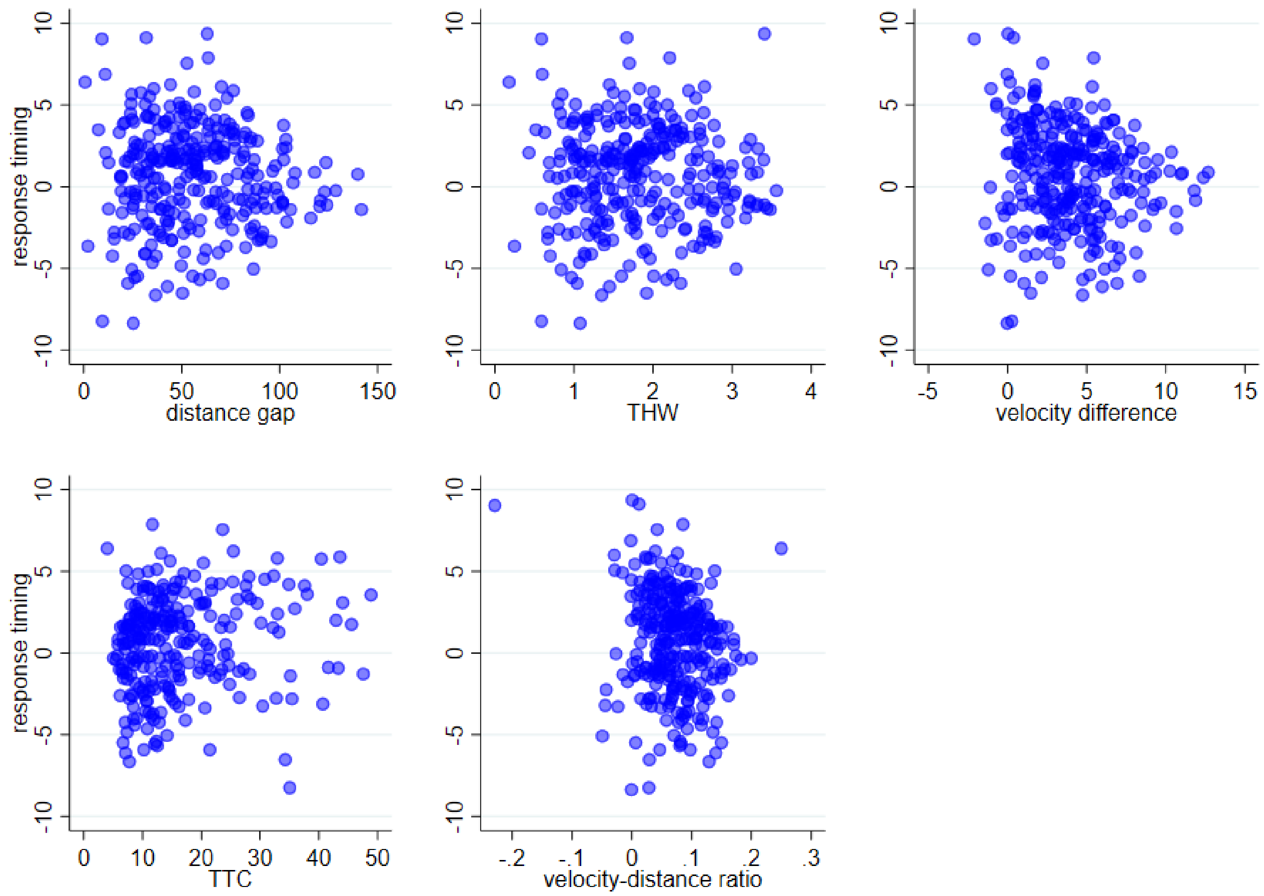


Figure C3

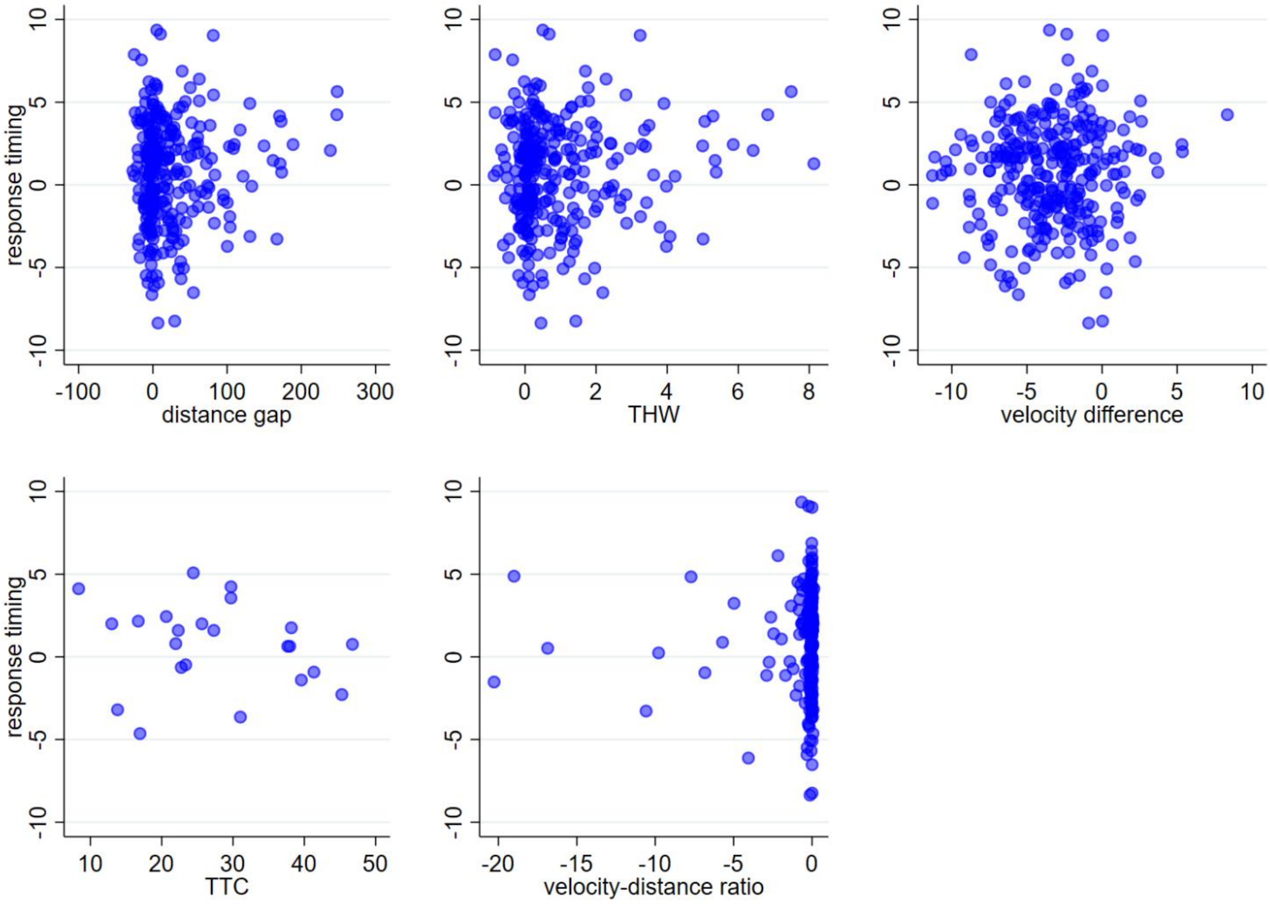
Response timing versus the relational variables between the follower and ego vehicles at the start of the lane change



Note. The TTC graph is cut-off at 50 seconds to highlight the relevant data and eliminate any extreme outliers that distort the visual representation.

Figure C4

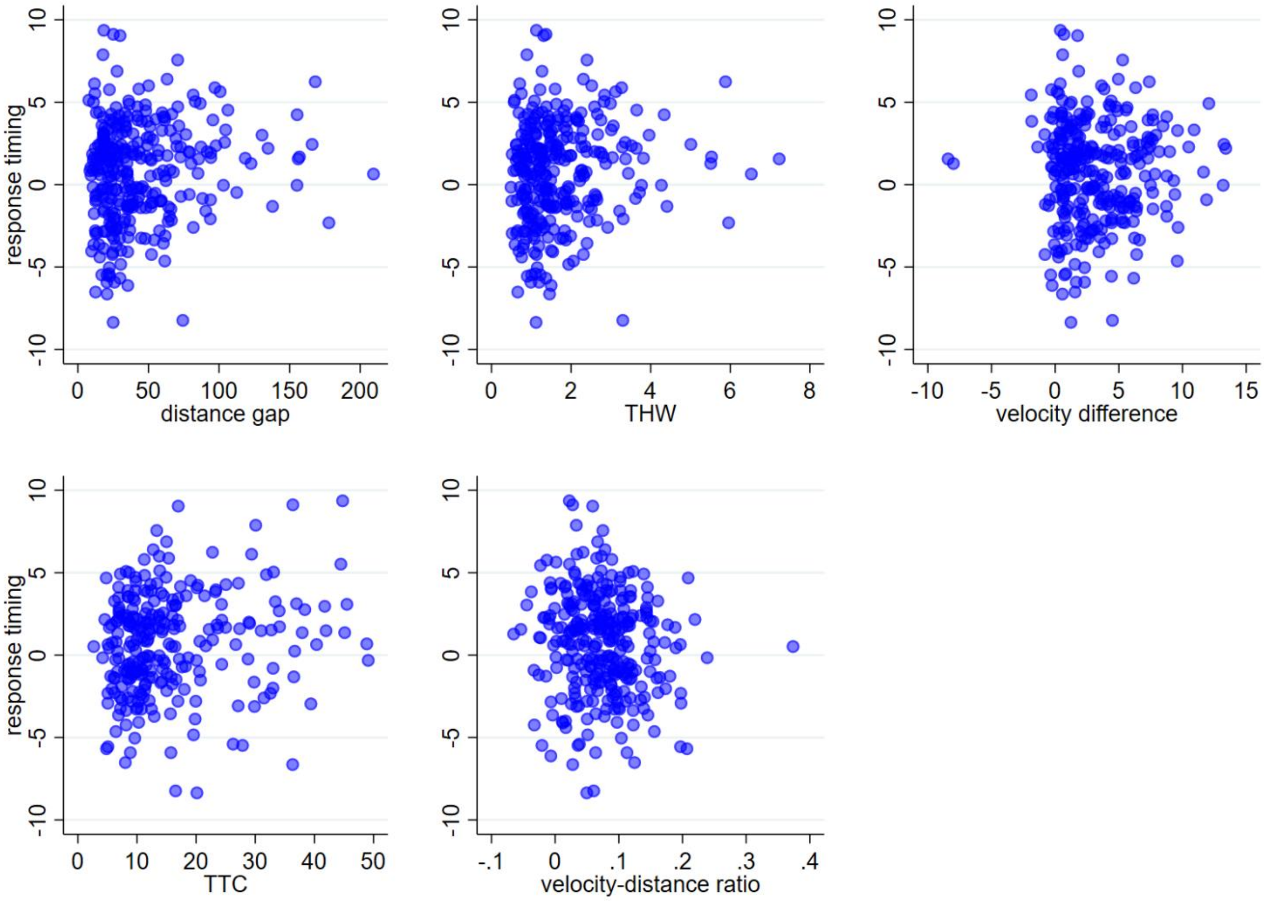
Response timing versus the relational variables between the leader and ego vehicles at the start of the lane change



Note. The TTC graph is cut-off at 50 seconds to highlight the relevant data and eliminate any extreme outliers that distort the visual representation.

Figure C5

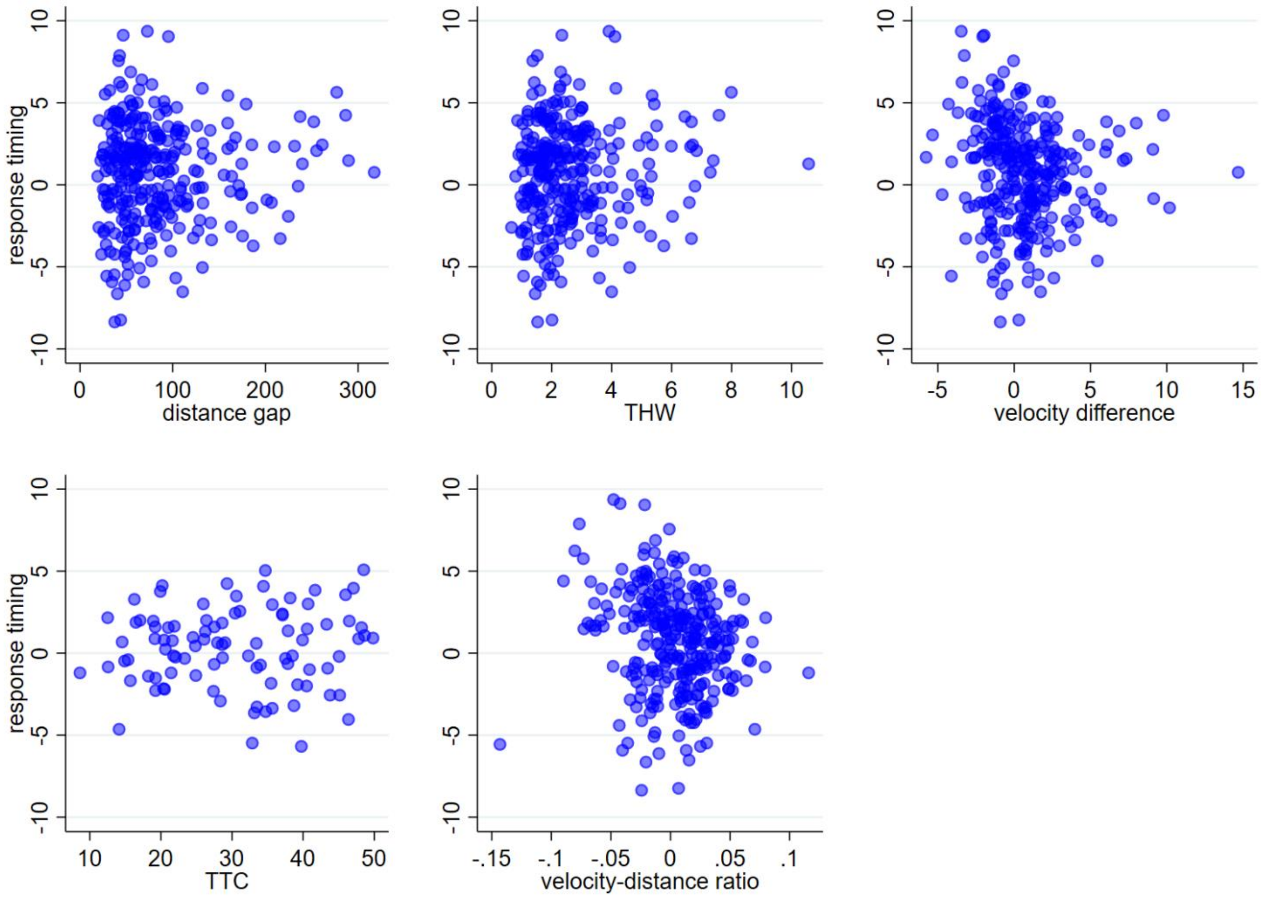
Response timing versus the relational variables between the slowlead and ego vehicles at the start of the lane change



Note. The TTC graph is cut-off at 50 seconds to highlight the relevant data and eliminate any extreme outliers that distort the visual representation.

Figure C6

Response timing versus the relational variables between the leader and follower vehicles at the start of the lane change



Note. The TTC graph is cut-off at 50 seconds to highlight the relevant data and eliminate any extreme outliers that distort the visual representation.

Table C1

Pearson correlation coefficient between the response timing and descriptive variables

Variable ($t_{startLC}$)	Observations	*r*	*p*
v_x^E	308	.03	.588
v_x^F	308	-.07	.243
v_x^L	300	-.00	.998
v_x^S	307	.02	.383
a_x^E	308	.21	< .001**
a_x^L	300	.25	< .001**
a_x^S	307	.21	< .001**
y_{centre}^E	308	.08	.160
a_y^E	308	-.19	< .001**
$\Delta v_x^{F,E}$	308	-.15	.010*
$\Delta v_x^{E,L}$	308	.03	.642
$\Delta v_x^{E,S}$	307	.01	.911
$\Delta v_x^{F,L}$	300	-.13	.025*
$THW^{F,E}$	308	-.02	.782
$THW^{E,L}$	300	.07	.225
$THW^{E,S}$	307	.12	.011*
$THW^{F,L}$	300	.07	.245
$\Delta x^{F,E}$	308	-.05	.362
$\Delta x^{E,L}$	300	.08	.156
$\Delta x^{E,S}$	307	.13	.019*
$\Delta x^{F,L}$	300	.05	.433
$TTC^{F,E}$	292	.16	.007**
$TTC^{E,L}$	37	.11	.508
$TTC^{E,S}$	281	.05	.382
$TTC^{F,L}$	167	.12	.136
$ratio_{\Delta v,\Delta x}^{F,E}$	308	-.16	.004**
$ratio_{\Delta v,\Delta x}^{E,L}$	176	.01	.927
$ratio_{\Delta v,\Delta x}^{E,S}$	307	-.12	.039*
$ratio_{\Delta v,\Delta x}^{F,L}$	300	-.19	< .001**

Note. * $p < 0.05$; ** $p < 0.01$

C. 2. Development of the Linear Regression Model

The development of the linear regression model for the follower vehicle's response timing involves multiple steps. These five steps are described, and the intermediate findings are discussed. The first step involved identifying the most likely significant predictor variables for the follower vehicle's response timing using a backward stepwise approach. The candidate predictor variables for the stepwise analysis were based on variables that previous literature suggested being important and the variables that are significantly correlated, being:

- Ego vehicle's acceleration
- Ego vehicle's lateral acceleration
- Velocity difference between the follower and ego vehicles
- Ratio of the velocity difference and distance gap between the follower and ego vehicles
- Leader vehicle's acceleration
- Velocity difference between the follower and leader vehicles
- Ratio of the velocity difference and distance gap between the follower and leader vehicles
- Slowlead vehicle's acceleration
- Distance gap between the slowlead and ego vehicles
- Ratio of the velocity difference and distance gap between the slowlead and ego vehicles

The backward stepwise approach identified four predictor variables: the acceleration of the ego and leader vehicles, the lateral acceleration of the ego vehicle, and the velocity-distance ratio between the follower and ego vehicles. These results provide insight into the importance of these variables in further analysis.

In the second step, the variables related to the ego and follower vehicles were more thoroughly investigated since the response timing of the follower vehicle is essentially a reaction to the ego vehicle. The following observations were made. First, the distance-related predictors (i.e., THW and distance gap) between the follower and ego vehicles were found not to be significant predictors. Second, the velocity of the ego and follower vehicles were also no significant predictors of the follower vehicle's response timing. Third, the velocity difference between the follower and ego vehicles was found to be as good a predictor as the velocity-distance ratio. Fourth, the longitudinal and lateral acceleration of the ego vehicle were determined to be the best predictors of the follower vehicle's response timing. Fifth, it was investigated whether there was an interaction effect between the ego vehicle's acceleration and its velocity, distance gap, and velocity difference with the follower vehicle. No interaction effect was found between the distance gap and velocity difference, but an interaction effect was found between the ego vehicle's acceleration and the velocity difference. The best linear regression model of the follower vehicle's response timing considering the descriptive variables of the follower and ego vehicles is presented in Table C2 ($F(3, 246) = 13.19$, $p < .001$, $R^2 = 0.14$).

Table C2

The linear regression model of the timing of the response using the descriptive variables of the follower and ego vehicles

Variable ($t_{startLC}$)	Coefficient	Standard Error	*t*	*p*	[95% confidence interval]
a_x^E	3.68	0.83	4.44	< .001	2.05, 5.31
$a_x^E * \Delta v_x^{F,E}$	-0.41	0.17	-2.44	.015	-0.74, -0.08
a_y^E	-9.46	2.30	-4.11	< .001	-14.00, -4.92
(constant)	1.97	0.41	4.87	< .001	1.17, 2.77

The third step extended the linear regression model by considering the influence of the leader vehicle. Results from the *t*-test indicated there was no difference in response timing between situations A and B, suggesting that the presence of a leader vehicle did not impact the response timing. A multilevel linear regression analysis also showed that the situation is not a nested group that would improve the model's fit. Namely, the likelihood-ratio test comparing the multilevel model based on the situation to the ordinary linear regression (as in Table C2) was not significant ($X^2(1) = 0.00$, $p = 1.000$). Nevertheless, the correlation results indicate that the leader's velocity difference and acceleration are significant predictors. The analysis of adding the descriptive variables related to the leader vehicle showed that the acceleration of the leader vehicle and the velocity-distance ratio between the leader and follower improved the model. However, only the leader vehicle's acceleration remained significant when added together. The interaction effect of the leader vehicle's acceleration and the velocity difference between the leader and follower vehicles was also investigated, but no significant interaction effect was found. The improved linear regression model for predicting the response timing of the follower vehicle is shown in Table C3 ($F(4, 233) = 14.01$, $p < .001$, $R^2 = 0.19$).

Table C3

The linear regression model of the timing of the response using the descriptive variables of the follower, ego, and leader vehicles

Variable ($t_{startLC}$)	Coefficient	Standard Error	*t*	*p*	[95% confidence interval]
a_x^E	2.99	0.83	3.61	< .001	1.36, 4.62
$a_x^E * \Delta v_x^{F,E}$	-0.42	0.16	-2.57	.011	-0.75, -0.10
a_x^L	2.00	0.56	3.57	< .001	0.89, 3.10
a_y^E	-9.21	2.26	-4.08	< .001	-13.66, -4.76
(constant)	1.95	0.40	4.90	< .001	1.17, 2.74

In the fourth step, the influence of the slowlead vehicle was investigated by considering additional descriptive variables related to the slowlead. However, none of the variables (i.e., the acceleration of the slowlead and the distance gap, velocity difference, and velocity-distance ratio between the slowlead and ego) were found to be significant predictors and improved the model's fit. In addition, no significant interaction effects were observed. Therefore, the linear regression model presented in Table C3 remains the best model for predicting the response timing of the follower vehicle.

In the fifth and final step, the presence of nested groups was tested. The groups were created based on the number of lanes on the highway or whether the ego vehicle changed lanes from the right or middle lane. The results of the multilevel linear regression analysis, using either of the nested groups, did not result in an improved model compared to the normal linear regression model in Table C3 ($X^2(1) = 0.00$, $p = 1.000$; $X^2(1) = 0.00$, $p = 1.000$). Hence, the final best regression model to predict the follower vehicle's response timing using the descriptive variables at the start of the lane change is presented in Table C3.

Appendix D.
Response Duration

This Appendix provides supplementary information on the analyses of the follower vehicle's response duration. First, the relationships between the descriptive variables and the response duration are examined through visualisation (see Figures D1 to D6) and the Pearson correlation coefficient (see Table D1). Second, the development and intermediate results of the linear regression model are described.

D. 1. Relationships Between Response Duration and Descriptive Variables

Figure D1

Response duration versus the behaviour of the ego vehicle at the start of the lane change

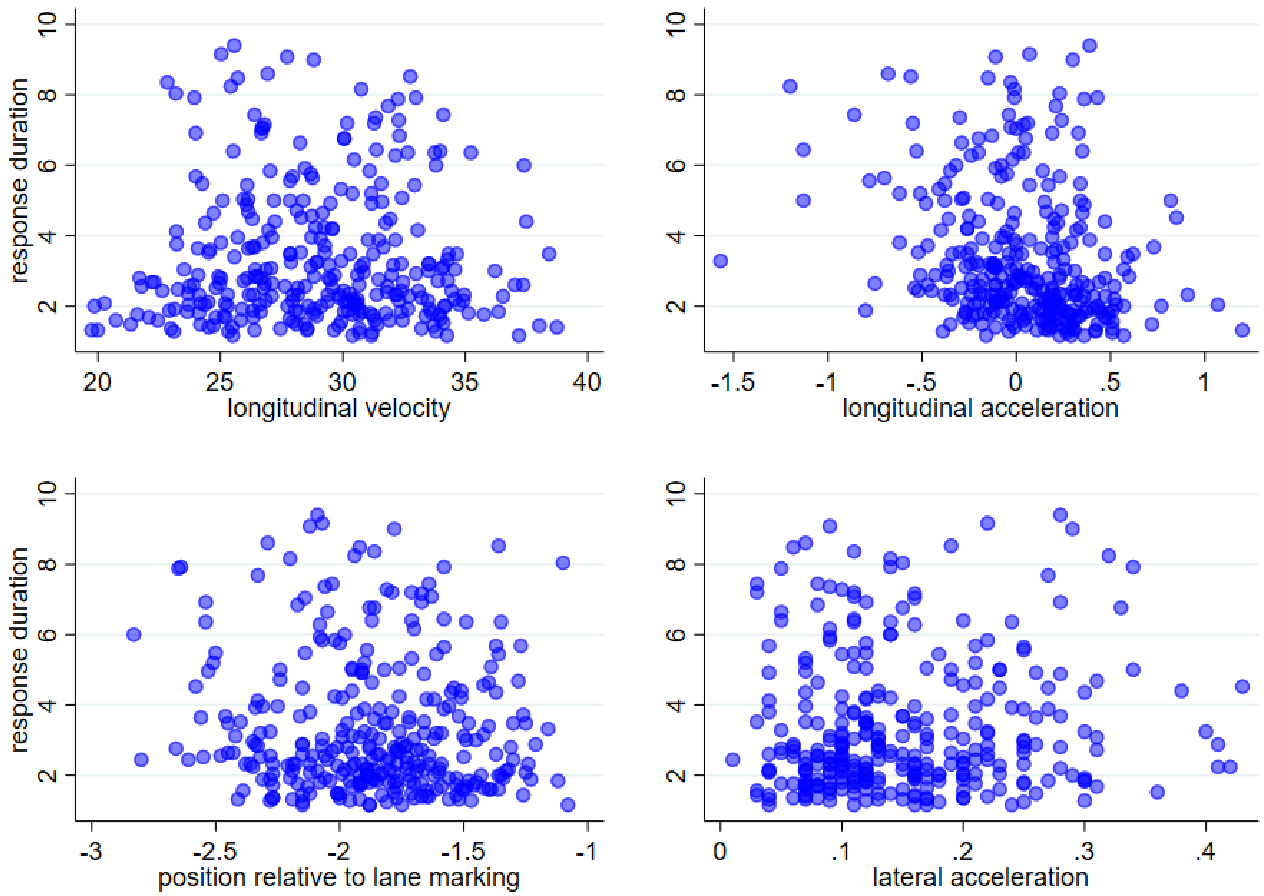


Figure D2

Response duration versus the longitudinal behaviour of the follower, leader and slowlead vehicles at the start of the lane change

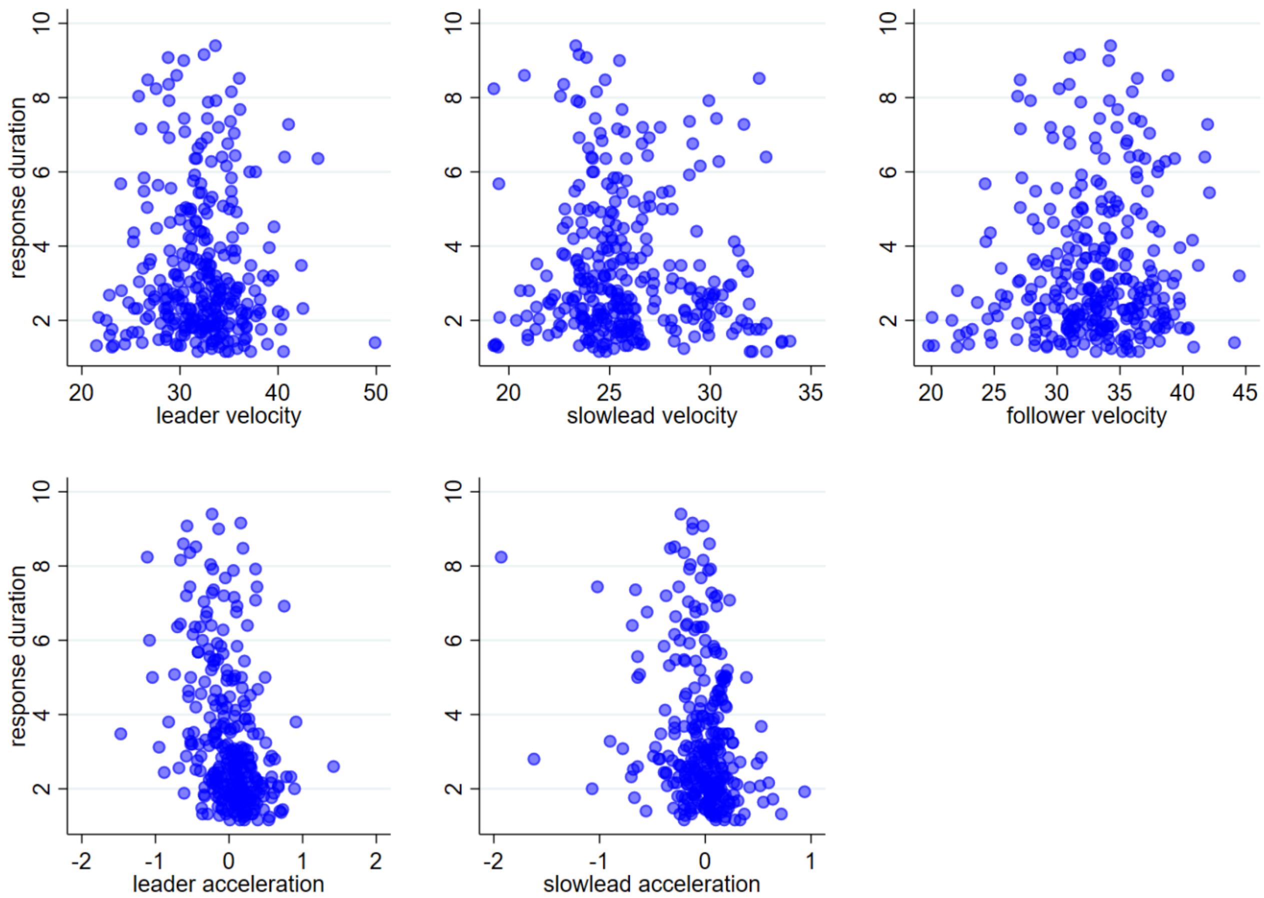
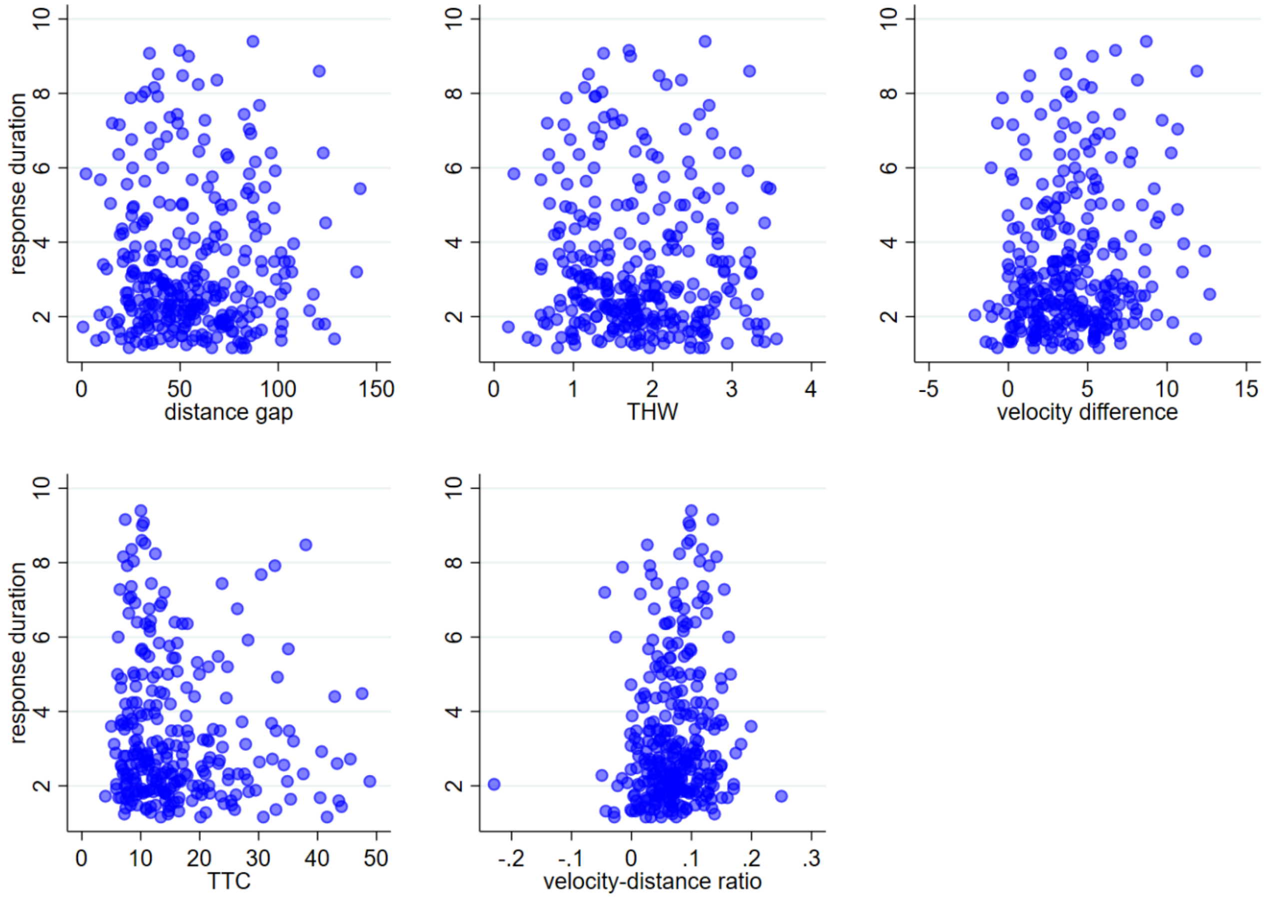


Figure D3

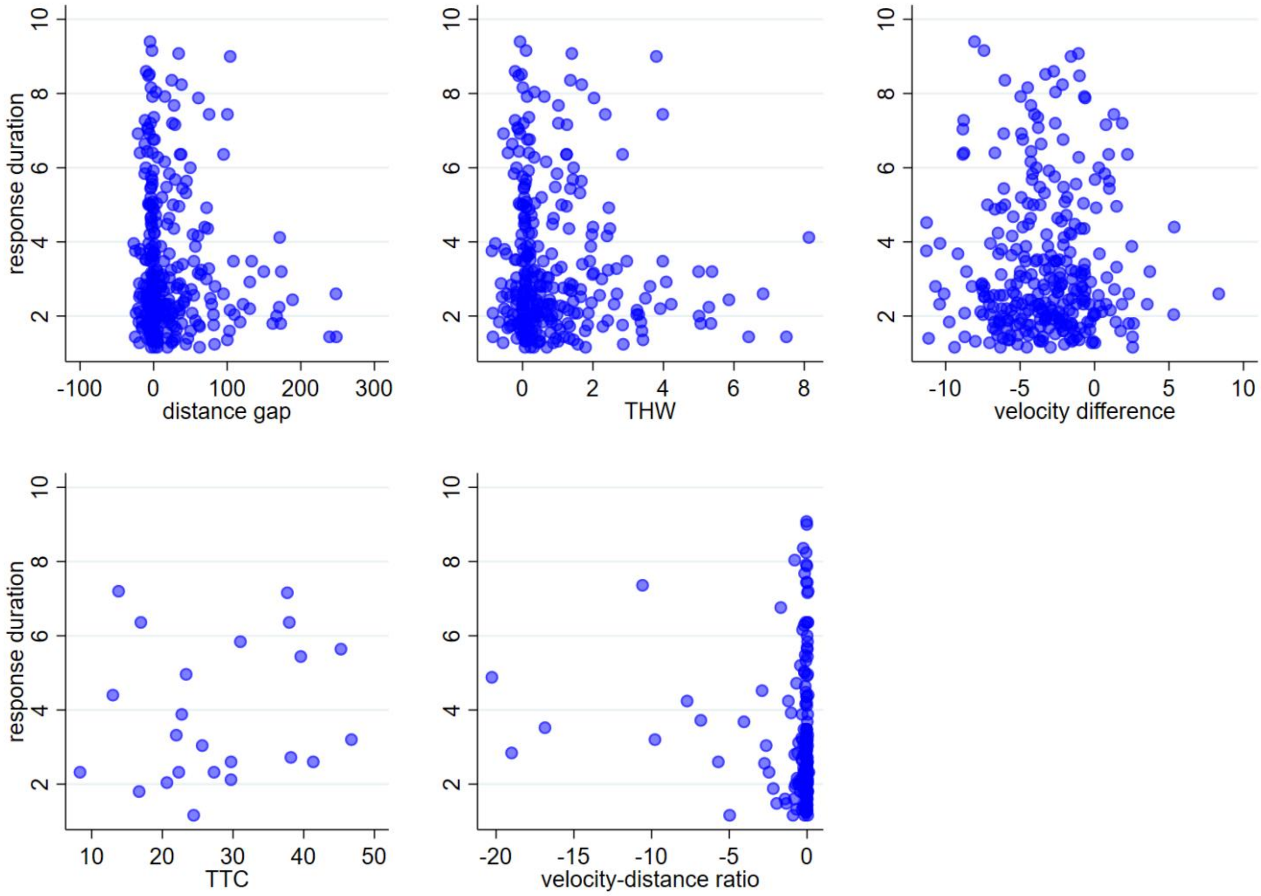
Response duration versus the relational variables between the follower and ego vehicles at the start of the lane change



Note. The TTC graph is cut-off at 50 seconds to highlight the relevant data and eliminate any extreme outliers that distort the visual representation.

Figure D4

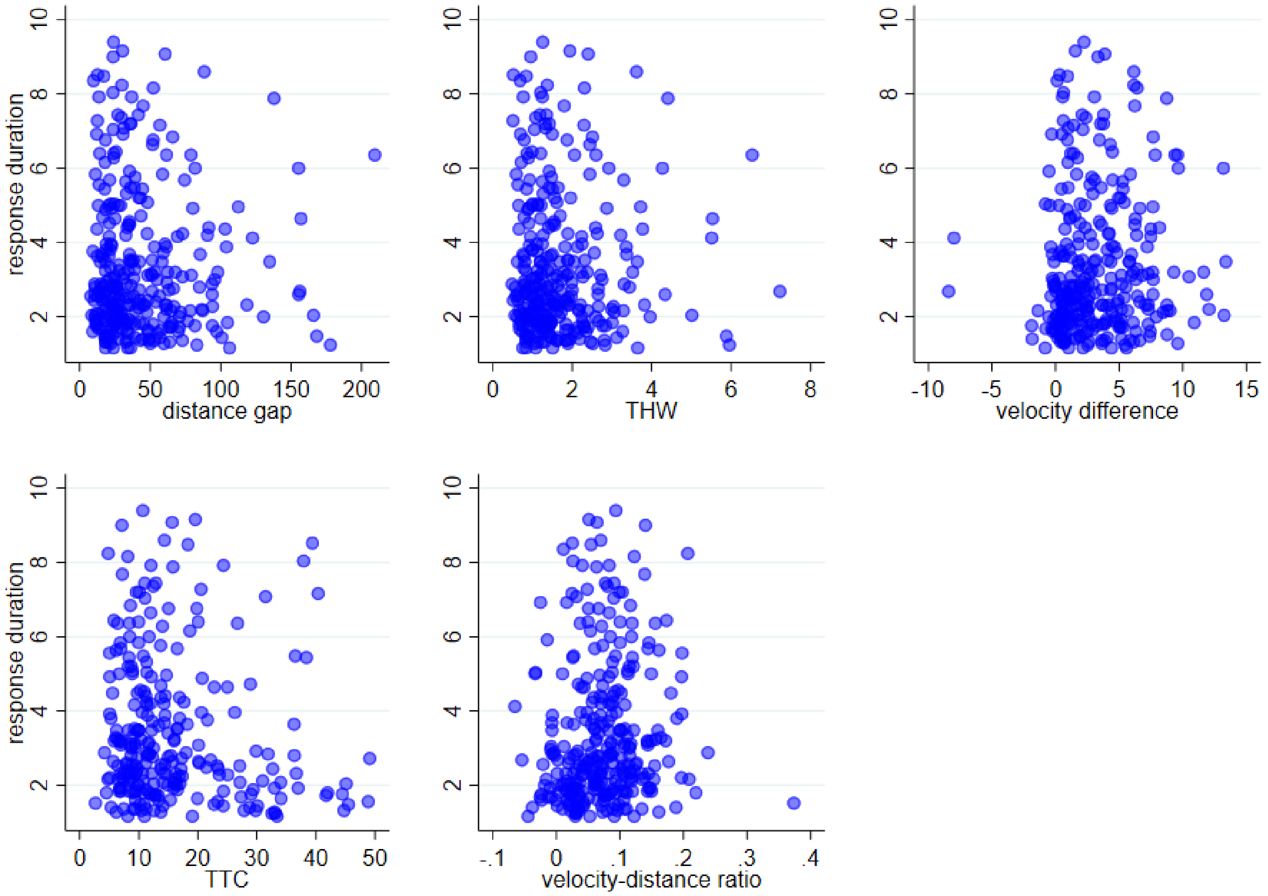
Response duration versus the relational variables between the leader and ego vehicles at the start of the lane change



Note. The TTC graph is cut-off at 50 seconds to highlight the relevant data and eliminate any extreme outliers that distort the visual representation.

Figure D5

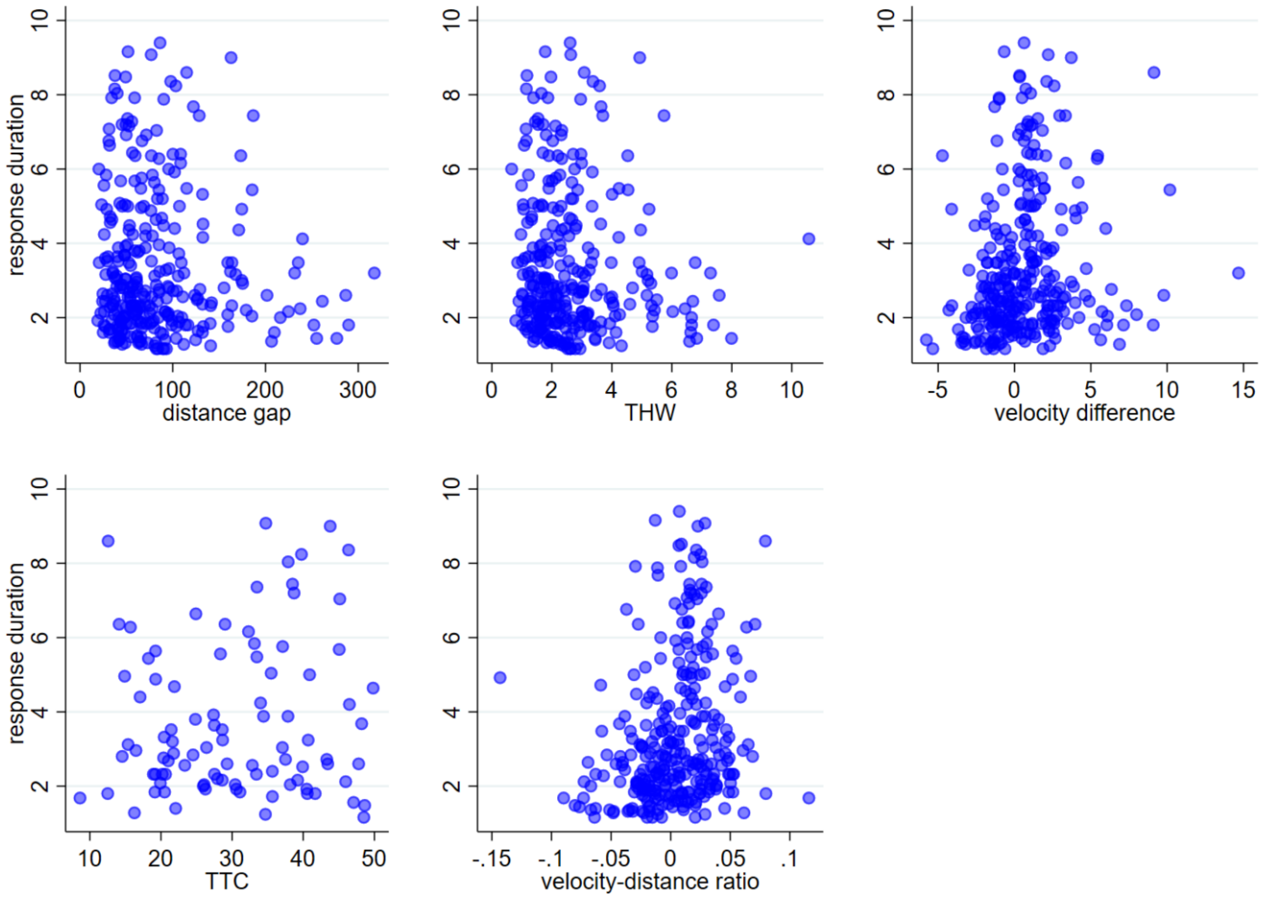
Response duration versus the relational variables between the slowlead and ego vehicles at the start of the lane change



Note. The TTC graph is cut-off at 50 seconds to highlight the relevant data and eliminate any extreme outliers that distort the visual representation.

Figure D6

Response duration versus the relational variables between the leader and follower vehicles at the start of the lane change



Note. The TTC graph is cut-off at 50 seconds to highlight the relevant data and eliminate any extreme outliers that distort the visual representation.

Table D1

Pearson correlation coefficient between the response duration and descriptive variables

Variable ($t_{startLC}$)	Observations	*r*	*p*
v_x^E	308	-.00	.974
v_x^F	308	.09	.110
v_x^L	300	-.01	.937
v_x^S	307	-.06	.278
a_x^E	308	-.26	< .001**
a_x^L	300	-.36	< .001**
a_x^S	307	-.23	< .001**
y_{centre}^E	308	-.10	.094
a_y^E	308	.07	.224
$\Delta v_x^{F,E}$	308	.14	.011*
$\Delta v_x^{E,L}$	300	.01	.937
$\Delta v_x^{E,S}$	307	.06	.281
$\Delta v_x^{F,L}$	300	.16	.006**
$THW^{F,E}$	308	-.03	.600
$THW^{E,L}$	300	-.08	.195
$THW^{E,S}$	307	-.01	.930
$THW^{F,L}$	300	-.08	.147
$\Delta x^{F,E}$	308	.01	.869
$\Delta x^{E,L}$	300	-.09	.126
$\Delta x^{E,S}$	307	-.02	.723
$\Delta x^{F,L}$	300	-.07	.257
$TTC^{F,E}$	292	-.08	.165
$TTC^{E,L}$	37	-.01	.939
$TTC^{E,S}$	281	-.11	.077
$TTC^{F,L}$	167	-.12	.140
$ratio_{\Delta v,\Delta x}^{F,E}$	308	.13	.023*
$ratio_{\Delta v,\Delta x}^{E,L}$	176	-.04	.368
$ratio_{\Delta v,\Delta x}^{E,S}$	307	.10	.096
$ratio_{\Delta v,\Delta x}^{F,L}$	300	.23	< .001**

Note. * *p* < 0.05; ** *p* < 0.01

D. 2. Development of the Linear Regression Model

The process of creating the best linear regression model to predict the follower vehicle's response duration involved several steps. In the first step, a backward stepwise approach was used to indicate the important predictors of the linear regression model. The candidate predictor variables for the stepwise analysis were identified based on previous literature and those that significantly correlated with the response duration. The list of candidate predictor variables was as follows:

- Ego vehicle's acceleration
- Velocity difference between the follower and ego vehicles
- Distance gap between the follower and ego vehicles
- Ratio of the velocity difference and distance gap between the follower and ego vehicles
- Leader vehicle's acceleration
- Velocity difference between the follower and leader vehicles
- Distance gap between the follower and leader vehicles
- Ratio of the velocity difference and distance gap between the follower and leader vehicles
- Slowlead vehicle's acceleration
- Ratio of the velocity difference and distance gap between the slowlead and ego vehicles

The results showed three predictors to be important: the acceleration of the ego and leader vehicles and the ratio of the velocity difference and distance gap between the follower and leader vehicle. These results highlight that these variables are likely of importance in further analysis.

The second step of the analysis focused on the relationship between the follower and ego vehicle variables and the follower vehicle's response duration. First, it was found that the velocity of either the follower or ego vehicle was not a significant predictor. Second, the velocity difference between the follower and ego vehicles seems to be a good prediction of the response duration. The velocity-distance ratio was not as good a predictor as the velocity difference in itself. Third, the acceleration of the ego vehicle was found to be a good predictor. There are no significant interactions between the acceleration of the ego vehicle and the ego vehicle's velocity, the distance gap, or the velocity difference between the follower and ego vehicles. Fourth, the distance gap between the follower and ego vehicles was a significant predictor when also combined with the velocity difference. Combining the best predictor variables caused the velocity difference between the vehicles to be non-significant. The resulting best linear regression model of the follower vehicle's response duration considering the descriptive variables of the follower and ego vehicles is presented in Table D2 ($F(3, 242) = 7.72$, $p < .001$, $R^2 = 0.09$).

Table D2

The linear regression model of the duration of the response using the descriptive variables of the follower and ego vehicles

Variable ($t_{startLC}$)	Coefficient	Standard Error	*t*	*p*	[95% confidence interval]
a_x^E	-1.35	0.35	-3.85	< .001	-2.04, -0.66
$\Delta x^{F,E}$	-0.02	0.01	-2.19	.029	-0.03, -0.002
$\Delta x^{F,E} * \Delta v_x^{F,E}$	0.002	0.001	2.79	.006	0.001, 0.003
(constant)	3.84	0.31	12.19	< .001	3.22, 4.46

The third step involved the analysis of the role of the leader vehicle on the follower vehicle's response duration. Results from a multilevel linear regression showed that the situation category was no nested group that could improve the fit of the model ($X^2(1) = 0.44$, p = .254). However, a comparison between situations A and B revealed that the response duration was longer when a leader vehicle was present (i.e., situation C). The correlation results showed that the acceleration of the leader vehicle and the velocity difference between the leader and follower vehicles were significant predictors of the response duration. The addition of the descriptive variables related to the leader vehicle to the linear regression model showed that the leader vehicle's acceleration and the velocity-distance ratio between the follower and leader vehicles are good predictors. No other significant predictors or interaction effects were found in relation to the leader and follower vehicles. However, adding both variables to the model resulted in the velocity-distance ratio between the follower and leader vehicles and the ego vehicle's acceleration being non-significant predictors. The model's fit still improved after removing the non-significant predictors. The resulting improved linear regression model of the follower vehicle's response duration is presented in Table D3 ($F(4, 234) = 16.60$, $p < .001$, $R^2 = 0.18$).

Table D3

The linear regression model of the duration of the response using the descriptive variables of the follower, ego and leader vehicles

Variable ($t_{startLC}$)	Coefficient	Standard Error	*t*	*p*	[95% confidence interval]
$\Delta x^{F,E}$	-0.02	0.01	-2.20	.029	-0.03, -0.002
$\Delta x^{F,E} * \Delta v_x^{F,E}$	0.002	0.001	2.52	.012	0.0004, 0.003
a_x^L	-2.13	0.33	-6.45	< .001	-2.78, -1.48
(constant)	3.87	0.31	12.65	< .001	3.26, 4.47

In the fourth step, it was investigated whether there are significant predictors related to the slowlead vehicle that would increase the fit of the linear regression model. The results showed that the distance gap, velocity difference, and the ratio of the velocity difference and distance gap between the slowlead and ego were no significant predictors of the response duration and did not improve the fit of the linear regression model. There were also no significant interaction effects between these variables. However, the acceleration of the slowlead was found to be a significant predictor of the response duration of the follower vehicle. The resulting linear regression model for the response duration of the follower vehicle is shown in Table D4 (F(4, 237) = 13.85, p < .001, R2 = 0.19).

Table D4

The linear regression model of the duration of the response using the descriptive variables of the follower, ego, leader and slowlead vehicles

Variable ($t_{startLC}$)	Coefficient	Standard Error	*t*	*p*	[95% confidence interval]
$\Delta x^{F,E}$	-0.02	0.01	-2.05	.042	-0.03, -0.00
$\Delta x^{F,E} * \Delta v_x^{F,E}$	0.002	0.001	2.44	.015	0.0003, 0.003
a_x^L	-1.95	0.34	-5.78	< .001	-2.62, -1.29
a_x^S	-0.94	0.42	-2.23	.027	-1.76, -0.11
(constant)	3.78	0.31	12.27	< .001	3.17, 4.39

The fifth and final step tested whether the number of lanes on the highway or whether the ego vehicle changes lanes from the right or middle lane are nested groups in the dataset. A multilevel linear regression analysis revealed that considering these groups would not lead to an improvement in the model's fit, as indicated in Table D4 ($X^2(1) = 0.00$, $p = 1.000$ and $X^2(1) = 0.00$, $p = 1.000$). Therefore, the final best linear regression model using the descriptive variables at the start of the lane change to predict the follower vehicle's response duration is presented in Table D4.

Appendix E.
Response Minimum Acceleration

This Appendix provides supplementary information on the analyses of the minimum acceleration of the follower vehicle response. First, the relationships between the descriptive variables and the minimum acceleration of the response are examined through visualisation (see Figures E1 to E6) and the Pearson correlation coefficient (see Table E1). Second, the development and intermediate results of the linear regression model are described.

E. 1. Relationships Between Response Minimum Acceleration and Descriptive Variables

Figure E1

Response minimum acceleration versus the behaviour of the ego vehicle at the start of the lane change

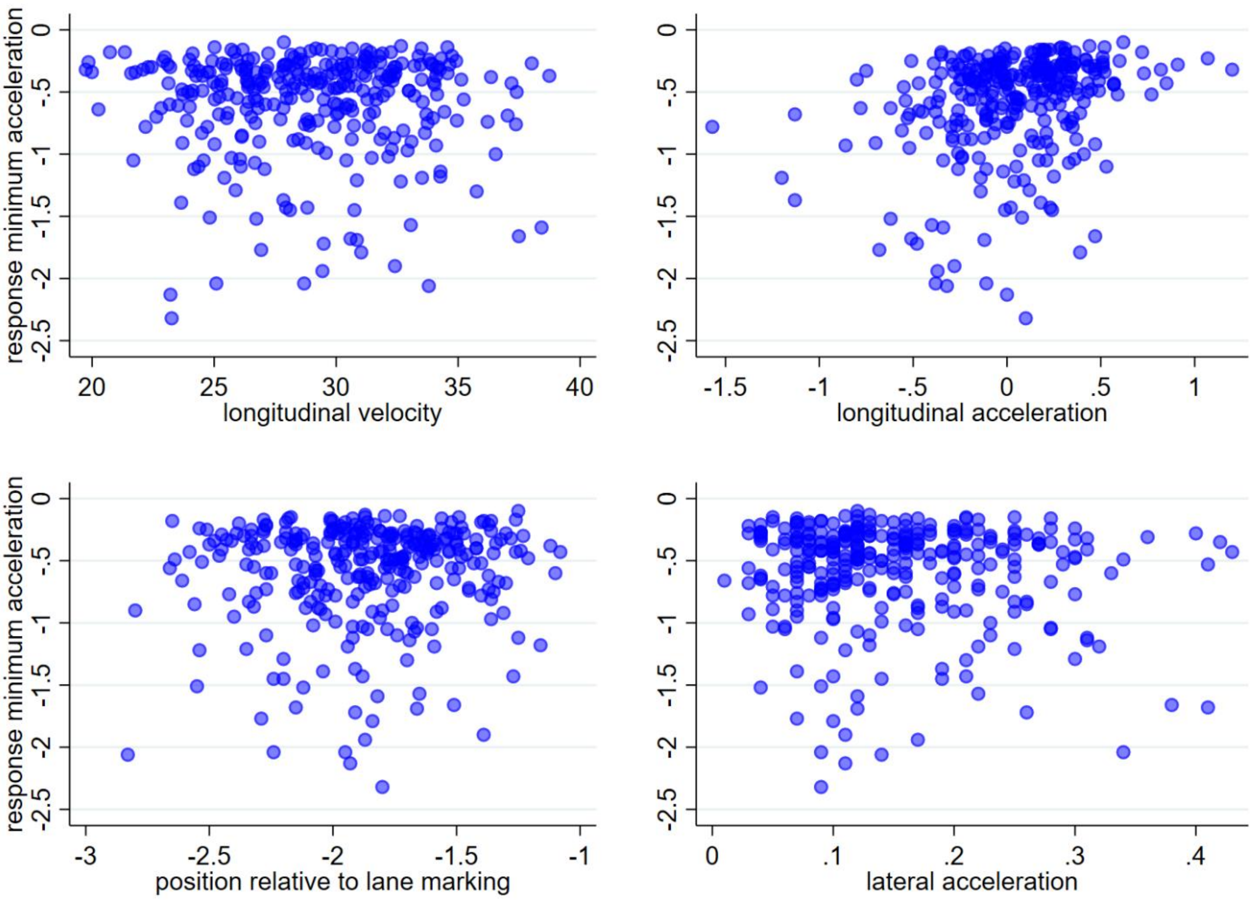


Figure E2

Response minimum acceleration versus the longitudinal behaviour of the follower, leader and slowlead vehicles at the start of the lane change

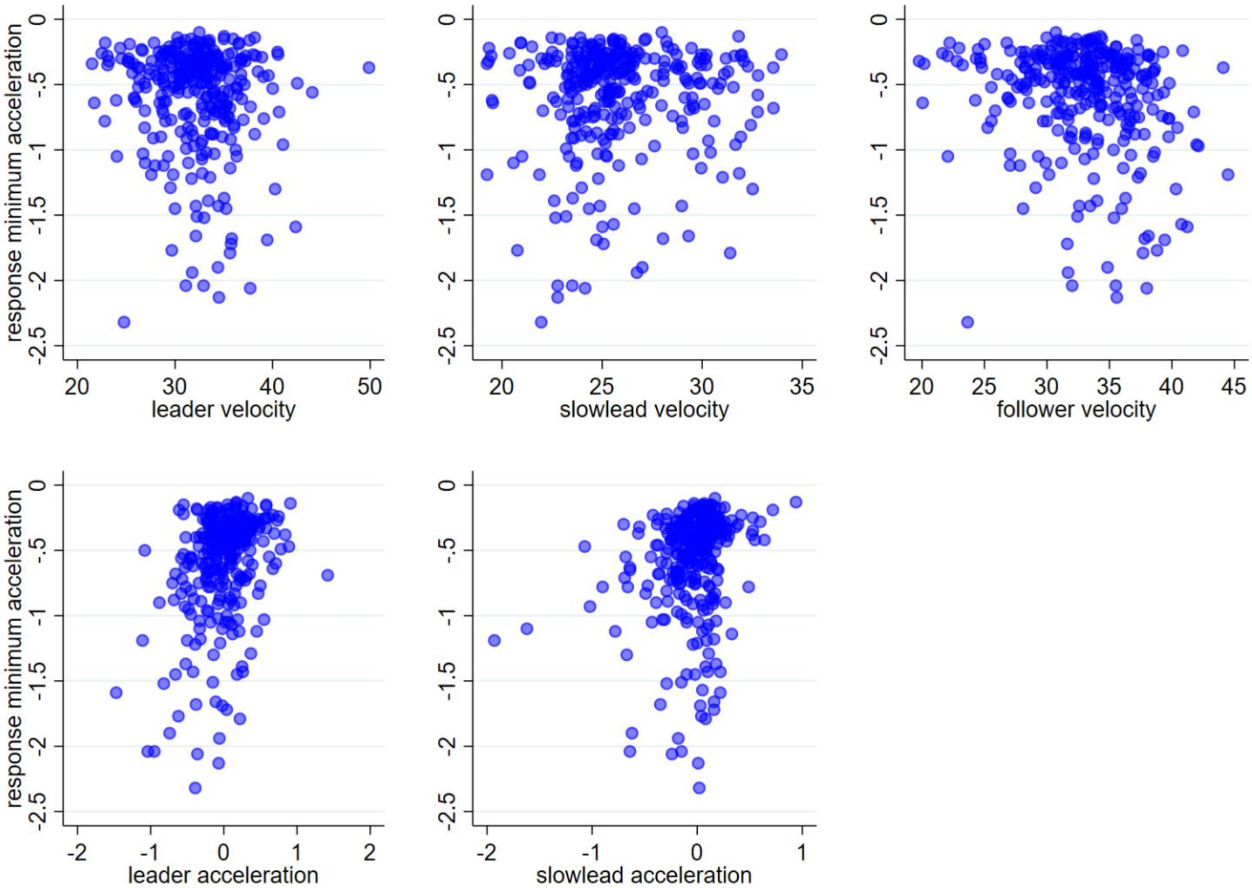
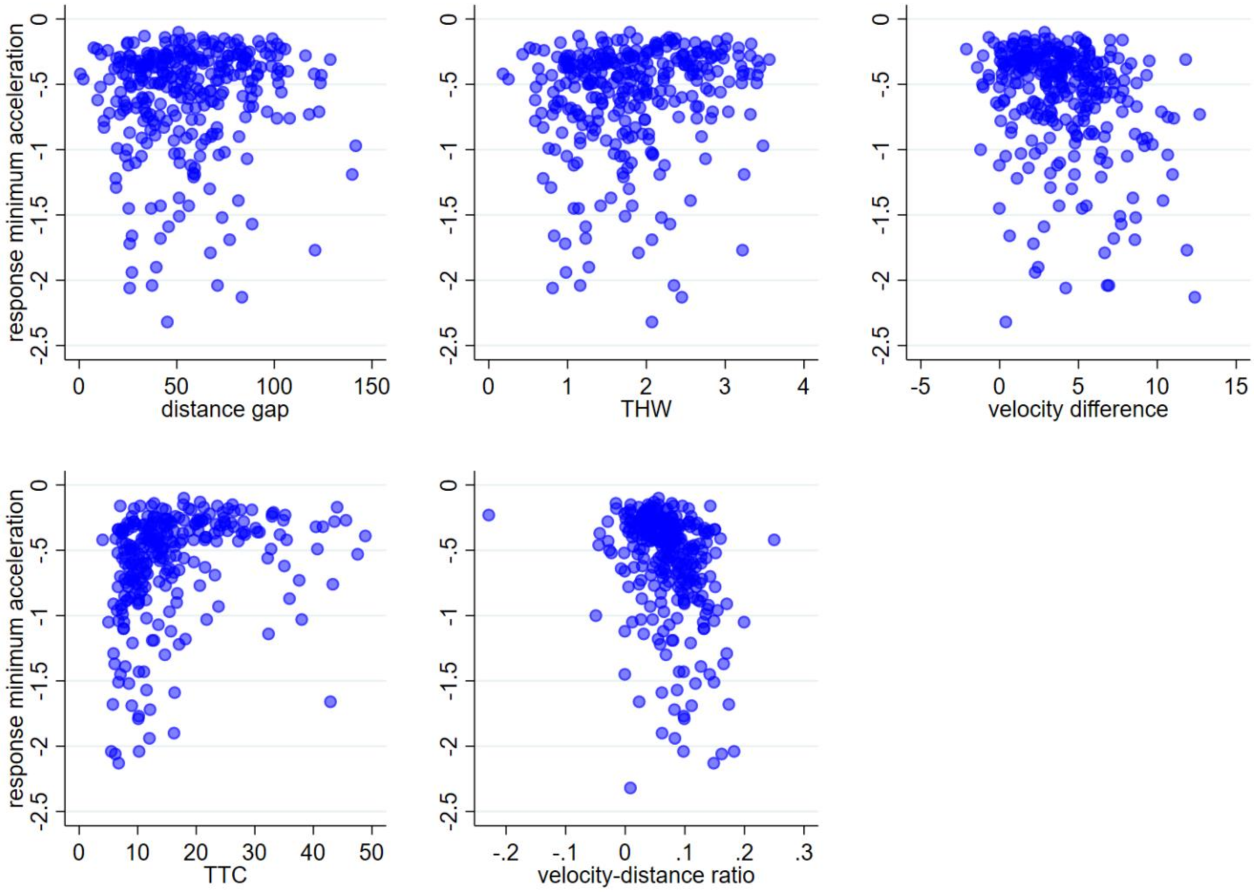


Figure E3

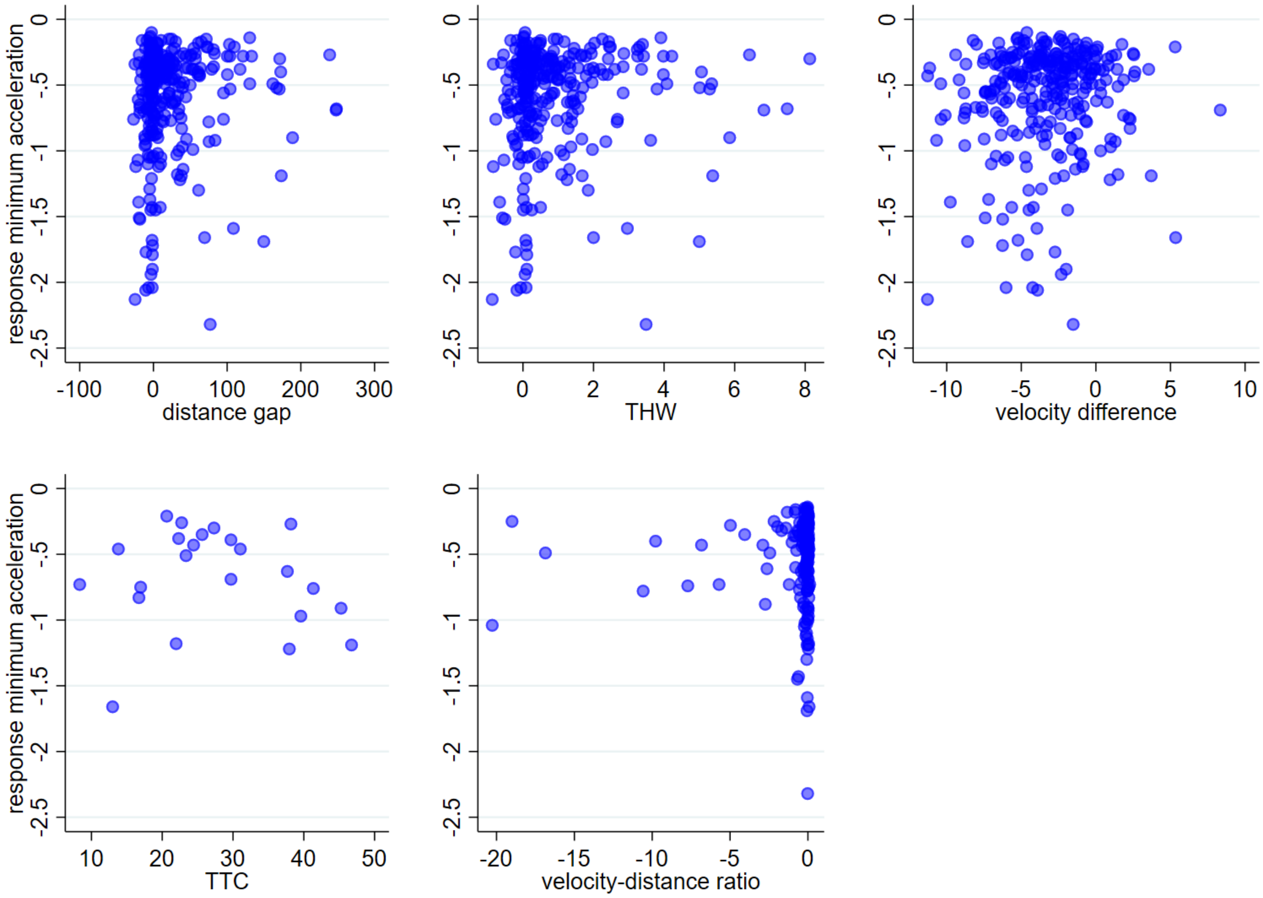
Response minimum acceleration versus the relational variables between the follower and ego vehicles at the start of the lane change



Note. The TTC graph is cut-off at 50 seconds to highlight the relevant data and eliminate any extreme outliers that distort the visual representation.

Figure E4

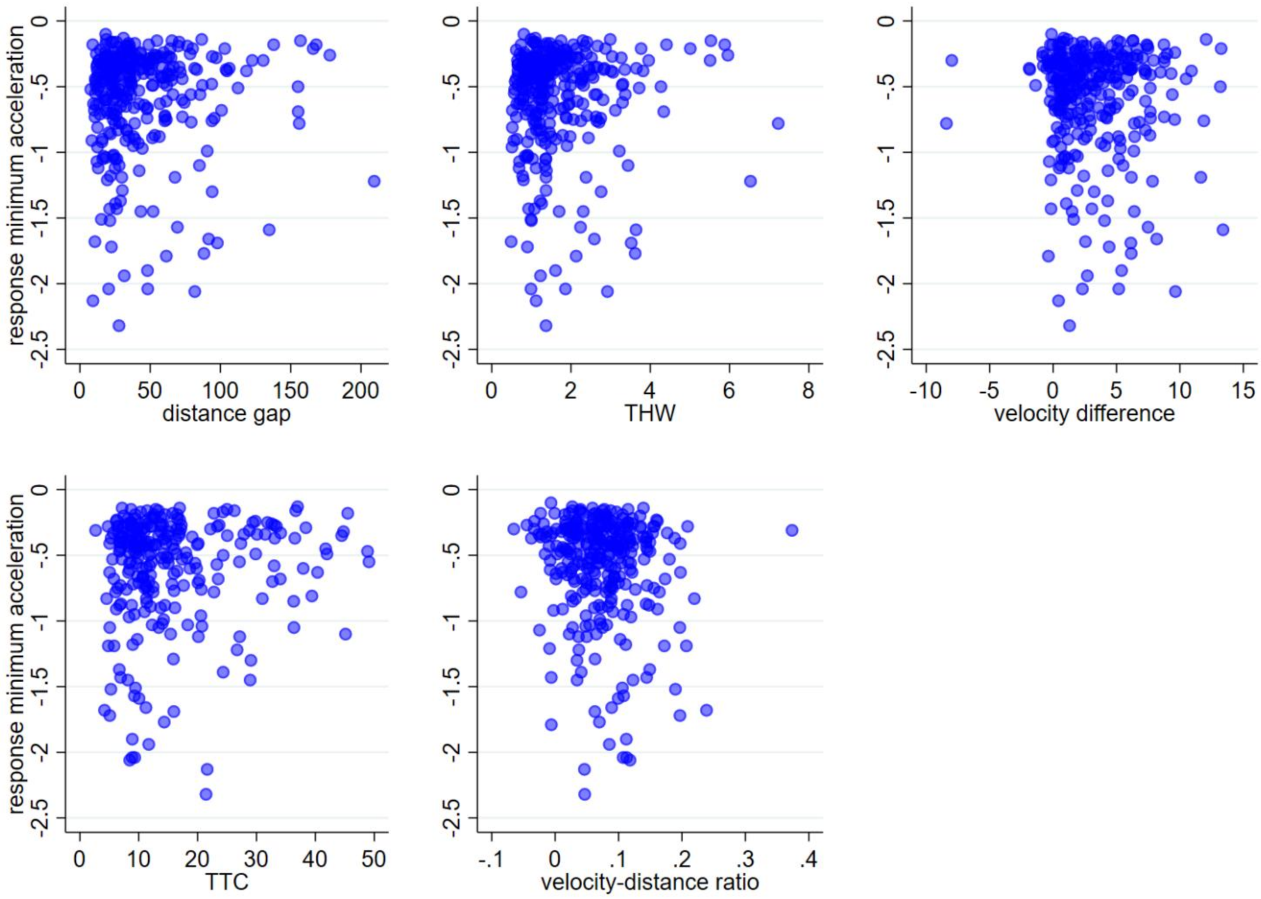
Response minimum acceleration versus the relational variables between the leader and ego vehicles at the start of the lane change



Note. The TTC graph is cut-off at 50 seconds to highlight the relevant data and eliminate any extreme outliers that distort the visual representation.

Figure E5

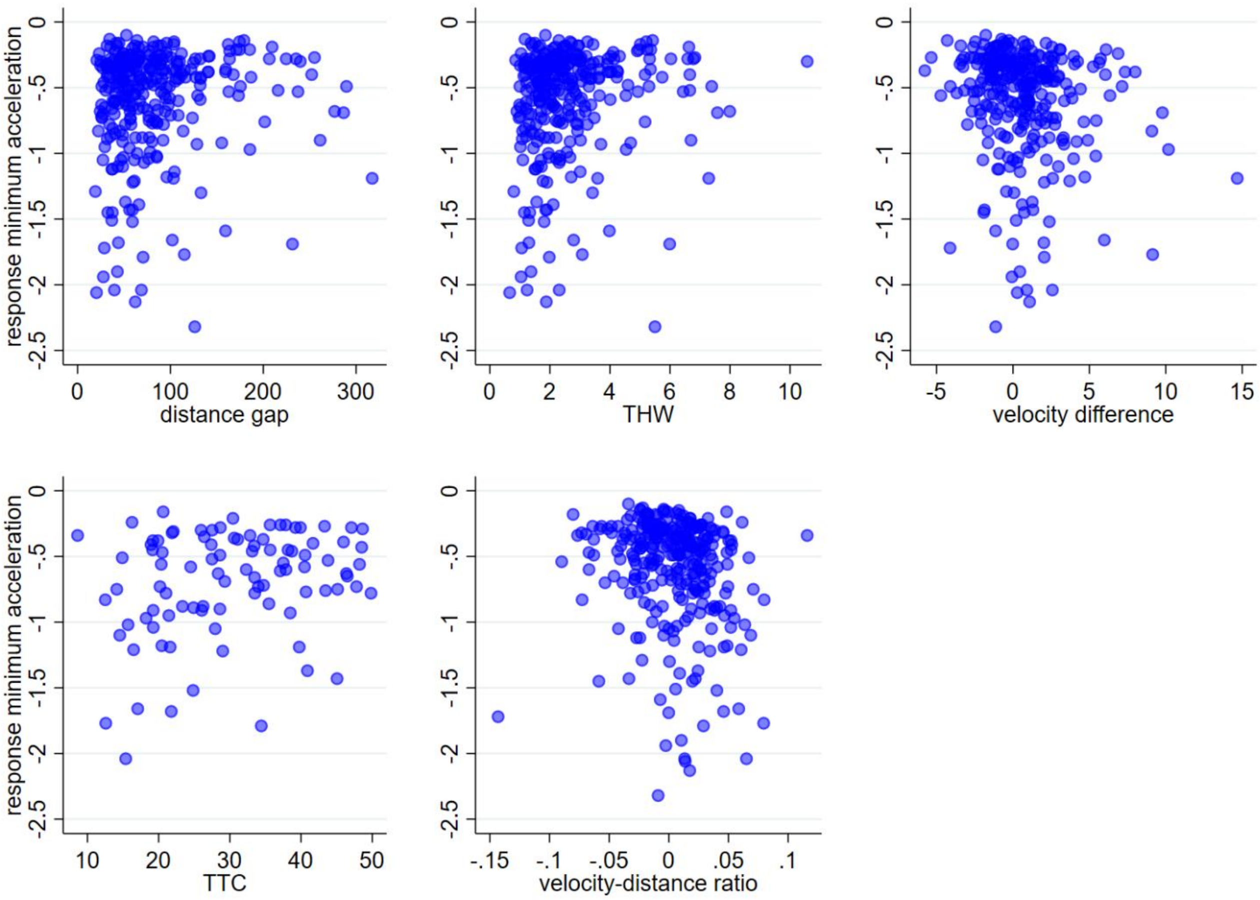
Response minimum acceleration versus the relational variables between the slowlead and ego vehicles at the start of the lane change



Note. The TTC graph is cut-off at 50 seconds to highlight the relevant data and eliminate any extreme outliers that distort the visual representation.

Figure E6

Response minimum acceleration versus the relational variables between the leader and follower vehicles at the start of the lane change



Note. The TTC graph is cut-off at 50 seconds to highlight the relevant data and eliminate any extreme outliers that distort the visual representation.

Table E1

Pearson correlation coefficient between the response minimum acceleration and descriptive variables

Variable ($t_{startLC}$)	Observations	*r*	*p*
v_x^E	308	-.03	.628
v_x^F	308	-.20	< .001**
v_x^L	300	-.10	.097
v_x^S	307	.03	.524
a_x^E	308	.28	< .001**
a_x^L	300	.37	< .001**
a_x^S	307	.22	< .001**
y_{centre}^E	308	.08	.142
a_y^E	308	-.07	.217
$\Delta v_x^{F,E}$	308	-.26	< .001**
$\Delta v_x^{E,L}$	300	.09	.106
$\Delta v_x^{E,S}$	307	-.06	.278
$\Delta v_x^{F,L}$	300	-.17	.003**
$THW^{F,E}$	308	.14	.014*
$THW^{E,L}$	300	.07	.262
$THW^{E,S}$	307	.02	.773
$THW^{F,L}$	300	.13	.024*
$\Delta x^{F,E}$	308	.07	.257
$\Delta x^{E,L}$	300	.06	.320
$\Delta x^{E,S}$	307	.02	.785
$\Delta x^{F,L}$	300	.08	.166
$TTC^{F,E}$	292	.08	.167
$TTC^{E,L}$	37	.23	.176
$TTC^{E,S}$	281	.04	.496
$TTC^{F,L}$	167	-.00	.988
$ratio_{\Delta v,\Delta x}^{F,E}$	308	-.31	< .001**
$ratio_{\Delta v,\Delta x}^{E,L}$	176	.02	.811
$ratio_{\Delta v,\Delta x}^{E,S}$	307	-.13	.023*
$ratio_{\Delta v,\Delta x}^{F,L}$	300	-.18	.002**

Note. * *p* < 0.05; ** *p* < 0.01

E. 2. Development of the Linear Regression Model

The linear regression model of the minimum acceleration of the follower vehicle's response is developed following several steps. In the first step, a backward stepwise approach is used to identify the essential predictor variables of the linear regression model. The list of candidate predictors was based on previous literature and correlation analyses, resulting in the following list:

- Ego vehicle's acceleration
- Velocity difference between the follower and ego vehicles
- Distance gap between the follower and ego vehicles
- Ratio of the velocity difference and distance gap between the follower and ego vehicles
- Leader vehicle's acceleration
- Velocity difference between the follower and leader vehicles
- Distance gap between the follower and leader vehicles
- Ratio of the velocity difference and distance gap between the follower and leader vehicles
- Slowlead vehicle's acceleration
- Ratio of the velocity difference and distance gap between the slowlead and ego vehicles

The results of the backward stepwise approach suggest that the four most essential predictors are the distance gap and velocity difference between the follower and ego vehicles, and the acceleration of the ego and leader vehicles. The use of either the distance gap or THW showed a similar result.

In the second step, the descriptive variables related to the follower and ego vehicles are more closely analysed. First, the ego vehicle's acceleration is a significant predictor. Second, the distance gap is as well a significant predictor, and the THW between the follower and ego vehicles is a similar good predictor as the distance gap. Third, the velocity difference between the follower and ego vehicles is a good predictor. Fourth, there is no significant interaction between the velocity difference and the distance gap between the vehicles. Similarly, the velocity-distance ratio between the follower and ego vehicles was found to be a weaker predictor than the velocity difference. Fifth, there is a significant interaction between the ego vehicle's acceleration and the velocity difference between the follower and ego vehicles. However, the ego vehicle's acceleration value is no longer significant when added together. The highest fit of the model is achieved when including the interaction effect instead of only the ego vehicle's acceleration. Six, the velocity of the follower vehicle is not a significant predictor. The resulting linear regression model of the follower vehicle's minimum acceleration considering the descriptive variables of the follower and ego vehicles is shown in Table E2Table E2 ($F(3, 246) = 24.22$, $p < .001$, $R^2 = 0.23$).

Table E2

The linear regression model of the minimum acceleration of the response using the descriptive variables of the follower and ego vehicles

Variable ($t_{startLC}$)	Coefficient	Standard Error	*t*	*p*	[95% confidence interval]
$\Delta v_x^{F,E}$	-0.07	0.01	-6.86	< .001	-0.09, -0.05
$a_x^E * \Delta v_x^{F,E}$	0.07	0.01	5.22	< .001	0.04, 0.10
$\Delta x^{F,E}$	0.01	0.001	5.10	< .001	0.003, 0.01
(constant)	-0.63	0.06	-11.29	< .001	-0.74, -0.52

The third step investigates the descriptive variables related to the leader vehicle. A multilevel linear regression analysis showed that the situation is no nested group that would improve the model's fit ($X^2(01) = 0.00$, $p = 1.000$). However, the results of the *t*-tests indicate that in situation B (i.e., the follower vehicle is not driving freely from the leader vehicle), the minimum acceleration is lower than in situation A. In addition, the correlation results showed that variables related to the leader vehicle significantly correlated with the follower vehicle's minimum acceleration. The linear regression analysis showed that only the leader vehicle's acceleration value is a significant predictor that increases the model's fit. Including the velocity difference, distance gap, THW, or velocity-distance ratio between the leader and follower vehicles did not improve the model. Furthermore, there were no significant interaction effects. The improved linear regression model by including the acceleration of the leader vehicle is presented in Table E3 ($F(3, 238) = 23.36$, $p < .001$, $R^2 = 0.29$).

Table E3

The linear regression model of the minimum acceleration of the response using the descriptive variables of the follower, ego, and leader vehicles

Variable ($t_{startLC}$)	Coefficient	Standard Error	*t*	*p*	[95% confidence interval]
$\Delta v_x^{F,E}$	-0.07	0.01	-6.37	< .001	-0.09, -0.05
$a_x^E * \Delta v_x^{F,E}$	0.05	0.01	3.24	.001	0.02, 0.07
$\Delta x^{F,E}$	0.01	0.001	5.26	< .001	0.004, 0.01
a_x^L	0.32	0.07	4.67	< .001	0.19, 0.46
(constant)	-0.66	0.05	-12.17	< .001	-0.77, -0.56

The fourth step of the analysis extended the linear regression model by considering the influence of the slowlead vehicle. Similar to the variables related to the leader vehicle, only the slowlead vehicle's acceleration is a significant predictor. The distance gap, THW, velocity difference, and velocity-distance ratio between the slowlead and ego are not significant, and there are no significant interaction effects. Table E4 shows the following best linear regression model when considering the descriptive variables related to the follower, ego, leader and slowlead vehicles ($F(3, 237) = 20.06$, $p < .001$, $R^2 = 0.30$)

Table E4

The linear regression model of the minimum acceleration of the response using the descriptive variables of the follower, ego, leader and slowlead vehicles

Variable ($t_{startLC}$)	Coefficient	Standard Error	*t*	*p*	[95% confidence interval]
$\Delta v_x^{F,E}$	-0.07	0.01	-6.51	< .001	-0.09, -0.05
$a_x^E * \Delta v_x^{F,E}$	0.04	0.01	2.84	.005	0.01, 0.07
$\Delta x^{F,E}$	0.01	0.001	5.16	< .001	0.003, 0.01
a_x^L	0.30	0.07	4.30	< .001	0.16, 0.43
a_x^S	0.17	0.08	2.00	0.046	0.003, 0.33
(constant)	-0.64	0.05	-11.66	< .001	-0.75, -0.53

In the fifth step, it is investigated whether there are nested groups in the dataset related to either the number of lanes on the highway or whether the ego vehicle changed lanes from the right or middle lane. A multilevel linear regression showed there are no nested groups that would improve the model's fit ($X^2(01) = 0.00$, $p = 1.000$; $X^2(01) = 0.00$, $p = 1.000$). Thus, the final best regression model predicting the minimum acceleration of the follower vehicle's response using the descriptive variables at the start of the lane change is shown in Table E4.