Driver's Response to Speed Advisory System and Implications on Traffic Performances

A Case Study of COBRA

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by

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Preface

This thesis is the final requirement to obtain my master's degree in Transport, Infrastructure and Logistics at the Technical University of Delft, Over the past three years, I have gained so much not only academically, but also in personal growth. I am grateful for every experience, and with this thesis, I bring this chapter of my life to a close. For this thesis project I would like to specially thank several people.

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Yi Yang
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Summary

This study investigates driver responses to a vehicle-based cooperative speed advisory system derived from the Cooperative Breakdown Prevention Algorithm (COBRA) in a simulated two-lane highway bottleneck environment. Although COBRA has demonstrated congestion-mitigation potential in single-lane, high automation scenarios, its performance in human-driven, two-lane contexts remains insufficiently explored, particularly regarding operational safety and efficiency.

A controlled driving simulator experiment was conducted using SCANeR, involving 21 participants who completed 12 systematically varied scenarios. Two key adjacent-lane factors were manipulated: the ego vehicle's relative position to the onset of adjacent-lane deceleration and its position within the adjacent-lane gap at advisory onset. The experiment integrated objective vehicle trajectory recording with pre- and post-experiment questionnaires capturing demographics, trust, perceived safety, and system acceptance. Safety was evaluated primarily through time-to-collision (TTC) and accepted gap measures, while efficiency was assessed by final speed, mean deceleration rate, and reaction times.

Results show that visible adjacent-lane deceleration substantially accelerated compliance with the advisory, whereas the absence of such cues led to delayed deceleration and occasional short-term acceleration after message delivery. Across all conditions, minimum TTC values remained above 6 s, indicating no elevated collision risk. The target final speed of 80 km/h was consistently achieved, but mean deceleration ($-1.74\ \mathrm{m/s^2}$) was significantly less severe than the nominal $-2.00\ \mathrm{m/s^2}$. Lane-change timing was strongly associated with the presence of adjacent-lane cues, while initial gap size had limited influence on lane-change probability.

Questionnaire responses reflected high clarity and acceptance ratings, moderate behavioural alignment with advisories, and lower perceived safety in scenarios lacking adjacent-lane deceleration. Open-ended feedback highlighted preferences for earlier advisory timing and enhanced confirmation of speed target achievement.

Overall, the findings indicate that COBRA can be effective in maintaining safety and meeting efficiency targets under human-driven, two-lane conditions, but real-world deployment would benefit from adaptive trigger logic accounting for two-lane interactions, driver comfort in deceleration, and the presence or absence of confirming visual traffic cues.

Contents

Nomenclature

Abbreviations

Abbreviation	Definition
C-ITS	Cooperative Intelligent Transport Systems
COBRA	Cooperative Breakdown Prevention Algorithm
CV	Connected Vehicle
FS	Final Speed
HMI	Human–Machine Interface
IDM	Intelligent Driver Model
ISA	Intelligent Speed Adaptation
LC	Lane Change
RT	Reaction Time
RT_{decel}	Reaction Time to Deceleration
RT_{lc}	Reaction Time to Lane Change
THW	Time Headway
TTC	Time-to-Collision
VSL	Variable Speed Limit

1 Introduction

Traffic flow and traffic congestion are fundamentally influenced by the interaction between vehicle demand and road capacity. Traffic flow refers to the number of vehicles on a road, and vehicle demand is the total desired travel volume, regardless of road constraints, while road capacity is defined as the maximum number of vehicles a road can accommodate without congestion [42]. Under uncontrolled conditions, the risk of road congestion increases as the traffic demand continues to grow. Congestion on highways not only affects the efficiency of traffic flow, but also has a negative impact on economic activity and the environment. Traffic congestion can be triggered by a variety of disruptions (e.g., frequent lane changes or emergency braking) as soon as the traffic flow gets close to or exceeds the road's capacity. These disruptions can trigger shock waves in the traffic flow, which activates queuing at bottlenecks in the road network. In addition, the phenomenon of congestion can lead to a temporary reduction in the actual capacity of the motorway by 3% to 30% [40], resulting in the so-called capacity drop. This temporary reduction in capacity can trigger more severe congestion during peak hours, thus prolonging the problem.

Beyond efficiency concerns, congestion also poses significant safety risks. Traffic congestion has complex safety implications, with studies generally indicating an increase in accidents as congestion levels rise [32]. Congested conditions are particularly linked to a higher crash risk on urban roadways, especially at lower average speeds, where reduced spacing between vehicles intensifies interactions and increases the likelihood of collisions [13]. This suggests that congestion not only affects traffic flow but also negatively impacts road safety, reinforcing the need for effective management strategies.

Researchers develop innovative techniques and concepts to address traffic congestion and reduce the possibility of traffic breakdowns. Widely adopted traffic management strategies include Variable Speed Limit (VSL), Route Guidance, and Ramp Metering [22], which directly control traffic flow to alleviate traffic pressure during peak periods. Meanwhile, Cooperative Intelligent Transport Systems (C-ITS) offer an advanced solution by allowing information exchange among entities on the road [2], potentially improving road use efficiency and reducing congestion.

Though the Connected and Automated Vehicles (CAVs) on the road are programmed to follow traffic rules and speed limits, human drivers tend to be less strict with following the rules [35]. A technology already in place to support human drivers is Intelligent Speed Adaptation (ISA). ISA makes use of automated Traffic Sign Recognition (TSR) which is used to automatically recognize traffic signs and present the information to the driver. These systems rely on cameras to visually detect/recognize traffic signs.

However, the implementation of such systems faces a number of challenges, including technical issues, the need for integration with vehicle controls, and issues related to human factors [37]. As a more direct solution, researchers are developing cooperative systems that do not directly control the vehicle, but instead provide advice and warnings to the driver through an in-vehicle advisory system. In the Connected Cruise Control project, researchers have developed a system that provides drivers with advice on speed, gap size, and lane choice to prevent or resolve suboptimal traffic flow situations [33].

1.1 Introduction to the problem

Despite advances in autonomous driving technology, most vehicle operations on public roads are still human-related. Human behaviour significantly impacts congestion. Driving behaviour in dense traffic often hovers on the edge of instability, where a single manoeuvre by a driver can cause widespread disturbances [7]. Such disruptions lead to temporary capacity loss and exacerbate congestion, further limiting the effective traffic flow. Individual variability in driving behaviour, such as differences in preferred follow-up distances and lane maintenance, also contributes. For instance, erratic lane changes can compress traffic further, reducing vehicle gaps and prompting braking, which disrupts traffic flow [18]. Additionally, limited driver anticipation, especially around bottlenecks, can cause vehicles to enter jams at a faster rate than they can exit, prolonging congestion [47]. Understanding these nuanced impacts of human behaviour is thus critical for effective congestion mitigation.

While technologies like Intelligent Speed Adaptation (ISA) support human drivers by using Traffic Sign Recognition (TSR) to present relevant information, COoperative BReakdown Prevention Algorithm (COBRA) aims to improve traffic flow without directly controlling the vehicle. [23]. COBRA is an advanced traffic control system designed to mitigate congestion and prevent traffic breakdowns, particularly near highway bottlenecks. Unlike traditional methods such as Variable Speed Limits (VSL) or Ramp Metering (RM), COBRA utilizes Cooperative Intelligent Transport Systems (C-ITS) to provide individualized speed advisories to connected vehicles. By dynamically adjusting vehicle speeds in real-time, COBRA aims to stabilize traffic flow and reduce congestion-induced disruptions. While COBRA has shown promising results in single-lane simulation studies, where it effectively managed traffic flow at high CV penetration rates, challenges remain in real-world applications. Factors such as multi-lane environments, varying penetration rates, and integration of diverse data sources for real-time control must be addressed to realize COBRA's full potential in practical traffic scenarios [23].

1.2 Research objective

This study aims to investigate how drivers respond to the COBRA system when applied in a real-world setting using a driving simulator. The focus is on observing and analysing the varied reactions of drivers to the COBRA's advisory system. The study seeks to understand how different factors influence driver decision-making and behaviour when receiving speed advisories.

To explore these driver responses in a controlled yet realistic setting, this study employs a driving simulator which enables a detailed investigation of how drivers react to COBRA's advisory system under different traffic conditions while maintaining experimental control. Additionally, driver feedback on the system's usability and perceived experience will be gathered through questionnaires to gain insights into their perspectives.

By capturing diverse responses, the findings will contribute to understanding the feasibility of safety implementing COBRA in real-world traffic conditions. While the results may inform discussions on the system's broader applicability, the primary objective is to explore driver responses rather than assess traffic efficiency improvements.

1.3 Research question

To reach the research objectives, the main research question of this study is:

How do drivers respond to a vehicle-based cooperative speed advisory system in simulated real-world conditions, and how can it be evaluated for its operational safety and efficiency?

To answer the main research question, the following sub-questions are formulated:

1. What are the key factors that influence driver response when receiving messages from a cooperative speed advisory system?
2. How do different traffic conditions, reflecting the identified factors, influence drivers' behavioural responses?
3. How can the operational safety and efficiency of the cooperative speed advisory system be evaluated under the tested experimental conditions?
4. What practical recommendations can be made to extend the COBRA for practical application?

1.4 Terminology and definitions

To address the research questions, it is first necessary to define the term *vehicle-based cooperative speed advisory system* as used in this study.

In this research, the term refers to the specific implementation of a cooperative speed advisory system applied within the driving simulator experiment. The system concept is derived from the *COoperative BReakdown Prevention Algorithm* (COBRA), which is designed to manage and optimise traffic flow, particularly in the vicinity of highway bottlenecks. Leveraging Cooperative Intelligent Transport Systems (C-ITS) technology, COBRA provides connected vehicles (CVs) with individualised speed recommendations aimed at harmonising speeds, preventing traffic breakdowns, and enhancing both efficiency and safety. It operates by utilising real-time data from connected vehicles and roadside infrastructure to deliver advisory cues to drivers.

However, due to the different objectives and constraints of this experiment – compared with large-scale macroscopic or detailed microscopic COBRA studies – the simulator implementation in this research does not employ the full dynamic COBRA control logic. Instead, a simplified *static advisory model* was adopted to represent the core concept. Throughout this thesis, the term *vehicle-based cooperative speed advisory system* is used to denote this experimental implementation.

In the context of this study, *traffic conditions* refer to the specific experimental scenarios developed within the controlled environment of the driving simulator. These scenarios are designed to reflect selected features of real-world driving environments that are relevant to the research objectives, while remaining within the constraints of the simulation setup. Scenario variables considered in this study include traffic density, available gap size and location, advisory timing, and road characteristics. By systematically varying these elements, the experiment focuses on capturing observable patterns in driver responses to advisory messages under the tested conditions.

1.5 Methodology

To address the research questions, the methodology is structured to ensure that each sub-question is investigated through a suitable combination of literature review, experimental design, and data analysis.

Sub-question 1: Factors influencing driver response
A systematic literature review will be conducted to identify human-related factors (e.g., reaction time,

trust, attention) and external factors (e.g., Human-Machine interface type, environmental conditions) that influence driver behaviour when receiving cooperative speed advisories. Insights from this review will be synthesized into a conceptual model that maps the relationships between these factors and expected driver responses. This model will form the theoretical basis for scenario design in the driving simulator.

Sub-question 2: Impact of traffic conditions on driver behaviour
A series of controlled driving simulator experimental scenarios will be designed to operationalise the factors identified in Sub-question 1. Scenario variables will include traffic density, gap size and location, advisory timing, and HMI presentation. Each participant will experience a set of scenarios in a randomised order to minimise learning effects. Driver performance data (e.g., speed profiles, acceleration rate, lane-change behaviour) will be recorded to assess behavioural differences across traffic conditions.

Sub-question 3: Evaluation of operational safety and efficiency
The evaluation will be conducted using objective performance indicators derived from the driving simulator experiment. For operational safety, metrics such as time-to-collision (TTC), and accepted lane-change gap size will be calculated for each scenario. For operational efficiency, indicators including final speed stabilization, mean acceleration, and compliance with advisory speed will be examined. These metrics will be computed from the processed vehicle trajectory data collected in each scenario. Statistical analyses will be applied to compare safety- and efficiency-related outcomes across different experimental conditions, enabling an assessment of how the cooperative speed advisory system performs under the tested scenarios.

Sub-question 4: Recommendations for COBRA extension
The behavioural data collected in the simulator experiment will be combined with performance metrics (e.g., final speed, mean acceleration) to evaluate the efficiency and safety outcomes of the advisory system. Based on these results, practical recommendations will be formulated for refining or extending the COBRA algorithm to better support safe and efficient driving in real-world conditions.

2

Literature Review

This chapter reviews prior research on factors influencing driver responses to cooperative speed advisory systems, with a particular focus on elements relevant to the Cooperative Breakdown Prevention Algorithm (COBRA). The literature highlights that driver behaviour under such systems is shaped by a combination of human-related characteristics (e.g., age, driving style, trust, and cognitive workload) and external situational factors (e.g., traffic conditions, gap availability, advisory timing, and HMI design). Understanding these factors is essential for evaluating how COBRA advisories may affect operational safety and efficiency.

The review is structured into five sections. Section 2.1 introduces the COBRA concept and its operational principles, outlining its relevance to driver compliance and behavioural responses. Section 2.2 examines human-related factors such as personality traits, cognitive and affective states, and socio-economic characteristics, and discusses their potential influence on advisory adherence. Section 2.3 addresses external factors, including road characteristics and HMI modalities, which can be manipulated or observed in experimental settings. Section 2.4 summarises representative experimental designs from the literature, illustrating how driving simulators are used to replicate traffic conditions and measure driver reactions. Section 2.5 reviews common evaluation methods and key performance indicators (KPIs) for assessing both safety- and efficiency-related outcomes.

2.1 COBRA as a speed advisory system

The COoperative Bottleneck Reduction Algorithm (COBRA) is a proactive traffic control strategy to prevent traffic breakdowns before they occur [23]. Unlike conventional measures such as Variable Speed Limits (VSL) or Ramp Metering, COBRA leverages connected vehicles and Cooperative Intelligent Transport Systems (C-ITS) to dynamically adjust vehicle speeds near bottlenecks. By sending individualised speed advisory signals, COBRA aims to maintain smooth flow and reduce the probability of congestion-induced breakdowns.

The operational effectiveness of COBRA ultimately depends on how drivers respond to these advisories. This study therefore focuses on understanding human driving behaviour when receiving COBRA's recommendations, with the aim of evaluating the system's potential for real-world application and its implications for traffic safety and efficiency.

2.1.1 Operational flow

COBRA continuously monitors traffic conditions, detects high-flow clusters, and applies targeted control to stabilise traffic. The process relevant to this study can be summarised as follows:

1. **Normal traffic monitoring**: Vehicle trajectories are tracked in real time, with speed, headway, and density data used to group vehicles into clusters.
2. **Cluster evaluation and instability prediction**: If the flow in a cluster exceeds a predefined threshold, the system predicts a risk of breakdown and prepares to intervene.
3. **Target state computation**: A desired speed–density combination is selected so that, if achieved, a stabilising shockwave will propagate upstream of the bottleneck. This is determined from the flow–density relationship and is central to the timing and positioning of advisories.
4. **Individualised advisory generation**: Each vehicle in the affected cluster is assigned a target trajectory, and a deceleration advisory is issued to bring the vehicle toward the target state. In connected automated vehicles, speed is adjusted automatically; in human-driven vehicles, the driver receives a visual or auditory advisory.
5. **Monitoring and adaptive adjustment**: If the driver under-decelerates, the target trajectory is maintained to preserve the desired average density. If the driver over-decelerates or slows earlier than advised, the target trajectory may be recalculated to match the actual position.
6. **Control release**: Advisories stop once vehicles have passed the bottleneck or when no further deceleration is needed.

2.1.2 Driving modes

To structure its control actions, COBRA employs three driving modes:

- **Mode N (Normal mode)**: No external control signal is applied; the vehicle follows its own driving rules.
- **Mode H (Holding mode)**: The vehicle is assigned a target trajectory but has not yet received a speed control signal.
- **Mode A (Advised mode)**: The vehicle receives a deceleration advisory to reach the computed target speed.

2.1.3 Relevance to driver behaviour

While the COBRA control logic assumes compliance with advisories, driver decisions are shaped by both external and internal factors. If congestion is not yet visible, drivers may doubt the necessity of slowing down; if a lane change appears to offer a faster alternative, they may prioritise that manoeuvre. Cognitive workload, emotional state, trust in the system, and driving style all influence these decisions, as do visual cues from surrounding traffic.

Understanding these dynamics is essential for testing COBRA in a simulator. The experimental scenarios in this study therefore focus on adjacent-lane conditions that are likely to affect compliance, allowing an evaluation of both safety and efficiency outcomes under controlled variations of these factors.

2.2 Human drivers' related factors

COBRA has been tested in single-lane simulation experiments, demonstrating its potential effectiveness in managing traffic. However, for real-world traffic applications, human factors become a significant influence on the efficiency of such Driving Assistance System (DAS). The system’s effectiveness can only be fully realized when drivers correctly follow the instructions provided by the system. Some factors that impact driving behaviour include individual factors such as attitude, subjective norms, habits, and distractions [11]; situational factors like traffic conditions and the behaviour of neighbouring vehicles [39]; and additional factors such as HMI, which encompasses the type and presentation of advisory information.

The research categorizes the human factors influencing driving behaviour into four groups [34]: (i) personality traits, (ii) affective, cognitive, and psychomotor functions, (iii) acceptance and trust, and (iv) socio-economic characteristics. Since some of these factors may be interrelated, it is crucial to conduct a comprehensive analysis of the impact of human factors on the effectiveness of any information assistance system.

2.2.1 Personality traits

The driving style of human drivers can be represented on a social/aggressive driving style scale. Aggressive or risk-taking behaviour refers to actions where drivers intentionally put others at risk. Such behaviours can range from honking and flashing lights to more hazardous actions, such as dangerous lane changes, short following distances, and blocking other drivers [25]. A more aggressive driving style is often indicated by a higher frequency of lane changes and shorter lane change durations [12]. Given that drivers with aggressive tendencies are less likely to adjust their speed according to advisory recommendations, this factor should be considered in future experimental designs, especially when examining multi-lane applications and scenario setups.

2.2.2 Affective, cognitive and psychomotor functions

Reaction time toward a speed advice system can significantly influence driving behavior by allowing drivers to respond promptly to alerts about speed-limited zones, intersections, and other points of interest. The model presented in the paper achieved success rates above 78% in delivering alerts at optimal distances, enhancing drivers' awareness and enabling safer driving decisions. [21].

Incorporating reaction time into speed advice systems acknowledges the variability in human cognitive processing and response capabilities. This approach can lead to more personalized and effective systems that cater to individual differences in reaction time [15].

By considering reaction time, developers can design systems that minimize driver overload and distraction, thereby enhancing the overall driving experience and safety [28].

Emotions

Studies have also shown that drivers' emotions significantly impact driving behaviour. It has been observed that anger increases the driver's cognitive load, resulting in an increased crash risk by 9.8 times higher [5]. Another research examined the effect of anger on driver behaviour using a dataset of naturalistic driving study and observed more violations and frequent aggressive driving behaviour related to anger [30].

Perceived headway

The research analysed the time headway for different categories of vehicles playing in a heterogeneous traffic condition and found that cars maintain larger headway while following trucks as compared to truck-truck interaction [30]. This finding suggests that vehicle spacing could be a critical factor to consider when developing traffic scenarios. When evaluating driver behaviour, these natural variations of headway should be taken into account. For example, in a speed advice system where the target trajectory lines display uniform spacing, a car driver maintaining a larger headway behind a truck does not necessarily indicate deviation from the advisory; instead, it reflects typical behaviour based on vehicle interaction dynamics.

Distraction

Evidence exists that distraction and inattention due to secondary task demand is the cause of crashes in the majority of the cases [44]. The secondary task includes the use of handheld cellular devices [6, 26, 51], conversation with the passenger [52], use of in-vehicle music player and use of instrumentation [30]. These activities distract the attention of the driver from driving the vehicle. Driving distractions can be categorized into three categories: visual distraction (looking at co-passenger or mobile phone), visual-manual distraction (texting, using infotainment system), and cognitive distraction (talking on a mobile phone or with co-passengers) [41].

2.2.3 Acceptance and trust

The behaviour of neighbouring vehicles can influence a driver's reliance on or trust in ADAS. For example, if a driver observes neighbouring vehicles travelling quickly and smoothly without apparent dependence on ADAS, they may begin to question the reliability of ADAS speed advisories, potentially reducing their trust in the system. Consequently, the behaviour of neighbouring vehicles may indirectly affect how drivers respond to ADAS advisories by shaping their perception of the system's effectiveness [43].

2.2.4 Socio-economic characteristics

Age and gender

A number of studies have shown that age has a greater impact on driving safety and other driving behaviours. It is evident from the literature that the driver's age has a significant effect on driving performance. Studies suggest that young drivers are at a higher risk of crashes than mid-age and older drivers because of their higher sensation-seeking and speeding behaviour [1]. When driving at a higher speed, it usually takes the driver more time and attention to react to some situation.[8]

In addition to age, the influence from gender has been widely discussed. Many of the studies suggests that male drivers drive vehicles more aggressively than female drivers, exhibiting higher risk of crashes [8, 16, 29]. A study was carried out to examine the effect of age and gender on braking behaviour [20] . It was observed in the study that male drivers brake later than female drivers, while the young aged drivers (age < 30) apply brakes later than older aged drivers (age > 30). It was also found that, on average, females brake at a TTC of 1.3 s higher than males because female drivers perceive the lead vehicle to be closer with a higher risk of collision when compared to male drivers.

Driving experience and education

Research has shown that driving experience and education levels play an important role in driving behaviour and traffic safety. It is reported that less driving experience is associated with a higher risk of road crashes [16] [27] . Better lane-keeping behaviour of drivers is observed with higher education and driving experience [3]. Moreover, drivers with previous involvement in road crashes are less likely to violate the speed limit regulations [24].

2.3 External factors

Road characteristics

Inconsistent geometric design further increases the driver's workload, causing an increase in the probability of road crash. Evidence exists that highway characteristics, such as geometric design, highway marking, traffic density and road conditions influence the driving behaviour of drivers.

On horizontal curves, it was observed that drivers generally decelerate their vehicle while entering the curve and gradually accelerate their vehicle while leaving the curve [4]. The research reported lower speeding behaviour among drivers at junctions, work zones, and during heavy congestion [9]. Moreover, during increased traffic flow conditions, the interaction between vehicles increases, which causes an increase in driver workload and crash risk.

Previous studies suggest that road functional class and driving duration significantly impact driving behaviour [14]. Longer over-speeding durations among drivers on roads were observed with a higher functional classification, such as express ways [14]. This is due to the reason that roads with a higher functional class offer better riding surface, better access control, wider lanes, and fewer interruptions. Furthermore, it was observed that on a lower class road, drivers experienced more interruption such as traffic lights, congestion, and low posted speed causing more aggressive behaviour among drivers.

HMIs for in-car system

In-car Human-Machine Interfaces (HMIs) for speed advice encompass various types, each with distinct features and impacts on driver behaviour and safety. The primary types include visual, auditory, and combined audio-visual systems. Visual systems provide speed advice through displays, which can be either static or dynamic, offering real-time feedback on speed limits and driving conditions [49][46]. Auditory systems, on the other hand, use sound cues to alert drivers about speed limits, which can be particularly effective in reducing distraction and ensuring timely responses [49]. Combined audio-visual systems integrate both modalities to enhance the effectiveness of speed advice, as they cater to different sensory preferences and can encourage better adherence to recommendations, especially among less experienced drivers [49].

Additionally, the integration of digital, physical, and voice interaction modes in HMIs can further enhance user experience and operational efficiency. While voice interaction is preferred for its user satisfaction, it often requires support from digital and physical modes to optimize efficiency and safety [17]. In intelligent connected vehicle environments, HMIs can also include guidance systems that provide real-time speed and voice guidance, which have been shown to improve speed control and cautious driving strategies during complex manoeuvrers like merging [48]. Overall, the choice of HMI type can significantly influence driver acceptance, workload, and eco-safe driving behaviour, with systems offering both advice and feedback being particularly effective in promoting positive driving habits [46].

2.4 Reference experimental designs

Existing studies have developed experimental scenarios tailored to different research objectives, ensuring alignment between study design and intended outcomes. By examining these studies, valuable insights can be gained into how experimental conditions are structured to investigate specific aspects of driver behaviour. The following section reviews three representative experimental designs, highlighting their setup and methodologies. Analysing these studies provides a broader framework for designing relevant scenarios in this research, helping to refine the experimental approach and ensure its alignment with key research questions.

There is a study investigating the effectiveness of in-vehicle display alerts in modifying driver behaviour, particularly in relation to speeding [31]. It aims to understand how different alert styles and locations can influence the frequency and duration of speed limit violations among drivers. The study examined two major factors regarding the visual cues: the location of the alerts and their style. The locations included the dashboard of the simulator, where a typical tachometer is displayed, and the centre console. This setup allowed researchers to analyse how the placement of alerts affects driver response. The styles of the alerts were categorized into two types: steady and flashing. The intention behind varying the style was to determine which type of alert would capture the driver's attention more effectively and lead to a quicker response to speed limit violations. The analysis of the period of incursion, which measures the time spent over the speed limit, showed that both the location and style of alerts significantly affected driver behaviour. In terms of alerting style, flashing style had a statistically significant impact on reducing speeding outcomes. The location of the alert also influenced driver behaviour. Alerts positioned in the mid-peripheral visual region were more effective, as they received an increased response rate from drivers in terms of observing speed limits.

Yadav et al. (2021) used a driving simulator to recreate urban and rural driving environments to study driver adherence to speed limits under different conditions. They created heterogeneous driving scenarios by controlling traffic density, road type, and speed limits. In rural areas, lower traffic density and open road designs encourage higher speeds, making it more challenging for drivers to follow speed limits. In contrast, urban environments, with their high traffic density and structured road features like intersections and medians, promote more cautious driving and greater alignment with posted speed limits [50].

Sharma et al. (2019) focused on driver behaviour in connected vehicle contexts, with a primary emphasis on driver compliance behaviour, which is the extent to which drivers adapt their longitudinal car-following actions when receiving vehicle-to-vehicle (V2V) information. Their simulator-based study examined how connected drivers adjusted their speed and headway compared to non-connected conditions, and used these metrics to calibrate a connected-vehicle trajectory model [35].

2.5 Evaluation methods of driving behaviour

Evaluating driver behaviour in response to speed advisory systems requires both suitable analytical methods and clearly defined key performance indicators (KPIs). This is because compliance with speed advisories involves not only observable actions such as braking or lane changing, but also perceptions, intentions, and attitudes, studies in this area face challenges in achieving consistent definitions and measurements.

Existing research employs a wide variety of evaluation approaches. Some studies use descriptive KPIs that directly quantify compliance-related behaviours. For example, the *period of incursion* measures the time between the moment a driver's speed exceeds the posted speed limit and the point at which it returns to within the limit [31]. Related measures include the *percentage of driving time spent speeding*—the proportion of total driving time above the limit—and the *frequency of incursions*, which counts the number of separate speeding episodes. These indicators are useful for capturing the intensity, duration, and recurrence of non-compliant behaviour in a straightforward manner.

Other studies adopt statistical modelling techniques to explore how different factors influence speed-related behaviour. For instance, Yadav et al. [50] applied a Generalized Linear Model (GLM) to examine the effects of road environment and driver characteristics on speed deviation from the posted limit. The GLM framework accommodates dependent variables that deviate from normality and allows multiple explanatory variables to be tested simultaneously, making it well suited for identifying significant predictors of speed regulation behaviour.

Beyond descriptive and statistical approaches, theoretical frameworks such as prospect theory, have been applied to model driver decision-making under advisory conditions [35]. By incorporating concepts of perceived gains and losses, reference points, and subjective probabilities, prospect theory offers a lens for understanding how trust in technology, acceptance of advisories, and perceived risk influence compliance. This perspective is particularly valuable for interpreting behavioural differences that cannot be explained by physical traffic conditions alone.

Overall, the literature demonstrates that both quantitative KPIs and behavioural theories are important for understanding driver responses to speed advisories. Descriptive measures offer direct, objective benchmarks, statistical models enable exploration of relationships between variables, and theoretical frameworks provide deeper insights into decision-making processes. Together, these approaches form a comprehensive toolkit for evaluating driver behaviour in speed advisory contexts.

2.6 Literature study conclusion

The reviewed literature provides a broad understanding of the factors that can influence driver responses to cooperative speed advisory systems such as the COoperative BReakdown Prevention Algorithm (COBRA). Prior studies highlight that driver characteristics, such as age, gender, and driving style, can affect compliance, trust, and reaction times. While these factors offer valuable context, the present study does not directly manipulate or perform detailed statistical analysis on them, due to the constraints of sample size and the fixed composition of participants. Instead, their potential influence is noted when discussing the representativeness and generalisability of the findings.

In contrast, situational variables that can be directly manipulated in a controlled simulator setting form the focus of the present work. The literature shows that traffic conditions, including available gap size and location, as well as the relative timing of speed changes in neighbouring lanes, play a key role in shaping both longitudinal and lateral driving behaviour. These insights have informed the experimental design by incorporating systematic variations in adjacent-lane gap position and in the timing of adjacent-lane deceleration relative to the participant's vehicle.

System-related aspects, such as HMI design, message clarity, and perceived reliability, are also recurrent themes in previous research. While the literature compares a wide range of interface modalities, the current study fixes the interface to a combined visual–auditory format refined during pilot testing, with variations in these elements intentionally excluded to maintain focus on traffic-related effects. Nevertheless, questionnaire-based measures of trust and perceived clarity will support the interpretation of observed behavioural responses.

Finally, the literature emphasises the importance of clear, quantitative indicators for assessing safety and efficiency, including measures such as time-to-collision, time headway, final speed, mean speed, and reaction times to deceleration and lane change. These indicators are well aligned with the intended evaluation framework of this study and will be computed from the simulator data for subsequent analysis.

In summary, the literature review not only frames the broader behavioural and system considerations for cooperative speed advisories, but also directly informs the choice of experimental variables and performance indicators in this study.

2.7 Refinement of study focus

This section builds on the literature review by identifying factors from previous studies that may influence driver responses to vehicle-based cooperative speed advisory systems, with a focus on the COBRA framework. These factors are grouped into categories, defined with reference to prior research, and mapped to variables that can be measured or controlled in this study. The chapter then narrows the scope to those factors that are most relevant and feasible for experimental investigation, concluding with a concise classification of the variables used in the study.

2.7.1 Factors from literature

Table 2.1 summarises the factors identified in the literature, grouped into three categories: external factors, personal characteristics, and system-related factors, providing an overview of these factors. The following subsections give detailed definitions with relevant citations.

Table 2.1: Factors identified from literature that may influence driver response to cooperative speed advisories

Category	Factors
External factors	Weather conditions
	Traffic-related factors
	Road design
	Surrounding traffic behaviour
Personal characteristics	Cognitive state
	Emotional state
	Driving styles
	Socio-economic characteristics
System-related factors	HMI type
	Perceived system reliability
	Advisory content

External factors

- **Weather conditions**: Environmental states such as rain, fog, or snow affect visibility and vehicle manoeuvre [3]. Poor conditions increase cognitive load and reliance on advisories.
- **Traffic-related factors**: Including road density, proportion of heavy vehicles, and traffic incidents that influence road dynamics [19]. Heavy vehicles can increase perceived risk, encouraging adherence to advisories.
- **Road design**: Features such as curves, gradients, and intersections influence workload [4]. High complexity may raise reliance or cause distraction-based disregard.
- **Surrounding traffic behaviour**: Observed speed choices, lane changes, and advisory compliance of other drivers affect trust in system recommendations [43].

Personal characteristics

- **Cognitive state**: Cognitive load, situational awareness, and reaction time determine how drivers process and respond to advisories [44].
- **Emotional state**: Stress, anger, and anxiety influence decision-making and risk tolerance [5].
- **Driving styles**: Habitual behaviours (aggressive, neutral, or conservative) influence adherence to advisories [25].
- **Socio-economic characteristics**: Variables such as age, gender, education, and driving experience affect variability in responses [1].

System-related factors

- **HMI type**: The mode of information presentation (visual, auditory, or combined) affects how easily drivers process advisories.
- **Perceived system reliability**: The extent to which drivers trust the accuracy of advisories influences compliance [34].

- **Advisory content**: Clarity, precision, and format affect the effectiveness of advisories [31].

2.7.2 Selection of factors for this study

In reviewing the broad range of factors identified in the literature, it became clear that a targeted selection was necessary to ensure a manageable and methodologically coherent experimental design. The focus was narrowed through a deliberate process that considered both the relevance of each factor to advisory compliance and the practical constraints of the simulation environment.

Priority was given to variables with a direct and measurable influence on driver responses, such as traffic density and the observable behaviour of surrounding vehicles. These elements are well suited to controlled manipulation and provide a clear basis for quantifying changes in longitudinal and lateral behaviour.

Factors that could not be consistently or realistically reproduced in a controlled driving simulator environment, such as adverse weather, night-time illumination, or complex road geometries, were excluded. Although these conditions are important in real-world contexts, their inclusion risked introducing artefacts or uncontrollable variability, potentially undermining the validity of the results.

The operational scope of COBRA further shaped the selection. As the system is intended for highway bottleneck scenarios on straight road segments, variables unrelated to this context, such as urban intersection design or varied HMI layouts, were less prioritised.

Within this refined scope, the influence of *adjacent lane traffic conditions* emerged as particularly relevant. In practice, the effectiveness of COBRA depends on driver compliance with proactive deceleration advisories. When adjacent lanes appear to move faster, drivers may hesitate to slow down, choose to change lanes, or delay deceleration. Likewise, when no visible congestion is present, which is common in COBRA's preventive operation, drivers may perceive little need to reduce speed, leading to partial or complete non-compliance.

Through this process, the study's focus crystallised around a small set of factors: traffic-related conditions, the behaviour of vehicles in adjacent lanes, and driver cognitive and emotional states. These variables form the foundation of the experimental manipulations and observations described in the following chapter.

3

Experimental design

This chapter presents the design of the driving simulator experiment developed to investigate how drivers respond to COBRA speed advisories under systematically varied traffic conditions. The experiment builds on the factor refinement described in Chapter 2, translating the selected variables into a controlled and repeatable set of driving scenarios. The chapter proceeds as follows: Section 3.1 defines the scope and objectives of the study; Section 3.2 details the scenario configuration, implemented algorithms, and experimental environment; and Section 3.5 describes the questionnaire design, pilot testing, and adjustments. This structured presentation ensures that the methodological choices are transparent and that the link between the theoretical framework and experimental execution is clearly established.

3.1 Experiment scope and plan

COBRA is a predictive, cooperative speed advisory system designed for highway bottleneck management. Its core principle is to act before congestion visibly forms, by sending advance deceleration instructions to upstream vehicles. This proactive approach aims to stabilise traffic flow, avoid capacity drop, and dampen the amplification of local speed disturbances. Unlike conventional reactive traffic control, COBRA relies on forecasted traffic states, adjusting speeds in anticipation rather than in response. However, its effectiveness depends not only on the accuracy of its calculations but also on how drivers respond to the advisories they receive. In multi-lane highway environments, such responses are often influenced by the behaviour of surrounding traffic, as drivers may interpret the credibility and necessity of a deceleration instruction based on the movement of vehicles in adjacent lanes. If neighbouring lanes appear to be moving faster or contain accessible gaps, drivers may delay slowing down, maintain their speed longer, or change lanes, potentially undermining the intended stabilising effect of the algorithm.

The present experiment therefore focuses on understanding how the behaviour of other vehicles shapes drivers' responses to cooperative speed advisories. By examining driver decisions in a controlled but realistic driving simulator environment, the study seeks to generate empirical evidence that can inform refinements to COBRA's triggering logic and HMI for future deployment. The detailed operationalisation of influencing factors and their variations is presented later in the scenario design section. To ensure comparability across conditions, the simulator reproduces a consistent two-lane highway bottleneck environment in which only the targeted traffic behaviour elements are systematically varied.

To translate the research purpose into a concrete and executable study, the experimental plan is built around a clear sequence that connects design, data collection, and analysis.

Scenario design

The experimental scenarios translate the behavioural factors identified in the literature review into controlled, repeatable conditions in the driving simulator. Each condition reflects a specific combination of adjacent-lane factors, such as relative deceleration position and gap position, while other road and traffic parameters (e.g., road geometry and bottleneck location) are held constant to isolate behavioural effects. A simplified nominal trajectory model is used only as an intermediate tool to derive advisory trigger points and to visualise expected vehicle behaviour across conditions; the execution of scenarios themselves does not rely on this nominal model.

Implemented algorithms

The implemented algorithms adapt COBRA's microscopic traffic control principles for an interactive, multi-lane simulation environment. They serve dual purposes: first, to reproduce the designed scenarios with precise timing and vehicle behaviours; second, to embed a working version of COBRA in the simulator so that its microscopic decision logic can be observed in a macroscopic, human-in-the-loop context. This integration is technically demanding because it must coordinate advisory triggers, car-following dynamics, and multi-lane interactions without compromising scenario comparability.

Data collection objectives

Two complementary data streams will be collected to capture both the objective and subjective dimensions of driver behaviour. **Objective data** from simulator logs will record longitudinal behaviour (speed profiles, deceleration onset time, deceleration rate, and distance to bottleneck), lateral behaviour (lane-change occurrence and timing), safety indicators (minimum time-to-collision), and efficiency indicators (final stable speed and bottleneck arrival time). **Subjective data** from pre- and post-experiment questionnaires will capture trust in the system, perceived relevance and clarity of advice, perceived workload and stress, and willingness to use COBRA in daily driving.

Workflow and validation

A **pilot test** will be conducted first to verify scenario feasibility, confirm the clarity of advisory messages, and fine-tune traffic parameters for realism. In the main experiment, each participant will experience the full set of scenario combinations in a randomised order to minimise learning and fatigue effects. Driving behaviour will be recorded and questionnaire responses will be collected for further processing and analysis.

Expected outcomes

The study aims to identify how specific adjacent-lane cues influence responses with cooperative speed advisory, quantifying the safety impacts of different lane conditions and operational efficiency of the system. In addition, a descriptive inspection of subjective measures will be conducted alongside objective behaviours to surface any exploratory patterns that may inform future work. Finally, this study aims to derive evidence-based recommendations for refining COBRA's activation logic for real-world deployment.

3.2 Scenario design

To investigate how drivers respond to COBRA's speed advisories under varying traffic conditions, the experiment applies a structured scenario design that directly reflects the key behavioural factors identified in the literature review. Two spatial dimensions of adjacent-lane influence are systematically varied: (1) the **relative position to adjacent-lane deceleration**; (2) the **relative position to a gap in the adjacent lane**. All other road geometry and traffic parameters are held constant to isolate the effects of these variables.

3.2.1 Target state selection through shockwave theory

As introduced in Section 2.1, COBRA determines the timing and location of speed advisories based on a predefined **target state** in the FD space. This target state determines the desired speed and density conditions upstream of the bottleneck so that a stabilising shockwave can be generated, preventing capacity drop.

The goal of the COBRA control strategy is to improve bottleneck throughput by preventing capacity drop, which often results from local speed disturbances and the onset of congestion. When traffic demand exceeds bottleneck capacity, even small disturbances, such as a driver reducing speed due to perceived discomfort in spacing or headway, can trigger oscillations in traffic flow. These oscillations propagate through following vehicles, increasing the likelihood of a breakdown. Due to traffic hysteresis, once a breakdown occurs, capacity is not only reduced at the bottleneck itself, but also at the resulting traffic jam. To mitigate this, control is applied upstream of the bottleneck, spreading high demand over space and time, and keeping the flow below capacity.

Based on this reasoning, the COBRA thesis recommends selecting a target traffic state that lies to the right of the uncontrolled state on the fundamental diagram as shown in Figure 3.1. This ensures that the control advice propagates upstream as a shockwave, aligning with natural disturbance dynamics in traffic.

In Figure 3.1, taking the left lane as an example, traffic initially operates in an uncontrolled high-flow state, represented by point A, where the traffic density is 17.5 veh/km and the flow reaches 2100 veh/h, exceeding the bottleneck capacity of 1800 veh/h. This state is unstable and can lead to flow breakdown if not corrected in time. To stabilize the traffic, the controller selects a target state C with higher density (22.5 veh/km) and lower speed (80 km/h). This ensures that the shockwave generated by the control intervention propagates in the upstream direction, allowing upstream vehicles to gradually adjust their speed and headway before reaching the bottleneck.

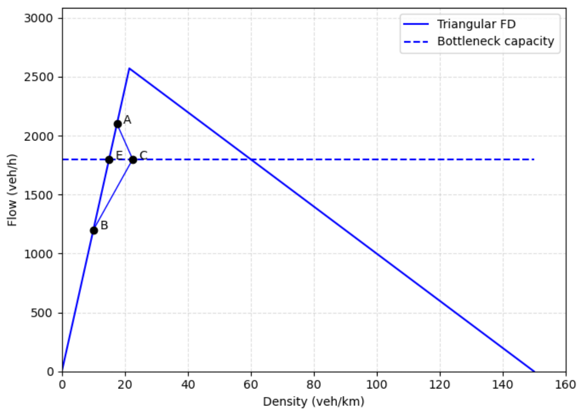


Figure 3.1: Fundamental diagram for the control example in the FD plane

3.2.2 Scenario reference state computation

While the target state defines the desired traffic condition in the FD plane, the experiment requires a systematic method to translate this macroscopic target into the microscopic state of each vehicle at the moment of advisory issuance. This section presents the reference state computation method, which determines where and when each vehicle should begin decelerating in the experimental scenarios.

The method serves two purposes:

1. To compute reference timings and positions for issuing speed advisories, ensuring consistency

Table 3.1: Variables used in discrete trajectory generation

Symbol	Description	Unit
i	Vehicle index (indexed per lane, increasing upstream)	–
j	Lane index ($j = 1$: fast lane; $j = 2$: slow lane)	–
k	Discrete time step index	–
t_k	Time at step k, $t_k = k \cdot \tau^{\text{ctrlr}}$	s
τ^{ctrlr}	Control update interval (controller step size)	s
$x_{i,j}(k)$	Position of vehicle i in lane j at step k	m
$v_{i,j}(k)$	Speed of vehicle i in lane j at step k	m/s
v^{target}	Target cruising speed after deceleration	m/s
a	Constant deceleration rate	m/s^2
x^{BN}	Spatial location of the bottleneck	m
$t_{i,j}^{\text{target}}(k)$	Desired arrival time of vehicle i at the bottleneck	s
$t_{i,j}^{\text{startC}}(k)$	Continuous-time deceleration start time	s
$t_{i,j}^{\text{start}}(k)$	Rounded discrete-time deceleration start time	s
$t_{i,j}^{\text{endC}}(k)$	Continuous-time when vehicle reaches v^{target}	s
$t_{i,j}^{\text{end}}(k)$	Discrete-time when vehicle stops deceleration	s
$x_{i,j}^{\text{start}}(k)$	Position where deceleration begins	m
$x_{i,j}^{\text{end}}(k)$	Position where deceleration ends	m
$d_{i,j}^{\text{dec}}(k)$	Length of deceleration phase	m
$t_{i,j}^{\text{dec}}(k)$	Duration of deceleration phase	s

across all scenarios.

2. To provide an idealised benchmark of vehicle behaviour under fully adherence, against which actual driver responses can be compared.

To maintain experimental control, congestion is not allowed to emerge dynamically. A fixed bottleneck location is predefined for all lanes, eliminating uncontrolled variability in congestion formation. This focuses the experiment on behavioural responses to advisories under controlled high-demand conditions.

The computation assumes vehicles travel at their initial speed until a specified deceleration phase begins. The discrete-time formulation uses a fixed control step τ^{ctrlr} to update a vehicle's speed and position in three phases: cruising at initial speed, decelerating to the target speed v^{target}, and cruising at the target speed until the bottleneck is reached.

The indices, parameters, and variables used in the discrete-time trajectory generation model are shown in Table 3.1. All vehicles are indexed by i and are associated with a specific lane indexed by j. The model assumes a fixed control step time τ^{ctrlr}, and piecewise updates the vehicle's speed and position accordingly. Each vehicle aims to arrive at the bottleneck at a preassigned target time $t_{i,j}^{\text{target}}$, and decelerates to a target speed v^{target} using a specified deceleration rate a.

Step 1: Determine deceleration start and end time

First, continuous-time deceleration values are calculated:

$$t_{i,j}^{\text{dec}}(k) = \frac{v^{\text{target}} - v_{i,j}(k)}{a}, \qquad \big(a < 0\big), \tag{3.1}$$

$$d_{i,j}^{\text{dec}}(k) = v_{i,j}(k)\, t_{i,j}^{\text{dec}}(k) + \frac{1}{2} a\, t_{i,j}^{\text{dec}}(k)^2, \tag{3.2}$$

$$t_{i,j}^{\text{startC}}(k) = \frac{x_{i,j}(k) + d_{i,j}^{\text{dec}}(k) - x^{BN} + v^{\text{target}}\big(t^{\text{target}}(k) - t_{i,j}^{\text{dec}}(k)\big)}{v^{\text{target}} - v_{i,j}(k)}. \tag{3.3}$$

To ensure that the deceleration instruction is only issued when the vehicle is truly on or downstream of its target line, the continuous-time start value is rounded up to the next controller time step:

$$t_{i,j}^{\text{start}}(k) = \left\lceil \frac{t_{i,j,\text{start}}^{\text{cont}}}{\tau^{\text{ctrlr}}} \right\rceil \cdot \tau^{\text{ctrlr}} \tag{3.4}$$

$$\tag{3.5}$$

$$x_{i,j}^{\text{start}}(k) = x_{i,j}(k) + v_{i,j}(k) \cdot t_{i,j}^{\text{start}}(k) \tag{3.6}$$

Step 2: Generate vehicle trajectories

The trajectory is simulated in three segments using the discrete control step τ^{ctrlr}:

- **Phase 1: Constant speed before deceleration**

$$x_{i,j}(k) = x_{i,j}(k) + v_{i,j}(k) \cdot (t_{i,j}^{\text{start}} - t_k) \quad \text{for } t_k < t_{i,j}^{\text{start}} \tag{3.7}$$

- **Phase 2: Discrete deceleration**

$$v_{i,j}(k+1) = \max\Big(v_{i,j}(k) + a \cdot \tau^{\text{ctrlr}},\ v^{\text{target}}\Big) \tag{3.8}$$

$$x_{i,j}(k+1) = x_{i,j}(k) + v_{i,j}(k) \cdot \tau^{\text{ctrlr}} + \frac{1}{2} a \cdot (\tau^{\text{ctrlr}})^2 \tag{3.9}$$

  In a discrete-time control system, vehicle speed is updated at fixed intervals τ^{ctrlr} using a constant deceleration rate a (for nominal model). This results in a quantized evolution of speed.

  Unless the target speed v^{target} happens to lie exactly on this discrete update grid, i.e., $v^{\text{target}} \in \{v^0 + n \cdot a \cdot \tau^{\text{ctrlr}}\}$ for some integer n, the vehicle will not be able to reach it precisely. Instead, the speed will gradually decrease past the target value. The control logic checks whether

$$v_{i,j}(k+1) \leq v^{\text{target}},$$

  and then explicitly sets the speed to v^{target} in subsequent steps.

- **Phase 3: Constant target speed**

$$x_{i,j}(k+1) = x_{i,j}(k) + v^{\text{target}}(k) \cdot \tau^{\text{ctrlr}} \quad \text{for } t_k > t_{i,j}^{\text{end}}(k) \tag{3.10}$$

  In this phase, the vehicle maintains the predefined target cruising speed v^{target} until it reaches the bottleneck location x^{BN}. This ensures that the vehicle arrives at the bottleneck in a stable traffic state with a uniform headway, minimising the risk of local speed oscillations or flow breakdown. By holding the speed constant, the system also prevents over-deceleration, which could otherwise reduce efficiency or create unnecessary gaps that disrupt upstream traffic flow.

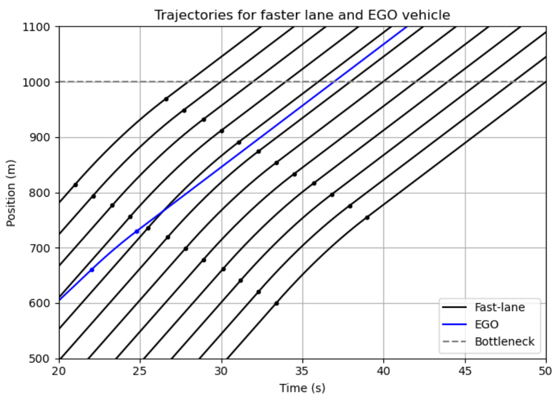
3.2.3 Relative position to adjacent-lane deceleration

One key factor examined in this study is the spatial relationship between the ego vehicle and the deceleration zone of vehicles in the adjacent lane at the moment the advisory is issued. This factor is intended to capture whether the driver observes confirming visual cues from adjacent traffic, which could influence their response towards the advisory.

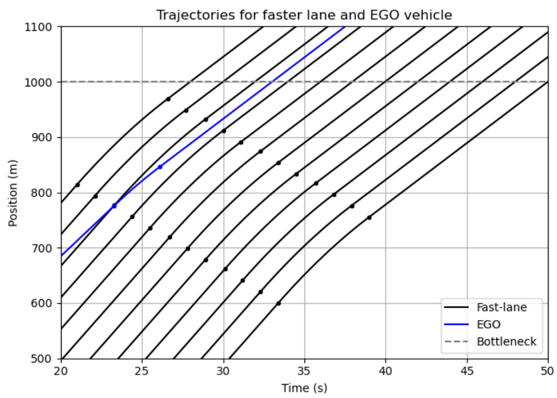
Three spatial categories are defined (Figure 3.2):

- **Upstream:** The ego vehicle is located upstream of the start of adjacent-lane deceleration. No deceleration is yet visible in the adjacent lane.
- **Same position:** The ego vehicle is aligned with vehicles in the adjacent lane that are currently in the deceleration phase.
- **Downstream:** The ego vehicle is downstream of the start of adjacent-lane deceleration, meaning that deceleration has already occurred ahead.

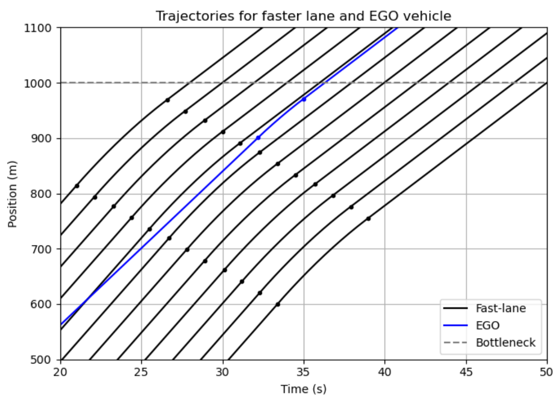
This categorisation allows for a structured investigation into how the presence or absence of visible deceleration cues affects the perceived urgency and credibility of the advisory.



(a) Upstream: ego vehicle upstream of deceleration zone



(b) Same position: ego vehicle aligned with decelerating vehicles



(c) Downstream: ego vehicle downstream of deceleration start

Figure 3.2: Relative position of ego vehicle to adjacent-lane deceleration

3.2.4 Relative position within adjacent lane gap at advisory onset

Another factor considered is the ego vehicle's position within the adjacent lane gap, defined as the longitudinal space between the lead and lag vehicles in the adjacent lane at the exact moment the speed advisory is issued. The adjacent lane gap is composed of two measurable components: the lead gap (distance from the ego vehicle to the lead vehicle in the adjacent lane) and the lag gap (distance from the lag vehicle in the adjacent lane to the ego vehicle).

Four discrete relative positions are defined (Figure 3.3) by evenly dividing the total adjacent lane gap into four equal segments. The ego vehicle's position is expressed as its alignment with the first four division points measured from the adjacent lane's lead vehicle. For example, if the adjacent lane gap length is 80 m, the configurations correspond to the ego vehicle being positioned with a lead gap of 0 m, 20 m, 40 m, or 60 m.

The position where the ego vehicle is directly aligned with the lag vehicle (i.e., lead gap = gap length) is excluded, as it coincides with the trailing vehicle and does not represent a feasible lane-change entry point.

Positions with a small lead gap (e.g., 0-20 m) place the ego vehicle near the front of the adjacent lane gap, potentially giving the driver more time and flexibility to delay slowing down or consider a lane change. In contrast, positions near the middle of the gap may heighten the perceived urgency to act in accordance with the advisory.

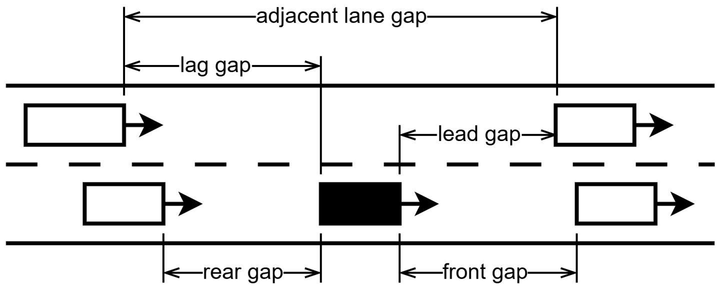
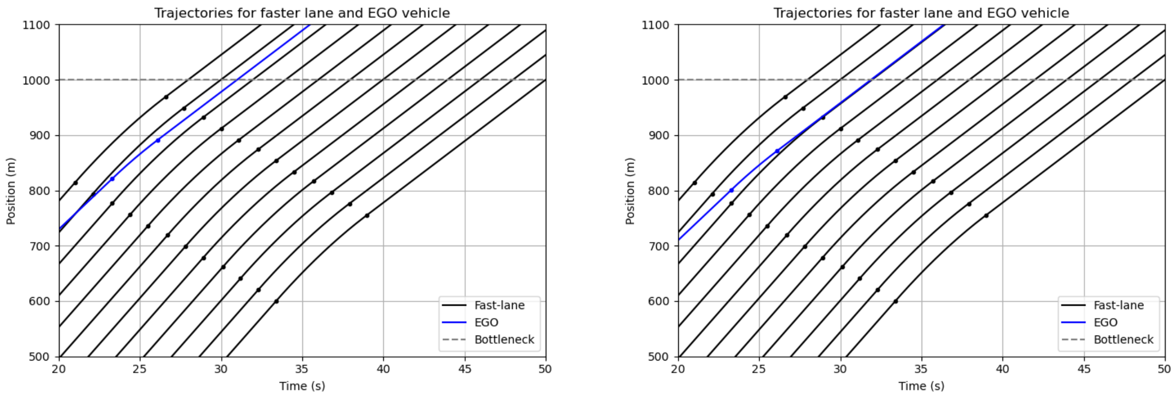


Figure 3.3: Definition of adjacent lane gap and its components



(a) ego vehicle positioned with larger gap behind

(b) ego vehicle positioned with smaller gap behind

Figure 3.4: Relative position of the ego vehicle to the adjacent gap

3.3 Experimental scenarios configuration

The experimental scenarios are constructed using a combination of static control parameters and systematically varied behavioural conditions. Control parameters define the baseline traffic and control environment, while each scenario round adjusts specific variables to isolate the effect of adjacent lane conditions.

3.3.1 Control parameter setup

Table 3.2 provides the predefined simulation inputs applied to each lane. These values ensure high flow conditions prior to advisory intervention, supporting the investigation of COBRA's effectiveness under near-saturation traffic scenarios.

Table 3.2: Control parameters for each lane

Parameter	Faster Lane	Slower Lane
Initial speed (km/h)	120	100
Control speed (km/h)	80	80
Deceleration (m/s²)	-2	-2
Initial headway (s)	1.71	1.80
Control headway (s)	2.0	2.0
Bottleneck location (m)	1500	1500

3.3.2 Scenario variables and round configuration

Each scenario round is defined by a specific combination of key variables:

- **Initial position** (x_{initial}): The position of the ego vehicle when the scenario starts (in meters).
- **Time to bottleneck** ($t_{\text{bn-ego}}$): The expected time for the ego vehicle to reach the bottleneck (in seconds).
- **Deceleration start location** (x_{start}): The computed position where deceleration begins.
- **Deceleration start time** (t_{start}): The time when the ego vehicle should start decelerating (in seconds).
- **Relative position**: The relative timing between the ego vehicle's deceleration and adjacent lane vehicle behaviour (upstream, during, downstream).
- **Gap position**: The ego vehicle's spatial distance to the leading vehicle in the adjacent lane (in meters).

The complete scenario configuration is shown in Table 3.3. Each row represents a unique driving condition constructed to isolate the influence of specific adjacent lane factors. The lead gap values differ between scenario groups due to the relative position of the advisory trigger. In the downstream group, by the time the participant receives the deceleration advisory, the adjacent lane traffic has already completed its deceleration and reached the target state, with a headway of 60 m corresponding to a time headway (THW) of 2 s. Dividing this headway evenly among the four vehicles in the reference cluster results in a lane gap of 15 m for each scenario in this group. In the same-position and upstream groups, the adjacent lane traffic is still in motion when the advisory is issued. To ensure that the adjacent lane offers a gap size that is neither prohibitively small nor unrealistically large for a lane change, the available lane gap at the moment of message delivery is set to 80 m, yielding a 20 m gap for each relevant scenario.

3.3.3 Scenario grouping

The 12 experimental scenarios are categorised along two orthogonal dimensions.

Longitudinal grouping: Relative position to adjacent-lane deceleration

This grouping is based on the ego vehicle's position relative to the start and completion of deceleration in the adjacent lane. The categories are:

Table 3.3: Scenario configurations with relative phase and gap position

Scenario	Relative position	Lead gap (m)
1	Downstream	0
2	Downstream	15
3	Downstream	30
4	Downstream	45
5	Same position	0
6	Same position	20
7	Same position	40
8	Same position	60
9	Upstream	0
10	Upstream	20
11	Upstream	40
12	Upstream	60

1. **Downstream**: The ego vehicle receives the advisory and begins decelerating after vehicles in the adjacent lane have already completed deceleration. This represents situations where clear visual deceleration cues are present before the driver acts.
2. **Same position**: The ego vehicle starts decelerating simultaneously with vehicles in the adjacent lane, providing synchronised visual cues.
3. **Upstream**: The ego vehicle begins decelerating while the adjacent lane is still in free flow, with no immediate visual confirmation available.

Lateral grouping: Lead gap at advisory onset

This grouping considers the available lead gap in the adjacent lane when the advisory is issued. The lead gap is defined as the distance from the ego vehicle to the leading vehicle in the adjacent lane within the same usable lane-change gap.

The absolute lead gap values differ across longitudinal groups due to scenario design constraints.

- In the **downstream** group, adjacent lane traffic has already reached the target state when the advisory is issued, with a headway of 60 m corresponding to a THW of 2 s. Dividing this headway evenly among the four vehicles in the reference cluster results in a lane gap of 15 m.
- In the **same position** and **upstream** groups, the adjacent lane is still decelerating or in free flow at the moment of message delivery. To maintain a gap size that is realistic yet not prohibitively small for a lane change, the total available gap is set to 80 m, yielding 20 m per segment.

Within each longitudinal group, four lead gap positions are defined based on evenly spaced division points along the total gap length, measured from the leading vehicle:

1. **Small lead gap**: ego vehicle is near the trailing quarter of the gap length.
2. **Medium small lead gap**: ego vehicle is between one-half and three-quarters of the gap length behind the leading vehicle.
3. **Medium large lead gap**: ego vehicle is between one-quarter and one-half of the gap length behind the leading vehicle.
4. **Large lead gap**: ego vehicle is aligned with, or just behind, the leading vehicle (first quarter of the gap length).

This grouping tests whether the perceived feasibility and urgency of a lane change influence the driver's response to the advisory.

3.4 Algorithms implemented in SCANeR

The implemented algorithms bridge the scenario design with real-time driver interaction in the SCANeR simulator. They adapt COBRA's microscopic traffic control principles to an interactive, two-lane simulation, ensuring that vehicle behaviours match the intended scenario conditions. This section also describes the physical and visual environment in which these algorithms operate.

The discrete-time trajectory generation logic described here is initially derived from an offline formulation that assumes no lane changes and constant speeds. This formulation is well suited for defining nominal trajectories for experiment design and visualisation purposes. However, when applied to interactive driving simulations such as those conducted in SCANeR, pre-defined static trajectories are insufficient to reproduce the dynamic spacing and ordering changes that occur when vehicles interact on multi-lane roads.

To address this, the simulator computes vehicle states in a step-by-step manner, updating positions, speeds, and accelerations at each simulation time step. This per-step update ensures that the simulated traffic flow reflects natural interactions such as lane changes and varying headways. In the present implementation, these updates follow the pre-defined control logic derived from COBRA's principles, but do not incorporate a full closed-loop feedback mechanism that adapts future advisories based on observed driver reactions. Instead, control triggers and target speed profiles are determined from the initial scenario conditions and remain consistent throughout each run, with dynamic updates applied only to maintain kinematic consistency and lane-change feasibility.

In summary, while the nominal offline formulation provides the baseline for scenario configuration, the SCANeR implementation uses dynamic per-step calculations to maintain realistic vehicle interactions during the experiment, without deploying an adaptive feedback control loop.

3.4.1 Theoretical dynamic control logic

The ideal dynamic implementation is based on a discrete-time feedback scheme that continuously determines whether each vehicle should decelerate, and if so, computes the required acceleration in real time. This allows the controller to adjust to surrounding traffic, especially in multi-lane conditions with possible lane changes.

Deceleration trigger condition

At each simulation step k, the system checks whether vehicle i in lane j should begin decelerating by comparing its current position $x_{i,j}(k)$ to a dynamically updated braking position:

$$x_{i,j}(k) \geq x_{i,j}^{\text{end}}(k) - \frac{v_{i,j}(k)^2 - (v^{\text{target}})^2}{2|a|} \tag{3.11}$$

Here, $x_{i,j}^{\text{end}}(k)$ is the desired deceleration end point (e.g., near the bottleneck), $v_{i,j}(k)$ is the vehicle's current speed, v^{target} is the target speed, and a is the nominal deceleration rate.

Dynamic acceleration computation

If the trigger condition is satisfied, the required acceleration to reach v^{target} within the remaining distance is:

$$a_{i,j}^{\mathrm{COBRA}}(k) = -\frac{1}{2} \cdot \frac{v_{i,j}(k)^2 - (v^{\mathrm{target}})^2}{x_{i,j}^{\mathrm{end}}(k) - x_{i,j}(k)} \tag{3.12}$$

The final longitudinal acceleration combines this COBRA-based logic with the standard Intelligent Driver Model (IDM) car-following output:

$$a_{i,j}(k) = \min\left(a_{i,j}^{\mathrm{IDM}}(k),\, a_{i,j}^{\mathrm{COBRA}}(k)\right) \tag{3.13}$$

This ensures that speed reductions required by the advisory take priority when necessary, but the baseline car-following remains realistic.

Target line recalculation mechanism

In theory, the dynamic model continuously updates the target trajectory line to adapt to real-time vehicle manoeuvrers. Once a lane change is detected, the system should:

1. Update the vehicle's current lane ID.
2. Re-identify its position in the new lane's vehicle order.
3. Recompute the target arrival time at the bottleneck and generate a new target speed trajectory.

Once deceleration begins, the target line is locked to avoid excessive fluctuation, but a valid lane change should always trigger a recalculation.

3.4.2 Simplified implementation in this study

In practice, implementing the full dynamic logic in a driving simulator is technically demanding due to real-time vehicle-to-vehicle dependencies, especially when multiple lane changes or manual overrides occur. To ensure experimental feasibility and repeatable scenario conditions, the following simplifications were made:

- The target line for the ego vehicle is computed once, at the start of each scenario, using the nominal trajectory model.
- The advisory message is triggered once at a fixed distance and time upstream of the bottleneck, based on the precomputed target line.
- All vehicles apply an IDM-based car-following model to maintain safe spacing, but do not dynamically adjust their target lines after a lane change.

Under this design, vehicles ahead of the ego vehicle are unaffected by its actions. Trailing vehicles may respond via IDM car-following, but these effects do not interfere with the experimental focus on ego driver response. Since the advisory is not recalculated after a lane change, any respose behaviour after switching lanes is not necessary. Therefore, the scenario terminates 5 seconds after a lane change occurs, capturing the driver's decision without introducing invalid advisory effects.

3.5 Experimental platform and environment setup

This section describes the physical and virtual setup used in the experiment, covering the driving simulator hardware, road network design, and the HMI for delivering COBRA advisories.

3.5.1 Driving simulator hardware

The driving simulator software used for this research is the SCANeR (v1.9) by AV Simulation. The simulator is built up from a fixed-base seating with three 4K high-resolution screens, providing participants a 180-degree vision, in combination with a Fanatec steering wheel and pedals. This type of setup can be categorized as a mid-level simulator. In addition to simulating various environments and designs, the simulator is also able to include technologies such as connected and automated driving and VMS in the experimental designs. The simulator is located at the Faculty of Civil Engineering and Geosciences, Delft University of Technology (Figure 3.5).

Figure 3.5: Driving simulator

3.5.2 Road network design

The experimental road layout was designed to simulate a realistic but controlled highway environment suitable for investigating driver responses to COBRA speed advisories. The virtual road is a straight, one-directional, two-lane highway segment with a total length of 2000 m. Each lane has a standard width of 3.5 m, reflecting typical European highway design guidelines.

To help drivers maintain a stable sense of speed and distance perception, rows of trees are placed uniformly along the roadside at 12 m intervals. This roadside environment provides visual cues that support longitudinal speed estimation, which is particularly important in a virtual driving simulator.

A fixed bottleneck is implemented at 1500 m from the starting point of the road. This bottleneck location serves as the point of interest for speed advisory activation and ensures that all advisory messages are triggered sufficiently upstream for drivers to make informed deceleration or lane changing decisions.

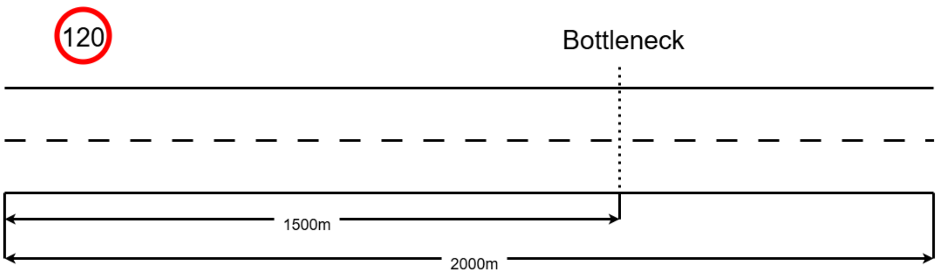


Figure 3.6: Schematic layout of the experimental road

3.5.3 HMI design

The advisory was presented using a speed limit symbol visually styled to resemble a conventional regulatory speed sign. It was displayed at the top of the simulated instrument cluster, in a position corresponding to a head-up display (HUD) in real vehicles, thereby aligning with the driver's natural line of sight.

Auditory feedback was provided simultaneously with the visual advisory. When the COBRA system issued a deceleration instruction, the system displayed the icon with "80" and played the spoken message *"Slow down to 80."* Upon entry into the bottleneck zone, an additional auditory cue, *"Keep to 80,"* was triggered to reinforce the target speed.

In automated driving segments preceding manual takeover, an additional HMI element was employed to facilitate a smooth transition of control. A textual message *"Take control in* x *seconds"* appeared centrally on the screen at eye level, accompanied by a real-time countdown. This countdown provided the driver with clear temporal information on when to prepare for deceleration and resume manual control, ensuring that the transition occurred in a timely and predictable manner.

(a) Speed advisory: 80 km/h visual cue

(b) Manual takeover countdown display

Figure 3.7: Visual human–machine interface elements presented to the driver.

3.6 Questionnaire design

The questionnaire design complements the objective driving behaviour data by capturing participants' subjective perspectives. It was developed in direct relation to the scenario design and implemented algorithms, allowing participants to reflect on both the traffic conditions they experienced and the advisories they received.

To complement the objective driving behaviour data, two structured questionnaires were designed and administered to capture participants' background characteristics, subjective perceptions, and self-reported responses related to the cooperative speed advisory system.

3.6.1 Pre-experiment questionnaire

Before starting the main driving scenarios, each participant completed a short background survey to collect demographic and behavioural baseline information. The pre-experiment questionnaire included:

- Demographic details: gender, year of birth, and highest educational level.
- Driving experience: years holding a valid driving license, average weekly driving hours on highways, and prior experience with driving simulators.
- Self-reported driving style and compliance: typical speed limit adherence and general attitude towards in-car speed advice systems.

3.6.2 Post-experiment questionnaire

Immediately after completing all scenarios, participants filled out a post-experiment questionnaire to reflect on their subjective impressions and decision-making processes. The post-experiment questionnaire consisted of Likert-scale items covering four dimensions:

- System information and trust: clarity, timing, perceived relevance of the advisories, and overall trust in the system.
- Personal state: perceived mental workload, stress, or tension experienced when responding to advisories.
- Behavioural response: reasons for slowing down or changing lanes, hesitation due to uncertainty or trailing vehicles, and risk perception during manoeuvrers.
- Acceptance and perceived safety: willingness to use such a system in everyday driving and its perceived contribution to traffic safety.

Additionally, participants were invited to provide open-ended feedback about specific moments when the advisory system was particularly helpful, confusing, or could be improved. This qualitative input supplements the quantitative data and provides insights into user acceptance and system usability.

3.7 Pilot test and adjustments

Before launching the main experiment, a pilot test was conducted to validate scenario feasibility, verify technical stability, and assess participants' understanding of the advisory system. The test revealed several aspects that required refinement in both the experimental procedure and scenario settings. Key observations and subsequent adjustments are summarised below.

Transition from automated to manual driving

The pilot assessed whether participants could smoothly adapt from automated driving to manual control. It was observed that the initial familiarisation session, which only introduced the basic operation of the driving simulator, was insufficient for preparing participants for the handover process. An additional familiarisation drive was therefore introduced before the main experimental trials, allowing participants to experience the automated-to-manual transition in advance and reducing potential confusion during the experiment.

Speed limit signage in the virtual environment

The original road design did not include speed limit signs, which could lead to unrealistic driving behaviour in the simulator. To align with real-world driving conditions, two 120 km/h speed limit signs were added to the road environment.

Human–machine interface presentation

In the initial setup, the advisory was displayed as a text message (*"Slow down to 80 km/h"*) at the top of the screen, which, when translated to real-world conditions, would correspond to a head-up display position on the windscreen. Pilot participants reported difficulty in noticing the advisory, and some entirely missed it, as the location caused excessive deviation of gaze from the road.

To address this, the advisory display was moved to align with the virtual instrument cluster height, minimising eye movement. However, participants then reported that the text contained too much information to be read quickly during driving. The HMI was therefore redesigned to use a simple visual icon accompanied by an auditory prompt (*"Slow down to 80"*), with an additional *"Keep to 80"* prompt upon entering the bottleneck zone.

Scenario termination after lane changes

In the original design, the scenario ended immediately upon a lane change, which unintentionally signalled to participants that lane changing might be penalised. This risked introducing bias in behaviour. The termination condition was therefore revised so that the scenario ends 5 seconds after a lane change, reducing this unintended influence.

Adjustment of reaction time parameter

The advisory reaction time parameter, initially set to 2.0 s, was found to be insufficient for capturing natural driver responses in the pilot test. This value was adjusted to 2.5 s to better reflect observed behaviour.

3.8 Summary

This chapter detailed the experimental design developed to investigate how drivers respond to a cooperative speed advisory system are influenced by surrounding traffic behaviour in a controlled highway bottleneck scenario. The scope and objectives were first outlined, followed by the systematic scenario design, the algorithmic implementation in SCANeR, the experimental platform setup, and the structure of the pre- and post-experiment questionnaires. Pilot testing ensured that the scenarios were technically stable, realistic, and clearly understood by participants, leading to several refinements in HMI presentation, road environment, and procedural details.

By integrating controlled variation of adjacent-lane traffic conditions with repeatable simulator runs, the design provides a robust framework for isolating the effects of spatial relationships, both in terms of deceleration position and available lane-change gaps, on drivers' responses. The resulting dataset, combining objective driving behaviour and subjective perceptions, forms the basis for the analysis presented in the next chapter.

4

Data processing

Building on the experimental design described in Chapter 3, this chapter details the procedures used to transform raw data from the driving simulator and questionnaires into a structured dataset suitable for quantitative and qualitative analysis. The processing workflow was designed to ensure that all behavioural indicators were defined consistently, computed accurately, and aligned with the study's research objectives. It includes quality assurance steps to remove noise and inconsistencies, standardised computations of efficiency, safety, and reaction-related metrics, and integration of subjective feedback. By establishing a transparent and replicable processing framework, this chapter provides the methodological foundation for the statistical analyses presented in Chapter 5.

4.1 Purpose of data processing

The purpose of data processing in this study is to transform the high-frequency, heterogeneous raw data collected from the driving simulator and questionnaires into a structured, high-quality dataset suitable for rigorous behavioural analysis. This transformation is essential to ensurevalidity,comparability, andreproducibility of the results across scenarios and participants.

The processing stage serves three main objectives:

1. **Data quality assurance:** Remove noise, implausible readings, and inconsistencies that may arise from simulator logging artefacts or participant-specific anomalies, thus preventing distortion of the analysis outcomes.
2. **Indicator computation and standardisation:** Convert raw telemetry (e.g., position, speed, lane ID) into well-defined behavioural indicators that have a clear interpretation, are supported by literature or standards [38] [45], and are consistently comparable across all conditions.
3. **Analytical readiness:** Organise the cleaned data into an analysis-ready structure, enabling grouping by scenario factors (e.g., relative timing of advisory, gap location) and direct input into statistical models.

The selection of indicators is directly guided by the research questions and the literature study:

- **Indicators related to system efficiency:** Mean speed and final speed quantify the degree to which drivers adjust their longitudinal behaviour following a speed advisory.
- **Indicator related to safety:** Time-to-collision (TTC_{min}) capture changes in spacing behaviour and identify potential high-risk situations.

- **Response time indicators:** RT_{decel} measures the time from the advisory trigger (t_{msg}) to the onset of significant deceleration, while RT_{lc} measures the time from t_{msg} to the start of a lane-change manoeuvre.
- **Lateral behaviour indicators:** The accepted lag gap (d_{lag}) and lead gap quantify the spatial margins available during a lane change, reflecting drivers' willingness and safety margin when changing lanes.

These quantities are necessary for analysis because they represent the observable behavioural outcomes that bridge the experimental manipulations and the theoretical constructs of driver trust, compliance, and safety. Without systematically defined and processed indicators, it would not be possible to conduct valid comparisons between scenarios, quantify behavioural differences, or test the mechanisms proposed in the conceptual model.

4.2 Definitions of indicators

Mean speed

The mean speed is defined as the average speed of the subject vehicle over a specific stretch of road. It is an indicator of the efficiency of traffic flow and can be compared across scenarios to assess behavioural responses to the speed advisory. [38]

Reaction time

Reaction time (RT) is the time between the presentation of an in-vehicle advisory and the driver's observable reaction in either longitudinal or lateral control [36]:

- For deceleration, RT_{decel} is calculated as the time from advisory trigger to the first significant drop in speed or onset of negative longitudinal acceleration.
- For lane change, RT_{lc} is defined as the time from advisory trigger to the start of the lane change manoeuvrer, identified via lateral deviation crossing the lane boundary.

Final speed

Final speed represents the stabilized speed after the driver's deceleration response to an advisory. It is defined as the speed at which longitudinal acceleration returns to approximately zero and the speed stabilizes within a ±0.05 m/s^2 threshold [35]. This indicates the steady-state condition reached after a speed adjustment.

Lane change duration

Following the SAE J2944 operational definition [38], the lane change duration is the elapsed time between the moment the leading front wheel of the subject vehicle first crosses the lane boundary and the moment the trailing rear wheel fully enters the target lane. Since direct wheel position data are not available in the driving simulator, lane change start and end points are approximated using the vehicle's lateral position relative to the lane centerline. Specifically, the maneuver is considered to start when the lateral offset from the current lane center exceeds ± 0.9 m (approximately one quarter of a standard 3.5 m lane width) toward the target lane, and to end when the offset from the target lane center returns within ± 0.9 m. Only events where the offset exceeds the threshold continuously are classified as valid lane changes. Maneuvers with a measured duration longer than 10 s are excluded to remove low-speed drift or gradual lateral wandering not indicative of intentional lane changes.

Gap size

The definition of gap size relevant for lane change behaviour follows the adjacent lane gap description in Section 3.2.4 and Figure 3.3. The adjacent lane gap is the longitudinal space between the lead and lag vehicles in the adjacent lane at the moment the advisory is issued. It is composed of:

- Leading gap (d_{lead}): the longitudinal distance from the ego vehicle to the lead vehicle in the adjacent (target) lane.
- Lagging gap (d_{lag}): the longitudinal distance from the lag vehicle in the adjacent lane to the ego vehicle.
- Same-lane spacing (d_{front}): the longitudinal distance from the ego vehicle to its lead vehicle in the current lane before initiating the lane change.

All distances are measured in meters at the moment of advisory onset. The leading and lagging gaps jointly describe the availability of an entry space in the adjacent lane, while the same-lane spacing indicates the immediate car-following context in the current lane [10].

Gap location

In this study, gap location refers to the ego vehicle's longitudinal position within the adjacent lane gap at the moment the speed advisory is issued. Four discrete relative positions are defined by evenly dividing the total adjacent lane gap into four equal segments, measured from the lead vehicle in the adjacent lane. For example, if the adjacent lane gap length is 80 m, the ego vehicle's lead gap positions correspond to 0 m, 20 m, 40 m, or 60 m. The configuration where the ego vehicle is directly aligned with the lag vehicle (lead gap equal to total gap length) is excluded, as it coincides with the trailing vehicle and does not represent a feasible lane-change entry point. Positions with smaller lead gaps (e.g., 0–20 m) place the ego vehicle near the front of the gap, potentially allowing more flexibility to delay compliance or initiate a lane change. Positions near the middle of the gap may heighten the perceived urgency to act in accordance with the advisory.

4.3 Raw data overview

The raw data used in this study consist of two main parts: driving simulator vehicle data and participant-reported questionnaire responses.

4.3.1 Driving simulator data

A total of 12 scenarios were designed and each participant completed all scenarios. With 21 participants expected, this would yield 252 simulator data files; however, due to one missing file, the final dataset comprises 251 files. Each file contains high-frequency (20Hz) vehicle telemetry recorded in SCANeR, including:

- *Vehicle dynamics:* position (`pos`), speed (`speed`), longitudinal and lateral acceleration (`accel`), wheel angle, gear status, engine and brake signals, ignition key status, and timestamps (`lastUpdate`).
- *Road information:* road and lane IDs (`roadId`, `laneId`), longitudinal position (`roadAbscissa`), lateral offset (`roadGap`), and gaps to surrounding vehicles (`laneGap`).

An example of the SCANeR export structure is shown in Figure 4.1.

4.3.2 Pre-experiment questionnaire

Before starting the driving tasks, each participant completed a brief survey covering demographic details (gender, age, education level), driving experience (years licensed, weekly highway driving hours),

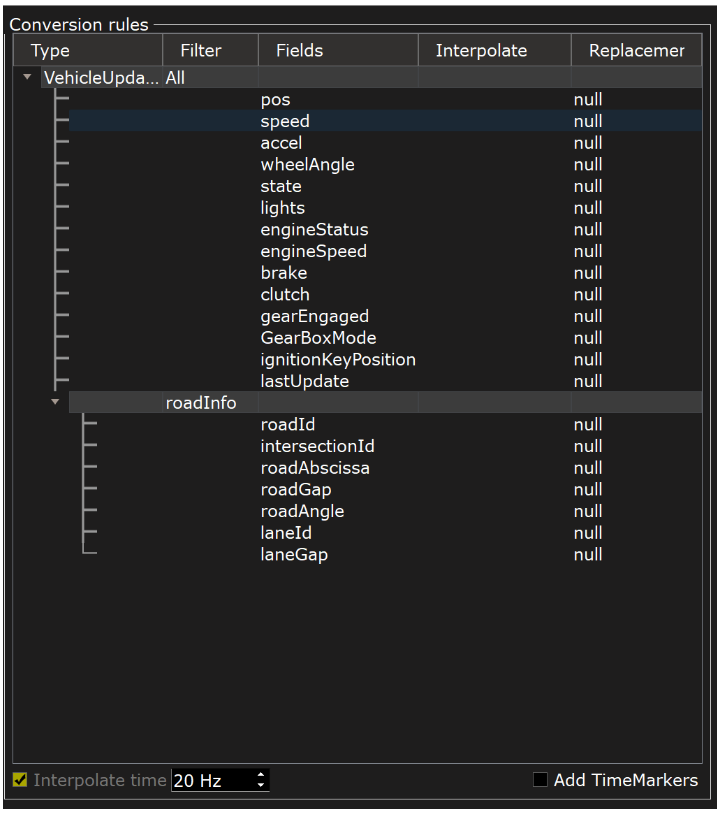


Figure 4.1: Example of SCANeR simulator raw data export structure.

familiarity with driving simulators, and general attitudes towards in-car speed advice systems. Participants also rated their typical driving style (e.g., calm, neutral, aggressive).

4.3.3 Post-experiment questionnaire

After completing all scenarios, participants filled out a subjective assessment. This included Likert-scale statements about:

- Trust in the speed advisory system (e.g., clarity, timing, perceived match with road conditions).
- Mental workload and tension while processing the advisory.
- behavioural response intentions (e.g., choosing to slow down or change lanes).
- Perceived safety (e.g., concern about rear-end or side collisions).
- Acceptance and willingness to use a similar system in daily driving.

Participants could also provide open-ended feedback about moments when the advisory was helpful or confusing, and suggestions for improvement.

Together, these raw data sources ensure a comprehensive basis for understanding both objective driving behaviour and subjective driver perceptions.

4.3.4 Raw data computation and combination

Following the acquisition of raw simulator files and questionnaire responses described above, all driving data were processed to compute the behavioural indicators defined in Section 4.2. For each participant–scenario combination, the raw CSV log exported from SCANeR was parsed to extract the participant

ID, scenario ID, and the advisory onset time (t_{msg}) associated with that scenario. The data sampling frequency was 20 Hz.

For each run, the following quantities were derived:

- **Mean speed** was calculated as the arithmetic mean of the ego vehicle's instantaneous speed over the scenario, expressed in both m/s and km/h.
- **Minimum and mean time-to-collision (TTC$_{\text{min}}$)** was determined over the entire run, considering only valid TTC values between 0 s and 10 s. The minimum TTC within the 10 s window after t_{msg} was also computed, as well as the average TTC over all valid frames.
- **Final speed** was identified as the stabilised speed in the last 3 s of the run, provided that the speed variation in this period did not exceed ± 1.0 m/s. If this stability criterion was not met, the final speed was set to missing.
- **Deceleration** were detected by smoothing the longitudinal acceleration signal with a 0.5 s moving average and applying a threshold of -0.5 m/s^2 for at least 1 s. For the first qualifying episode, the start time, end time, and mean deceleration were recorded.
- **Lane change detection** used the lateral offset (y) relative to the lane centreline, with a threshold of ± 0.9 m to identify crossing events. The start time of the first lane change was stored, along with the leading gap (d_{lead}) and lagging gap (d_{lag}) at that moment.
- **Reaction time to deceleration** (RT_{decel}) was computed as the time from t_{msg} to the onset of sustained braking, defined as 0.5 s of continuous negative acceleration below -0.98 m/s^2 accompanied by a monotonic decrease in speed.
- **Reaction time to lane change** (RT_{lc}) was calculated as the time from t_{msg} to the start of the first valid lane change.

Each processed file thus yielded a single summary row containing the participant and scenario identifiers, t_{msg}, and the full set of computed indicators. All scenario summaries were concatenated into a single combined dataset, which was subsequently used for statistical analysis in Chapter 5. This procedure ensured that all behavioural metrics were computed consistently across participants and scenarios, with definitions aligned to established standards and the specifications in Section 4.2.

5

Experimental results

This chapter presents the experimental results obtained from the driving simulator study on driver responses to a vehicle-based cooperative speed advisory system. The focus is on the objective measurement of driving behaviour and the corresponding subjective perceptions reported by participants. Quantitative indicators were derived from processed simulator trajectory data, while qualitative insights were obtained from the post-experiment questionnaire to provide complementary user-centred perspectives.

The results are organised into sections covering longitudinal behaviour, reaction times, efficiency-related indicators, safety-related indicators, lateral behaviour, and subjective questionnaire responses. Within each section, numerical results are presented alongside descriptive observations of the patterns identified in the data, without in-depth interpretation or theoretical comparison.

The dataset used in this chapter corresponds to the processed outputs described in Chapter 4, where raw simulator trajectories were transformed into structured indicators for each participant–scenario combination. Unless otherwise specified, results are grouped by the relative position of advisory message delivery (Downstream, Same Position, and Upstream) and, where applicable, by lane-change status (lane-changing versus non-lane-changing drivers).

5.1 Longitudinal behaviour indicators

5.1.1 Speed profile

Lane-changing drivers

The speed–time profiles for lane-changing drivers (Figure 5.1) show consistent acceleration before the advisory ($t < t_{msg}$) from approximately 100 km/h to over 110 km/h in all three timing groups: Downstream (Figure 5.1a), Same Position (Figure 5.1b), and Upstream (Figure 5.1c). This acceleration coincided with higher speeds observed in the adjacent lane.

For the Downstream group (Figure 5.1a), the mean RT_{decel} was -2.30 s, with deceleration starting slightly before t_{msg} and coinciding with adjacent-lane deceleration.

In the Same Position group (Figure 5.1b), the mean RT_{decel} was 3.08 s. Deceleration commenced almost immediately after t_{msg}, with a sharp speed drop within seconds, coinciding with the onset of adjacent-lane deceleration.

For the Upstream group (Figure 5.1c), the mean RT_{decel} was 3.66 s. Despite an earlier t_{msg} (15.2 s), drivers delayed deceleration, and some accelerated briefly after the message before slowing down.

In the Downstream condition, earlier lane changes often occurred before the advisory and coincided with adjacent-lane slowing. In the Same Position condition, lane changes typically occurred shortly after the advisory and the onset of adjacent-lane deceleration. In the Upstream condition, lane changes were generally delayed, with some trajectories showing continued travel at or above pre-advisory speeds before slowing down and changing lanes once larger forward gaps appeared (Figure 5.1c).

A truncation in the speed curves is visible because the scenario ended exactly 5 s after the lane change was detected as completed. Post–lane-change behaviour was outside the study scope and is not analysed further here.

Non-lane-changing drivers

For non-lane-changing drivers (Figure 5.2), pre-advisory speeds remained near 100 km/h, with slight acceleration to around 105 km/h in some cases after manual control.

The Downstream group (Figure 5.2a) had a mean RT_{decel} of 3.24 s, with deceleration typically beginning just after t_{msg}, corresponding with changes in the speed of the in-lane lead vehicle.

In the Same Position group (Figure 5.2b), the mean RT_{decel} was 2.94 s, showing a prompt and consistent reaction.

For the Upstream group (Figure 5.2c), the mean RT_{decel} was 4.37 s, significantly later than Same Position ($p = 0.02$). Speeds stabilised around 78–80 km/h after 30 s.

Across all timing groups, non-lane-changing speed trajectories displayed smooth patterns with gradual accelerations and decelerations.

5.1.2 Reaction time for deceleration

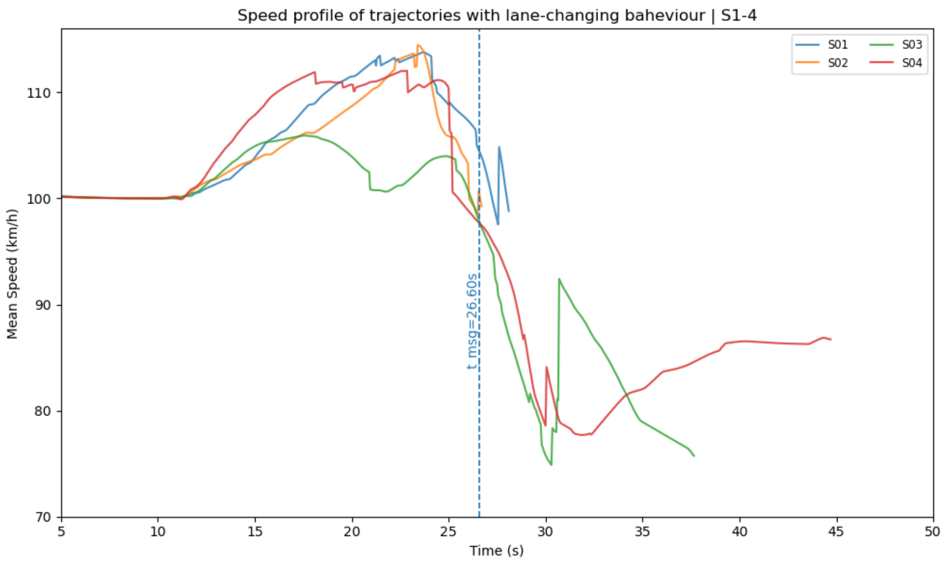
Table 5.1 summarises the mean RT_{decel} for each scenario, separated by lane-changing and non-lane-changing drivers.

Table 5.1: Mean RT_{decel} by Scenario ID for lane-changing and non-lane-changing drivers

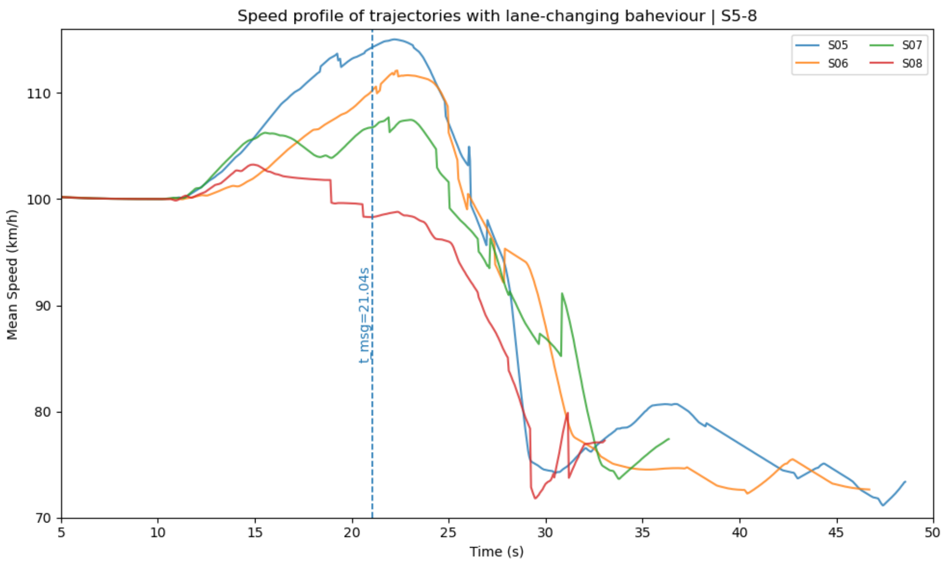
Scenario ID	Lane-change	Non lane-change
1	-1.32	1.59
2	-2.66	2.63
3	-3.08	4.19
4	-0.55	4.87
5	3.08	3.48
6	4.76	3.48
7	2.28	1.69
8	3.05	3.11
9	3.74	4.37
10	4.58	3.63
11	3.45	4.10
12	2.39	5.23

For interpretation, scenarios are grouped into three timing categories in Table 5.2: Downstream (1–4), Same Position (5–8), and Upstream (9–12).

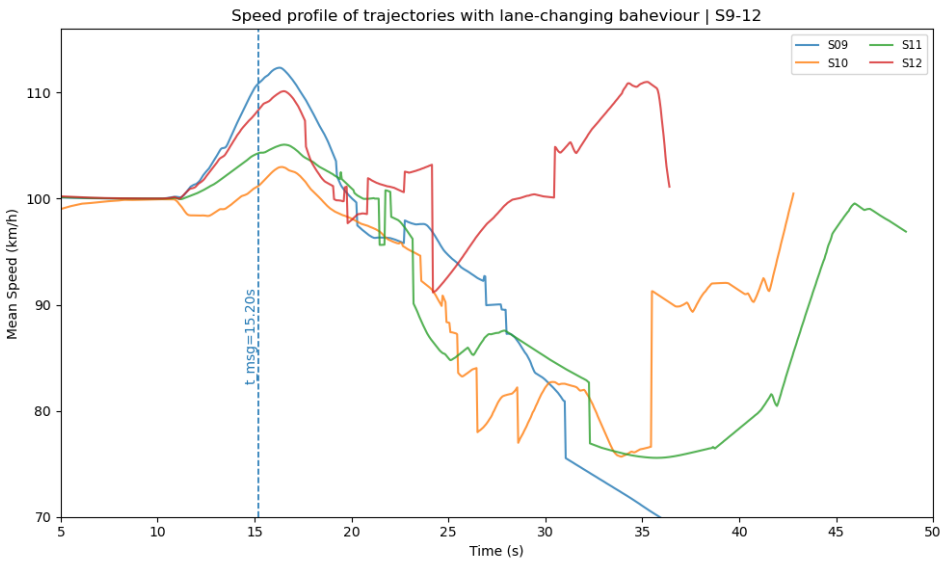
In the lane-changing group, Downstream scenarios produced the earliest deceleration (-2.30 s), significantly earlier than Same Position and Upstream ($p < 0.001$). Same Position and Upstream did not



(a) Downstream scenarios S1–4

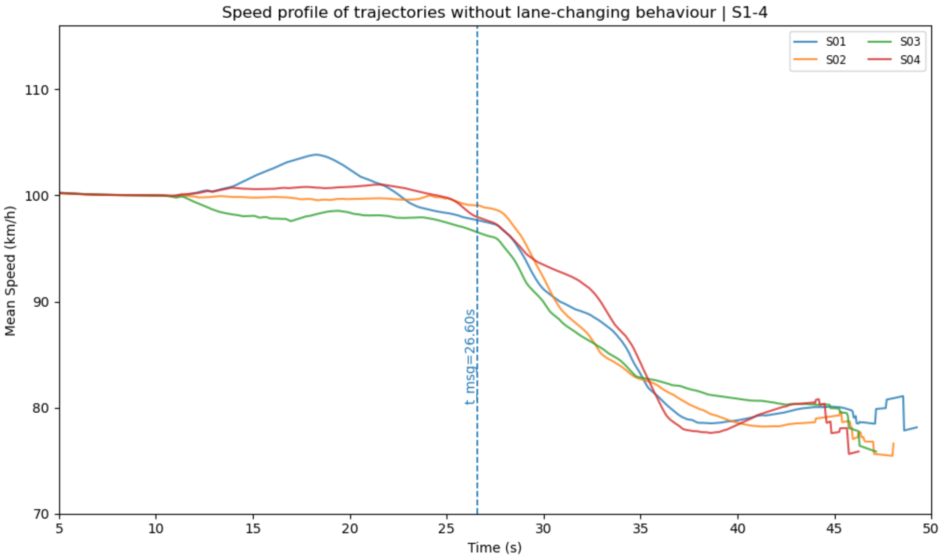


(b) Same Position scenarios S5–8

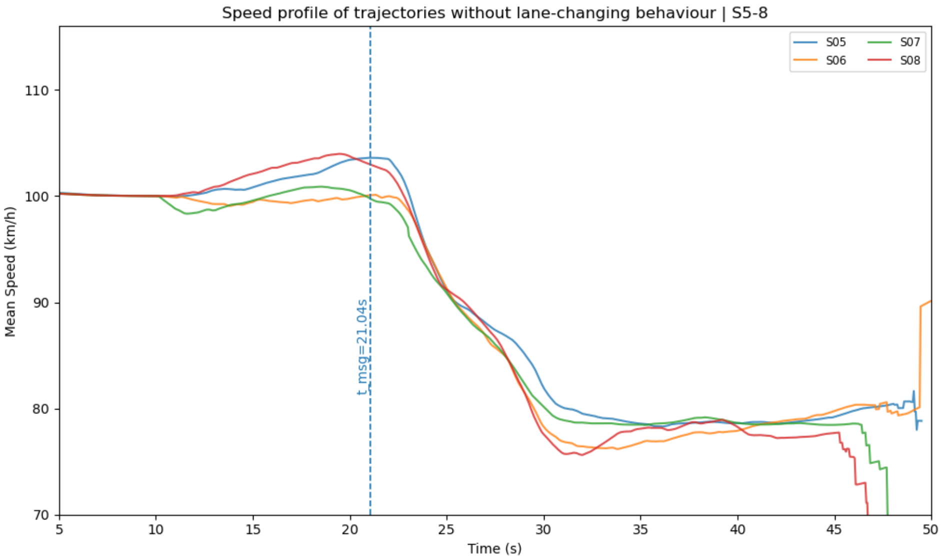


(c) Upstream scenarios S9–12

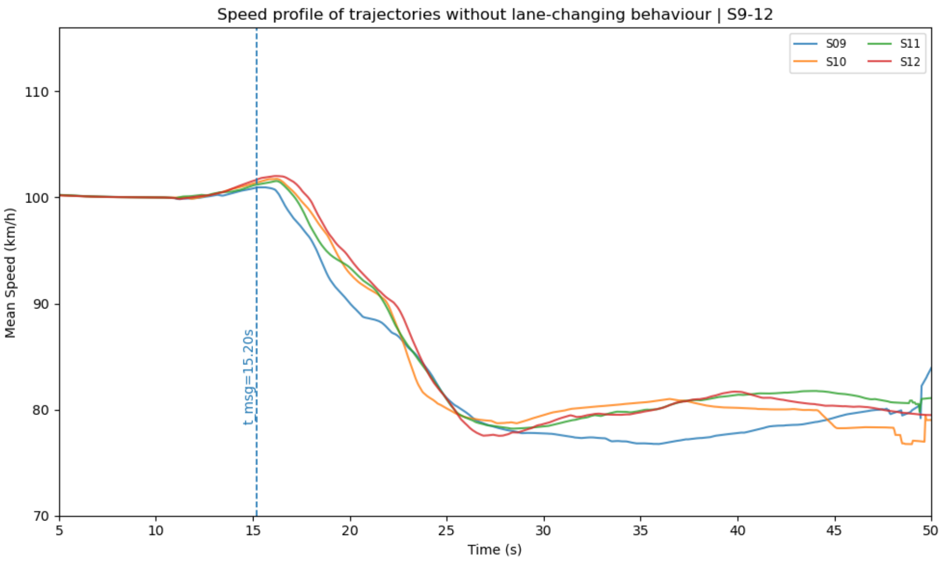
Figure 5.1: Speed profile of trajectories with lane-changing behaviour



(a) Downstream scenarios S1–4



(b) Same Position scenarios S5–8



(c) Upstream scenarios S9–12

Figure 5.2: Speed profile of trajectories without lane-changing behaviour

Table 5.2: Mean RT_{decel} by Scenario Group for lane-changing and non-lane-changing drivers

Scenario Group	Lane-change	Non lane-change
Downstream (1–4)	-2.30	3.24
Same Position (5–8)	3.08	2.94
Upstream (9–12)	3.66	4.37

differ significantly ($p = 0.329$); in the Upstream condition, no adjacent-lane deceleration was observed before the advisory.

In the non-lane-changing group, Same Position drivers decelerated significantly earlier than Upstream ($p = 0.020$). Downstream and Same Position did not differ significantly.

The reference reaction time in the experimental design was 2.5 s. Except for the Downstream group with early deceleration, RT_{decel} in all other scenarios exceeded this reference.

The statistical results for group means and one-sided pairwise t-tests are presented in Table 5.3.

Table 5.3: Group means, sample sizes, and one-sided pairwise t-tests for RT_{decel}

Group / Comparison	Mean	n	t / p
Non-lane-changing			
Downstream (1–4)	3.24	34	G1 < G2: $t = 0.35$, $p = 0.636$
Same Position (5–8)	2.94	38	G1 < G3: $t = -1.50$, $p = 0.070$
Upstream (9–12)	4.37	41	G2 < G3: $t = -2.10$, $p = 0.020$
Lane-changing			
Downstream (1–4)	-2.30	19	G1 < G2: $t = -4.18$, $p < 0.001$
Same Position (5–8)	3.08	20	G1 < G3: $t = -4.81$, $p < 0.001$
Upstream (9–12)	3.66	22	G2 < G3: $t = -0.45$, $p = 0.329$

5.1.3 Final speed and mean deceleration rate

Table 5.4 summarises the mean final speed and mean deceleration for each scenario.

Table 5.4: Final speed and mean deceleration by scenario

Scenario ID	Final speed (km/h)	Mean deceleration (m/s^2)
1	79.68	-1.59
2	79.63	-1.59
3	79.70	-1.74
4	80.22	-1.53
5	80.18	-2.05
6	81.18	-1.65
7	81.16	-1.94
8	78.60	-1.94
9	80.54	-1.63
10	78.22	-1.68
11	80.71	-1.79
12	80.68	-1.73

One-sample t-tests were performed for both final speed and mean deceleration (Table 5.5).

Table 5.5: One-sample t-tests for overall means vs. targets

Metric	Mean	Target	t	p	N
Final speed ($\mathrm{km/h}$)	80.04	80.00	0.10	0.92	12
Mean deceleration ($\mathrm{m/s^2}$)	-1.74	-2.00	4.35	0.00003	12

Across all scenarios, the mean final speed was $80.04\ \mathrm{km/h}$, not significantly different from the target ($p = 0.92$). The mean deceleration was $-1.74\ \mathrm{m/s^2}$, significantly less severe than the target of $-2.00\ \mathrm{m/s^2}$ ($p = 0.00003$).

5.1.4 Time to collision

Table 5.6: Minimum and mean TTC by scenario for non lane-changing and lane-changing drivers

Scenario ID	Non lane-change		Lane-change	
	Minimum TTC (s)	Mean TTC (s)	Minimum TTC (s)	Mean TTC (s)
1	8.13	8.89	4.93	7.73
2	9.16	9.46	–	7.24
3	–	–	6.35	7.63
4	9.45	9.60	6.20	6.96
5	6.17	7.57	6.43	7.70
6	6.12	7.79	6.80	8.06
7	7.26	8.49	7.49	7.50
8	7.52	8.19	4.43	6.97
9	8.51	8.94	5.44	7.27
10	6.19	7.83	7.30	7.65
11	8.50	9.01	8.68	8.27
12	6.82	8.00	5.69	6.50

All mean TTC values were above 6 s.

For lane-changing drivers, mean TTC values were similar across groups (7.3–7.6 s) with no statistically significant differences.

In the non-lane-changing group, Downstream scenarios had the highest mean TTC ($9.276\ \mathrm{s}$), significantly greater than Same Position and Upstream; in these scenarios, deceleration occurred earlier relative to t_{msg}.

5.2 Lateral behaviour indicators

The lateral behaviour indicators summarised in Table 5.7 provide an overview of the lane-changing dynamics observed across all experimental scenarios. For each scenario, the table reports the average reaction time for lane change (RT_{lc}), the mean accepted forward gap (d_{lead}), the mean accepted rear gap (d_{lag}), and the lane-change ratio, defined as the proportion of participants who executed a lane change within the scenario. Reaction times are measured relative to the issuance of the advisory message, with negative values indicating that the manoeuvre began before the message was displayed. The forward and rear gaps represent the spatial distances to the leading and lagging vehicles in the target lane at the moment of lane change initiation.

Table 5.7: Lateral behaviour indicators by scenario

Scenario ID	RT_{lc} (s)	d_{lead} (m)	d_{lag} (m)	Lane change ratio
1	-8.56	27.43	50.78	0.52
2	-8.31	12.83	65.35	0.33
3	-3.72	20.53	52.41	0.62
4	-6.74	26.89	35.10	0.52
5	-0.50	31.02	42.92	0.57
6	-1.06	22.17	53.89	0.57
7	0.68	28.08	42.96	0.48
8	0.24	19.99	50.26	0.38
9	6.13	22.84	45.46	0.43
10	6.51	22.85	49.61	0.52
11	4.12	24.11	49.46	0.48
12	2.08	38.06	35.04	0.43

5.2.1 Lane-changing occurrence

A univariate linear regression model was constructed with the gap prompt distance (m) as the explanatory variable and the lane-change ratio as the dependent variable. The regression coefficient was -0.0010 (p = 0.406), indicating no statistically significant relationship under the tested conditions. The model's R^2 was 0.070.

5.2.2 Reaction time for lane-change

Grouping by longitudinal timing (Table 5.8) showed that Downstream drivers initiated lane changes on average 6.54 s before t_{msg}, Same Position drivers acted nearly synchronously (-0.24 s), and Upstream drivers delayed by $+4.79$ s. All pairwise differences were statistically significant ($p \leq 0.001$).

When grouped by absolute gap location (Table 5.9), differences in RT_{lc} were small and not statistically significant.

5.2.3 Gap location

In the longitudinal grouping, Upstream drivers had larger d_{lead} values than Downstream drivers (26.68 m vs. 22.72 m, $p = 0.044$). No statistically significant differences were found in d_{lag} across timing groups.

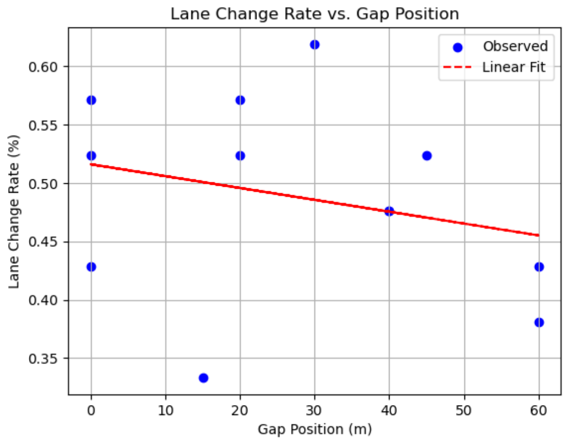
When grouped by absolute gap location, the 45/60 m group exhibited significantly larger d_{lead} than both the 15/20 m ($p = 0.002$) and 30/40 m groups ($p = 0.048$). For d_{lag}, the 0 m group was significantly smaller than the 15–20 m group (46.34 m vs. 54.99 m, $p = 0.004$).

Table 5.8: Reaction time for lane change and gap acceptance by longitudinal timing group

Longitudinal Position Group	RT_{lc} Mean (s)	d_{lead} Mean (m)	d_{lag} Mean (m)
Downstream (Scenarios 1–4)	-6.54	22.72	49.60
Same Position (Scenarios 5–8)	-0.24	25.69	47.46
Upstream (Scenarios 9–12)	4.79	26.68	45.25

Variable	Coefficient	t	p-value
Intercept	0.5160	12.753	<0.001
Gap position (m)	-0.0010	-0.868	0.406
R^2			0.070
Observations			12

(a) Ordinary Least Squares (OLS) regression results



(b) Lane-change ratio vs. gap position with linear regression fit. The blue points represent observed lane-change ratios for each scenario, while the red line shows the fitted linear regression model.

Figure 5.3: Relationship between lane-change ratio and gap position

Table 5.9: Reaction time for lane change and gap acceptance by absolute gap location group

Gap Location Group	RT_{lc} Mean (s)	d_{lead} Mean (m)	d_{lag} Mean (m)
Gap at 0 m (Scenarios 1, 5, 9)	-1.41	27.49	46.34
Gap at 15/20 m (Scenarios 2, 6, 10)	0.02	20.24	54.99
Gap at 30/40 m (Scenarios 3, 7, 11)	-0.01	23.90	48.65
Gap at 45/60 m (Scenarios 4, 8, 12)	-1.91	28.51	39.41

Table 5.10: Significant or marginally significant pairwise comparisons for RT_{lc}, d_{lead}, and d_{lag}

Grouping	Metric	Comparison	t	p (one-sided)
Longitudinal	RT_{lc}	L1 (1–4) < L2 (5–8)	-4.938	0.000
Longitudinal	RT_{lc}	L1 (1–4) < L3 (9–12)	-8.050	0.000
Longitudinal	RT_{lc}	L2 (5–8) < L3 (9–12)	-3.271	0.001
Longitudinal	d_{lead}	L1 (1–4) < L3 (9–12)	-1.731	0.044
Absolute gap location	d_{lead}	G2 (2,6,10) < G4 (4,8,12)	-3.033	0.002
Absolute gap location	d_{lead}	G3 (3,7,11) < G4 (4,8,12)	-1.696	0.048
Absolute gap location	d_{lag}	G1 (1,5,9) < G2 (2,6,10)	-2.777	0.004

5.3 Questionnaire results

The questionnaire results provide additional insight into how participant background and subjective impressions may have shaped the behavioural patterns reported in Sections 5.1–5.2. The pre-experiment survey contextualises the driving styles and prior attitudes of the participant pool, while the post-experiment survey evaluates their perceptions of the advisory system in terms of clarity, trust, workload, safety, and acceptance.

5.3.1 Pre-experiment questionnaire

The participant sample ($n = 21$) was predominantly young-to-middle-aged (mean age 28.0 years, SD = 8.0) with moderate driving experience (mean 8.3 years licensed, SD = 9.4). Most participants reported less than 10 years of licensure, and more than half had no prior simulator experience. These characteristics suggest a group generally familiar with modern in-vehicle technologies but without extensive high-speed highway exposure, which may partly explain the relatively cautious and smooth behavioural profiles observed in the simulator.

Gender distribution was 60.9% male and 39.1% female. Self-reported driving styles leaned towards *calm* (39.1%) and *neutral* (30.4%), with only 4.3% identifying as *aggressive*. This self-perception is consistent with the absence of abrupt acceleration or high-magnitude braking in the objective data.

Attitudes towards in-car speed advisory systems were mostly *positive* (52.2%) or *neutral* (39.1%), with very few extreme opinions. Educational attainment was high (87.0% held a bachelor's, master's, or doctoral degree), suggesting strong general comprehension skills, which may have contributed to the consistently high clarity ratings in the post-experiment results. Detailed statistics for all pre-experiment variables are presented in Appendix C.

5.3.2 Post-experiment questionnaire: system evaluation

System information and trust

The *system information and trust* construct received a high score (4.02 ± 0.86), indicating that most participants found the advisory clear and relevant. The highest-rated item, clarity of the advisory content (4.57), supports the observation that drivers were quick to understand the intended target speed. However, the lower score for "The advisory matched the actual road situation" (3.65) reflects instances, especially in upstream conditions, where drivers hesitated to decelerate because adjacent-lane vehicles were still travelling at high speed. This discrepancy mirrors the longitudinal results, where reaction times in upstream scenarios were significantly longer, suggesting that alignment between advisory messages and visible traffic behaviour was an important determinant of trust.

Acceptance

Acceptance scored highest among all constructs (4.32 ± 0.48), with participants expressing strong willingness to use such a system in daily driving (4.50). This high acceptance rate aligns with the efficiency findings in Section 5.1, where most drivers achieved the target final speed.

Behavioural response

The *behavioural response* score (3.24 ± 0.69) reflects a moderate but noticeable alignment between advisory recommendations and driver actions. Participants rated "I slowed down because I believed it was the safer option" (3.91) higher than items related to hesitation due to close following vehicles (2.74) or uncertainty (2.87).

Perceived safety

Perceived safety scored lower overall (2.68 ± 1.03), mainly due to rear-end collision concerns after slowing down (2.41). Side-collision concerns during lane changes were somewhat higher (3.05). These perceptions parallel the TTC and gap acceptance findings, where some manoeuvres involved relatively small time gaps, and the absence of adjacent-lane deceleration cues in upstream scenarios increased perceived rearward risk.

Personal state

The *personal state* construct scored low (2.54 ± 1.24), indicating that the advisory did not significantly increase workload or stress. The low tension rating (2.09) aligns with the smooth deceleration profiles observed in the objective data.

5.3.3 Open-ended feedback themes

Open-ended responses reinforced the quantitative findings. A recurring theme was a preference for earlier advisory timing, especially when visible traffic cues were limited, to reduce hesitation. Several participants suggested improving display visibility and providing clearer confirmation when the target speed was reached. Safety-related feedback often referenced rear vehicles in the adjacent lane, which in some cases influenced the decision to delay deceleration or change lanes. A smaller group suggested that the system could benefit from adaptive target speeds or integrated lane-change guidance. Full thematic summaries and representative quotes are provided in Appendix B.

5.4 Summary

The results show that driver responses to the advisory system varied across timing conditions, visual traffic cues, and lane-change intentions. Longitudinal and lateral behaviours were interrelated. Safety outcomes, measured by TTC, were maintained above 6 s in all conditions. Efficiency targets for final speed were met, with mean deceleration rates generally lower than the nominal target.

Subjective questionnaire results showed high ratings for *system information and trust* and *acceptance*, lower ratings for *perceived safety*, and moderate *behavioural response* alignment with advisories. The *personal state* scores indicated limited reported stress or workload.

Differences between conditions corresponded with variations in traffic context. Broader interpretation of these patterns, their relation to previous research, and the scope of the study's limitations are examined in the next chapter.

6

Discussion and limitations

This chapter interprets the experimental results presented in Chapter 5, linking the observed behavioural patterns to the study objectives and highlighting their implications for the design and evaluation of cooperative speed advisory systems. The discussion draws on both objective measurements and subjective evaluations to explain the mechanisms behind the identified trends and to position the findings within the broader context of existing research. While the controlled simulation environment and structured experimental design allowed for precise measurement of timing effects and contextual influences, they also introduced certain scope-specific constraints. These are addressed in the limitations section, which clarifies the boundaries of applicability and identifies opportunities for extending this research. Overall, the evidence presented here indicates that, despite some methodological boundaries, the study offers novel insights into how advisory timing and visual traffic cues interact to shape driver behaviour, providing a strong foundation for further system refinement and field validation.

6.1 Discussion

This section discusses the experimental findings from Chapter 5, following the same structure as the reported results. Objective measurements and subjective evaluations are integrated to interpret driver responses to the cooperative speed advisory system, with relevant insights from previous studies used to contextualise and explain observed patterns.

6.1.1 Longitudinal behaviour

For lane-changing drivers, the speed–time profiles revealed distinct patterns linked to the relative timing of the advisory message. Before the advisory ($t < t_{msg}$), all three timing groups (Downstream, Same Position, and Upstream) showed a consistent acceleration trend, increasing from approximately 100 km/h to over 110 km/h. This behaviour indicates that upon taking manual control, drivers sought to align with the faster flow in the adjacent lane.

In the Downstream condition, where participants received the advisory message further downstream than adjacent-lane drivers and had already observed the full deceleration phase in that lane, the mean RT_{decel} was -2.30 s. Most drivers began decelerating before receiving the advisory, and the gradual decline in speed slightly before t_{msg} suggests that visual cues from adjacent-lane vehicles triggered early anticipation.

In the Same Position condition, where the advisory coincided with the onset of deceleration in the adjacent lane, the mean RT_{decel} was 3.08 s. Here, speed profiles showed a sharp drop within seconds after t_{msg}, implying that drivers acted on a combination of advisory information and concurrent visual cues.

In the Upstream condition, where the advisory was issued well before any visible deceleration in the adjacent lane, produced the latest responses (3.66 s) and, in some cases, temporary acceleration immediately after the message. In these scenarios, the absence of observable lane-change or braking behaviour from neighbouring vehicles removed an important external trigger for early action. Moreover, because the advisory was received earliest in all group, the adjacent lane was still moving at relatively high speeds, which may have further reduced drivers' willingness to decelerate at that moment. This suggests that even without explicit deceleration cues, the prevailing speed of surrounding traffic can influence the ego driver's decision timing, and neighbouring behaviour may continue to play a role beyond the presence or absence of visible braking.

The reasons for initiating a lane change in these contexts likely reflect a combination of mechanisms. First, in Downstream scenarios, anticipation based on visible slowing of adjacent-lane vehicles encouraged earlier lane changes, allowing drivers to pre-empt congestion and stabilise their trajectory. Second, in Same Position scenarios, perceived efficiency benefits and alignment with the faster lane motivated lane changes, with visual cues reducing uncertainty about the manoeuvre's advisability. Third, in Upstream scenarios, the lack of external confirmation heightened uncertainty, prompting some drivers to wait for larger forward gaps before committing. As observed in some Upstream cases, vehicles continued at speed or even accelerated for several seconds after the advisory before eventually slowing, suggesting that drivers delayed action until they perceived the manoeuvre as more advantageous.

For non-lane-changing drivers, pre-advisory speeds remained near 100 km/h, with slight acceleration to around 105 km/h after manual control in some cases. These drivers generally responded later than lane-changing drivers in the Downstream condition (mean RT_{decel} = 3.24 s), typically braking just after t_{msg}, suggesting reliance on in-lane lead vehicle behaviour rather than adjacent-lane cues. In the Same Position condition, the mean RT_{decel} was 2.94 s, a prompt and consistent response similar to that of lane-changing drivers, reinforcing the role of concurrent cues in accelerating compliance. The Upstream group showed the latest reaction (4.37 s) and more gradual deceleration, with speeds stabilising around 78–80 km/h after 30 s. Across all timing groups, non-lane-changing drivers displayed smoother trajectories with gradual accelerations and decelerations.

6.1.2 System efficiency and safety indicators

The system consistently achieved the target final speed of 80 km/h across all scenarios, with no significant deviation from the target ($p = 0.92$). This confirms that the primary efficiency goal was met. However, the average deceleration magnitude was $-1.74\ \mathrm{m/s^2}$, significantly less than the nominal $-2.0\ \mathrm{m/s^2}$ ($p < 0.001$). This consistent under-deceleration supports Ozkan et al.'s (2010) [25] observation that drivers moderate braking to maintain comfort and avoid abrupt changes, particularly those with conservative driving styles. Consistent with this interpretation, some participants commented in the post-experiment questionnaire that the advised deceleration felt "slightly too aggressive" for their comfort, although this was not a universal view.

From an operational perspective, the observed under-deceleration implies that vehicles may reach the designated target line later than assumed in the COBRA design. Because drivers in the experiment slowed down more gradually (mean $-1.74\ \mathrm{m/s^2}$ vs. nominal $-2.0\ \mathrm{m/s^2}$), part of the speed reduction occurred closer to the bottleneck rather than being distributed over the intended upstream distance. In mixed traffic, where not all vehicles are system-equipped, such behaviour could trigger backward-propagating congestion waves and reduce the system's ability to pre-emptively smooth traffic flow. Consequently, the efficiency gains expected from COBRA's advisory timing may be partially offset unless the algorithm accounts for realistic driver deceleration tendencies by adapting advisory parameters or trigger distances.

TTC analysis as a safety indicator analysis, showed that all mean and minimum values exceeded 6 s, indicating no elevated collision risk. For non-lane-changing drivers, Downstream scenarios had the highest mean TTC (9.28 s), linked to earlier braking relative to t_{msg}. Among lane-changing drivers, TTC values were relatively stable across timing groups, suggesting that gap acceptance decisions effectively maintained safety margins regardless of advisory timing.

However, subjective safety ratings told a different story. Perceived safety was lower in conditions without visible adjacent-lane deceleration, especially in the Upstream condition. This aligns with Teh et al. (2012) [43], who found that mismatches between advisory messages and observed traffic behaviour can reduce trust and perceived safety, even when objective risk remains low.

6.1.3 Lateral behaviour

Lane-change ratios and gap acceptance patterns emphasised the influence of dynamic traffic context. Absolute gap position in the advisory had limited predictive value for lane-change initiation, whereas adjacent-lane deceleration cues had a strong effect on timing. Downstream drivers often initiated lane changes well before the advisory (-6.54 s), while Upstream drivers delayed manoeuvres by an average of 4.79 s.

Although the four gap location groups were defined in the scenario design to create different initial spatial configurations at the moment of advisory issuance, the actual front and rear gaps at the time of lane-change initiation did not necessarily match these preset values. This is because drivers were free to change lanes at any time during the scenario, and some manoeuvres occurred earlier or later than the advisory moment, often under different relative positions to the surrounding vehicles.

When examining the measured gaps at the actual initiation of the lane change, the results show that d_{lead} was largest in the 45/60 m group and smallest in the 15/20 m group, while d_{lag} was smallest in the 0 m group and largest in the 15/20 m group. This pattern suggests that drivers in the rearward position (45/60 m) tended to initiate the manoeuvre when more forward space was available, potentially perceiving it as less restrictive. Conversely, in the 0 m group, although the initial design placed the ego vehicle at the very front of the gap, some drivers delayed their manoeuvre, during which time the lag vehicle closed in, resulting in a smaller d_{lag} at the moment of lane change.

6.1.4 Questionnaire results

Subjective evaluations mirrored the behavioural patterns observed. High scores for *system information and trust* (4.02) and *acceptance* (4.32) suggest that participants valued the advisory's clarity and were generally willing to use such a system. Lower *perceived safety* scores (2.68) indicated concerns about rear-end and side-collision risks, particularly in scenarios lacking adjacent-lane deceleration cues. These perceptions were consistent with the tendency to delay braking and lane changes under such conditions, and mirror the findings of Atiyeh and Vaezipour (2018) [46] that interface design and environmental cues jointly shape user confidence.

The moderate *behavioural response* score (3.24) and the observed tendency to apply milder decelerations than prescribed suggest that drivers actively balanced system compliance with their own comfort and situational judgement. The low *personal state* score (2.54) indicated that the advisory did not significantly increase workload or stress, consistent with the smooth speed profiles recorded in the simulator data.

6.2 Limitations

While this study was designed to address its research objectives within a controlled simulator environment, some limitations should be acknowledged. These limitations are mostly inherent to the scope and methodology chosen, highlighting opportunities for further research and refinement.

6.2.1 Experimental scope and environmental assumptions

The driving scenarios were implemented in a highly controlled simulation environment to ensure repeatability and isolate the influence of advisory timing and traffic context. As a result, certain real-world complexities were not represented. The road section was limited to a straight, two-lane highway segment, which allowed for clear measurement of the targeted behaviours but may not capture all dynamics of more complex geometries. These simplifications were appropriate for an initial exploration of COBRA performance. However, as noted in the discussion of adjacent-lane visual cues, the lack of varied geometry or environmental conditions may have influenced the relative importance of these cues. Extending the evaluation to more diverse road types and conditions would improve generalisability.

6.2.2 Traffic and system modelling assumptions

Surrounding vehicles followed pre-defined trajectories with fixed speeds and headways, ensuring that differences in driver response were attributable to experimental variables rather than uncontrolled traffic interactions. The penetration rate of the cooperative system was set at full compliance, with all other vehicles assumed to follow the advisory. The algorithm generated trajectories based on static traffic assumptions without real-time adaptation to lane changes or manual driver interventions. While these modelling choices allowed for a focused examination of timing and contextual effects, they do not capture the variability and unpredictability of real highway traffic. This constraint may have amplified certain observed effects, such as the delayed deceleration in the Upstream condition where no adjacent-lane deceleration cues were present. Future studies should investigate mixed traffic environments, varying compliance levels, and adaptive algorithms capable of responding dynamically to evolving traffic states.

6.2.3 System interface configuration

The human-machine interface (HMI) was deliberately kept simple, presenting only visual and auditory messages without additional dynamic visualisations or multi-modal feedback. This ensured that the measured differences were due to message timing and traffic context rather than interface complexity. However, it also limits the extent to which the findings can be transferred to systems with more sophisticated interaction modes. Prior research suggests that richer feedback can influence driver confidence and compliance, indicating a potential avenue for further refinement.

6.2.4 Procedural and participant-related factors

All participants drove in a laboratory setting, which ensured control over environmental variables but may have influenced behaviour through observation effects. The experimental procedure included a familiarisation phase, yet session duration and the fixed order of scenario exposure may still have allowed minor learning or fatigue effects. The participant pool was relatively small and skewed toward younger drivers with higher technological familiarity. This profile is suitable for an initial proof-of-concept but limits the extent to which results can be generalised to other demographic groups.

6.2.5 Questionnaire design and administration

The post-experiment questionnaire was administered once, after all scenarios, to capture overall impressions rather than scenario-specific feedback. While this provided a concise measure of user perceptions, it also meant that any scenario-dependent variations in trust, workload, or perceived safety could not be isolated. Open-ended responses nevertheless offered valuable qualitative insights into timing preferences and safety perceptions, which complemented the behavioural data.

6.2.6 Data processing and external validity

The analysis focused on scenario-level averages to enable clear comparisons between experimental conditions. This approach is suitable for identifying systematic differences but may smooth over short-term fluctuations or extreme individual cases that could reveal additional risk factors or adaptation strategies. The findings therefore apply most directly to the tested conditions. Consequently, while the simulator results provide a proof-of-concept for COBRA's preventive potential, further on-road trials are needed to account for driver distraction, heterogeneous compliance, and environmental variability that cannot be fully replicated in the laboratory.

Overall, these limitations define the boundaries within which the results are valid and frame the interpretation of the behavioural patterns discussed in Section 6.1. They also point toward clear directions for extending this research in future simulation and field-based evaluations.

7
Conclusion

This chapter presents the conclusions of this study and provides recommendations for future research and development. The conclusions are structured around the main research question and the four sub-questions introduced in Chapter 1. The study aimed to evaluate how drivers respond to a vehicle-based cooperative speed advisory system, based on the COBRA concept, under simulated highway bottleneck conditions, and to determine how such a system can be assessed for its operational safety and efficiency. The investigation combined a controlled driving simulator experiment (12 scenarios $\times$ 21 participants) with objective driving behaviour analysis and a post-experiment questionnaire to capture subjective perceptions. Building on these findings, the chapter concludes with recommendations to enhance future experimental design, broaden the applicability of results, and guide the further development of cooperative speed advisory systems.

7.1 Conclusion

Based on the analysis presented in this section, several conclusions can be drawn regarding driver responses to the cooperative speed advisory system under the tested conditions. These conclusions address the main research question and its sub-questions, highlighting the key behavioural patterns, safety and efficiency outcomes, and potential avenues for system enhancement. They form the basis for the recommendations that follow, which aim to improve experimental design, extend the applicability of findings, and inform the practical development of COBRA for real-world deployment.

Main research question

How do drivers respond to a vehicle-based cooperative speed advisory system in simulated real-world conditions, and how can it be evaluated for its operational safety and efficiency?

The results indicate that driver responses were shaped by multiple factors, including the relative position of the advisory trigger with respect to the bottleneck, the availability of visible traffic cues in adjacent lanes, and lane-change intentions. Safety margins, as measured by minimum time-to-collision (TTC), were consistently maintained above conservative thresholds across all tested conditions. Efficiency objectives were generally met, with final speeds stabilising near the 80 km/h target, although decelerations were typically gentler than the system's nominal recommendation. Subjective responses reflected high clarity and acceptance ratings, but lower perceived safety, particularly in conditions where visible adjacent-lane deceleration cues were absent.

Sub-question 1: Key influencing factors

What are the key factors that influence driver response when receiving messages from a cooperative speed advisory system?

From the literature review, three broad categories of factors emerged as influential for driver responses to in-vehicle speed advisories: external driving conditions, system-related aspects, and driver characteristics. External factors include traffic density, patterns of speed change in adjacent lanes, and road geometry. System-related aspects refer to the content, modality, and placement of advisory information within the driver's field of view. Driver characteristics encompass individual differences such as risk perception, driving style, and previous experience with similar technologies.

Drawing on these insights, the present study focused on specific factors that could be operationalised in the simulator experiment. These included the relative position of the advisory trigger with respect to the bottleneck (categorised as Downstream, Same Position, or Upstream), the presence or absence of visible decelerating vehicles in the adjacent lane, the driver's lane-change intention, and the gap position on adjacent lane. These factors were chosen for their potential to influence both the immediacy and manner of driver responses.

Sub-question 2: Influence of traffic conditions

How do different traffic conditions, reflecting the identified factors, influence drivers' behavioural responses?

The results show that the relative position of the advisory trigger was associated with noticeable differences in driver behaviour. When the advisory was issued in a Downstream position, drivers tended to decelerate earlier and were more likely to maintain their current lane. In contrast, Upstream positioning often coincided with delayed deceleration and a higher proportion of lane changes, suggesting that drivers in such conditions may prioritise manoeuvres they consider more flexible for responding to the advisory and downstream traffic. Scenarios where decelerating vehicles were visible in the adjacent lane tended to show higher advisory compliance, indicating a potential link between clearer visual cues and driver responses. Additionally, situations with smaller following gaps from vehicles in the adjacent lane were often accompanied by delayed deceleration or lane changes, implying that perceived rearward pressure from the target lane may be related to deviations from the intended speed adjustment.

Sub-question 3: Safety and efficiency evaluation

How can the operational safety and efficiency of the cooperative speed advisory system be evaluated under the tested experimental conditions?

Safety was assessed primarily through TTC measurements and the analysis of lane-change gaps. Across all scenarios, TTC values remained above conservative safety thresholds, although a few lane changes occurred with relatively small time gaps. Efficiency was evaluated based on the extent to which drivers reached and maintained the target speed of 80 km/h and on the characteristics of their deceleration profiles. Most participants achieved the target speed, but tended to decelerate less aggressively than the nominal -2.0 m/s^2 recommended by the system, reflecting a preference for smoother, more comfortable speed adjustments. The post-experiment questionnaire provided additional insight into participants' subjective impressions, indicating high ratings for system clarity, trust, and acceptance, alongside lower ratings for perceived safety. These subjective results are presented here as a separate descriptive perspective and should not be interpreted as having a statistically validated relationship with the objective findings.

Sub-question 4: Practical recommendations for COBRA application

What practical recommendations can be made to extend the COBRA for practical application?

From an algorithmic perspective, the present implementation of COBRA in the simulator adopts a simplified, open-loop control logic that does not adapt advisory triggers after driver interventions such as lane changes. For practical deployment, the control strategy should be extended to operate in a fully dynamic, closed-loop fashion, continuously recalculating target arrival times and speed trajectories in response to real-time traffic state updates. This would allow the system to maintain stability and relevance even when unexpected manoeuvres occur.

In multi-lane environments, the current single-lane control logic should be expanded to incorporate cross-lane interactions. This includes predicting the impact of lane-changing vehicles on both the controlled and uncontrolled lanes, and integrating these predictions into the advisory decision-making process. For example, if a vehicle in the target lane is likely to merge into the ego lane within the advisory horizon, the system should anticipate the resulting change in headway and adjust speed targets accordingly.

The feedback mechanism could also be generalised to coordinate advisories across multiple lanes simultaneously, supporting scenarios such as staggered decelerations in both lanes to maintain balanced flow and avoid bottleneck spill-back. This would require extending the underlying shockwave-based logic to a lane-aggregated or lane-coupled control formulation.

In human-in-the-loop contexts, the model should explicitly account for heterogeneous driver compliance and reaction times. Adaptive estimation of driver behaviour parameters could allow the algorithm to tune its trigger timing and deceleration rates to the current traffic mix. Additionally, coupling the algorithm with short-term predictive models of individual vehicle trajectories would improve robustness in mixed compliance environments.

Finally, for large-scale real-world deployment, the control logic should be validated under partial penetration rates and integrated with connected vehicle data streams, ensuring that the advisory remains effective when only a subset of vehicles is equipped and compliant.

7.2 Recommendations

Based on the findings of this study and the limitations discussed in Chapter 6.2, several recommendations are proposed to guide future research and experimental design. These recommendations are aimed at enhancing methodological rigour, broadening the applicability of results, and supporting the continued development and validation of cooperative speed advisory systems.

Methodological improvements

Future experiments could benefit from a more diverse range of driving scenarios that reflect the complexity of real-world highway environments. This includes incorporating varied road geometries such as curves, ramps, and gradients, as well as different environmental conditions including weather, lighting, and surface states. The diversity of traffic flow could also be increased by simulating a broader range of vehicle types and mixed penetration rates of connected and automated vehicles.

In addition, future studies could integrate the collection of subjective driver perceptions during specific experimental conditions, including assessments of workload, trust, and perceived risk at different stages of the driving task. These subjective measures could then be examined in relation to objective driving behaviour indicators such as time-to-collision, lane-change gaps, and speed convergence, providing richer insight into the behavioural mechanisms behind advisory compliance and manoeuvre decisions.

Participant diversity

Expanding the participant pool to include a wider demographic spectrum will help improve the generalisability of findings. This should encompass variations in age, gender, driving experience, and familiarity with in-vehicle technologies. Including professional drivers as a comparison group could offer valuable insights into differences between trained and general driving populations.

Future research directions

One important direction for future work is to evaluate system performance under mixed penetration rates and varying levels of driver compliance, which more closely resemble real-world traffic conditions. This would help identify potential thresholds at which the system's safety and efficiency benefits are maximised or diminished.

Another area for development is the exploration of COBRA's feasibility in multi-lane traffic environments. This requires not only adapting the advisory algorithms to manage vehicles across multiple lanes but also considering strategies for prioritising advisory messages and coordinating between lanes to avoid conflicting manoeuvres.

Finally, further investigation is warranted into how COBRA influences platoon control and overall traffic flow stability in human-in-the-loop environments. This would allow the system's effects on both individual behaviour and collective traffic dynamics to be assessed in settings that combine simulated automation with human driving variability.

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A

Informed Consent Form

A.1 Information Sheet for Participants

Please read this information sheet carefully before signing the consent form. If you decide to participate, your signature will be required. If you desire a copy of this information sheet and consent form, you may request one.

Purpose of Study

The purpose of this research study is to investigate how human drivers respond to cooperative speed advisories generated by the COBRA (COoperative BReakdown prevention Algorithm) system under different traffic conditions. Your participation will help analyse behavioural patterns when drivers receive personalised speed advice. This study forms part of a master's thesis project and may contribute to future scientific publications.

Experimental Procedure and Instructions

You will participate in a driving experiment using the SCANeR driving simulator at TU Delft. During the experiment, you will drive on a simulated highway where you may receive various speed advisories, instructing you to adjust your speed under certain traffic conditions. You are free to decide whether to follow the advisories based on your own judgement.

Before starting the scenarios:

- You will fill out a short background questionnaire (e.g., age group, driving experience).
- You will complete a familiarisation drive to get comfortable with the simulator.

During the experiment:

- You will experience scenarios with varying traffic conditions and advisory timings.
- The entire session, including briefing, driving, breaks, and surveys, will take approximately 45–60 minutes.

Risks and Safety

We believe the risks are minimal. However, some participants may experience:

- Mild simulator sickness (nausea, dizziness)

- Psychological discomfort when feeling pressured by nearby vehicles or unsure about advisory signals

If you feel uncomfortable, you may withdraw at any time without providing a reason.

Data Storage and Confidentiality

Your data will be stored securely in TU Delft OneDrive. Personal data (e.g., name, contact information, demographics) will be deleted when this project is finished (about one month after data collection). Driving behaviour data and survey responses will be anonymised and aggregated. Anonymised data may be shared publicly via 4TU.ResearchData for future academic research. After anonymisation, it will no longer be possible to identify individual participants. If you wish to access or delete your personal data, please contact the researcher within one month of your participation.

A.2 Consent Form

Please read this consent form carefully before agreeing to participate.

Taking part in the study

- I have read and understood the study information sheet.
- I have had the opportunity to ask questions and received satisfactory answers.
- I voluntarily consent to participate in this study.
- I understand that I can withdraw at any time without giving a reason.
- I understand that participation involves driving in a simulator, receiving speed advisories, and completing questionnaires.

Risks associated with participating

- I understand that simulator driving could cause mild nausea or psychological discomfort, and I can withdraw at any time.

Use of the information

- I understand that anonymised data will be used in academic reports or publications.
- I understand that personal identifying information will be deleted after data processing.
- I agree that anonymised quotes from my survey responses may be used.

Future use and reuse

- I give permission for my anonymised data to be archived in the TU Delft repository (4TU.ResearchData) for future research purposes.

Hygiene

- I understand that all surfaces and equipment will be disinfected before and after each use.

B

Questionnaire

This appendix presents the questionnaires used in the experiment. Two separate forms were employed: a pre-experiment questionnaire to capture demographic and driving background information, and a post-experiment questionnaire to assess participants' subjective impressions of the cooperative speed advisory system and their driving experience during the experiment.

B.1 Pre-experiment Questionnaire

Purpose

The pre-experiment questionnaire aimed to collect participants' demographic information, driving experience, and general attitudes towards in-vehicle speed advice systems. This information provided contextual background for interpreting behavioural responses in the simulator.

Questions

1. **Gender:** Male / Female / Prefer not to say
2. **Year of birth: ____**
3. **Highest educational level:** Secondary / Bachelor / Master / PhD / Other
4. **Years holding a valid driving licence: ____**
5. **Average weekly driving hours on highways: ____**
6. **Prior experience with driving simulators:** Yes / No
7. **Typical compliance with posted speed limits:** Always / Often / Sometimes / Rarely / Never
8. **Attitude towards in-car speed advice systems:** Very positive / Positive / Neutral / Negative / Very negative

B.2 Post-experiment Questionnaire

Purpose

The post-experiment questionnaire was used to assess subjective impressions of the cooperative speed advisory system, including clarity, trust, workload, perceived safety, and acceptance. It also gathered qualitative feedback on specific experiences during the experiment.

Construct-level items (5-point Likert scale: 1 = Strongly disagree, 5 = Strongly agree)

1. **System information and trust**
   (a) The advisory messages were clear and easy to understand.
   (b) The timing of the advisories was appropriate.
   (c) The advisories were relevant to the driving situation.
   (d) I trusted the advisory system.
2. **Personal state**
   (a) Responding to the advisories required significant mental effort.
   (b) I felt stressed or tense while following the advisories.
3. **Behavioural response**
   (a) I slowed down when advised, even if I did not see any reason in the traffic ahead.
   (b) I hesitated to slow down if there was a vehicle close behind me.
   (c) I changed lanes instead of slowing down when possible.
4. **Acceptance and perceived safety**
   (a) I would be willing to use this system in my daily driving.
   (b) The system improved overall traffic safety in the scenarios I experienced.

Open-ended questions

1. Describe any situations where the advisory system was particularly helpful.
2. Describe any situations where the advisory system was confusing or unhelpful.
3. If you chose not to follow an advisory, please explain why.
4. Do you have any suggestions for improving the system?

C

Questionnaire results

C.1 Pre-experiment questionnaire

Table C.1 summarises the demographic characteristics and self-reported driving habits of all participants. These results provide contextual information for interpreting behavioural responses in the simulator.

Table C.1: Pre-experiment questionnaire responses ($n = 21$)

Category	**Response option**	**Percentage (%)**
Gender	Male	60.9
	Female	39.1
Education level	Bachelor's, Master's, or Doctoral degree	87.0
	Bachelor's or Master's (HBO)	4.3
	Secondary education (HAVO, MAVO)	4.3
	Primary education	4.3
Weekly highway driving hours	< 1 h	82.6
	1–5 h	17.4
Simulator experience	No	56.5
	Yes	43.5
Speed limit following	Most of the time	47.8
	Always	34.8
	Sometimes	17.4
Driving style	Calm	39.1
	Neutral	30.4
	Very calm and cautious	26.1
	Aggressive	4.3
Attitude to in-car speed advice	Positive	52.2
	Neutral	39.1
	Very positive	4.3
	Very negative	4.3
Years licensed	Mean $\pm$ SD (median)	8.3 ± 9.4 (5)

C.2 Post-experiment questionnaire

Table C.2 presents the construct-level scores derived from the post-experiment questionnaire. Each construct was measured using multiple items on a five-point Likert scale.

Table C.2: Construct-level statistics of post-experiment questionnaire ($n = 21$ unless noted)

Construct	Mean ± SD
System information and trust	4.02 ± 0.86
Personal state	2.54 ± 1.24
Behavioural response	3.24 ± 0.69
Perceived safety ($n = 21$)	2.68 ± 1.03
Acceptance ($n = 21$)	4.32 ± 0.48

C.3 Open-ended feedback

Participants were invited to provide free-text feedback on the system. Responses were grouped into four main themes:

1. **Advisory timing**: Requests for earlier advisory onset, particularly when adjacent-lane cues were absent.
2. **Visual interface and positioning**: Suggestions for improved HUD placement and clearer feedback on speed target achievement.
3. **Safety concerns during lane changes**: Comments on potential rear-end or side-collision risks influencing compliance.
4. **Adaptive strategy expectations**: Proposals for flexible target speeds or integrated lane-change guidance.

Representative comments:

- “If the message came earlier, I would feel more confident about slowing down.”
- “The advisory display should be more in my direct line of sight.”
- “I hesitated because the car behind me was too close.”
- “It would be good if the system also advised whether to change lanes.”

D

Scientific Paper

Driver's Response to Speed Advisory System and Implications on Traffic Performances

A Case Study of COBRA

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***Abstract*—This study investigates driver responses to a cooperative speed advisory system based on the Cooperative Breakdown Prevention Algorithm (COBRA) in a simulated two-lane highway bottleneck. Twenty-one participants completed 12 scenarios in a driving simulator, with controlled variations in adjacent-lane deceleration timing and gap position at advisory onset. Results show that visible adjacent-lane deceleration significantly accelerated compliance, while its absence led to delayed or hesitant responses. Across all conditions, minimum time-to-collision exceeded 6 s, indicating no elevated collision risk. The target speed of 80 km/h was consistently reached, though mean deceleration ($-1.74\ \mathrm{m/s^2}$) was less than the nominal $-2.00\ \mathrm{m/s^2}$. Lane-change timing was strongly influenced by adjacent-lane cues, but initial gap size had limited effect. The findings suggest COBRA can maintain safety and efficiency in human-driven, two-lane contexts, but real-world application requires adaptive trigger logic, integration of lane interactions, and consideration of driver comfort.**

***Index Terms*—Driver behaviour, Cooperative Breakdown Prevention Algorithm, Speed advisory, C-ITS, Driving simulator, Bottleneck**

I. Introduction

Traffic congestion on highways arises when vehicle demand approaches or exceeds road capacity, leading to reduced throughput, longer travel times, and increased crash risk. Congested flow conditions are often triggered by disturbances such as sudden braking or frequent lane changes, which can generate backward propagating shockwaves and cause a *capacity drop* of 3% to 30% [1]. Beyond its economic and environmental impacts, congestion is associated with elevated crash rates, particularly in dense, low speed conditions [2].

Conventional traffic management strategies such as Variable Speed Limits (VSL), Route Guidance, and Ramp Metering seek to mitigate congestion through infrastructure based control. Cooperative Intelligent Transport Systems (C-ITS) offer a complementary approach by enabling information exchange between vehicles and roadside infrastructure [3]. In this context, the COoperative BReakdown Prevention Algorithm (COBRA) provides real time, individualised speed advisories to connected vehicles with the aim of stabilising flow upstream of bottlenecks and preventing breakdowns [4].

While COBRA has shown potential in microscopic single lane simulations, its effectiveness in real world, multi lane environments remains uncertain. In practice, human drivers may not fully comply with advisories, particularly when visual traffic cues in adjacent lanes contradict the system recommendations. Factors such as advisory timing, lane change opportunities, and perceived relevance are likely to influence compliance.

This study investigates driver responses to a vehicle based cooperative speed advisory system derived from COBRA under simulated highway bottleneck conditions. The research focuses on three main objectives. First, it examines how the timing of advisories, relative to the deceleration of vehicles in adjacent lanes, influences both longitudinal and lateral driving behaviour. Second, it evaluates operational safety by considering indicators such as time to collision and gap acceptance, alongside measures of efficiency such as final speed stabilisation and deceleration rate. Third, it explores subjective perceptions, including clarity of the advisory, trust in the system, perceived workload, safety, and overall acceptance.

The overarching research question is:

> *How do drivers respond to a vehicle based cooperative speed advisory system in simulated real world conditions, and how can it be evaluated for its operational safety and efficiency?*

Four sub questions guide the investigation:

- What key factors influence driver response when receiving cooperative speed advisories?
- How do different traffic conditions, reflecting these factors, influence behavioural responses?
- How can safety and efficiency be evaluated under the tested conditions?
- What practical recommendations can be made to extend COBRA for real world application?

II. Literature review

This section reviews prior research on factors influencing driver responses to cooperative speed advisory systems, with a particular focus on elements relevant to the Cooperative Breakdown Prevention Algorithm (COBRA). The literature highlights that driver behaviour under such systems is shaped by a combination of human-related characteristics (e.g., age, driving style, trust, and cognitive workload) and external situational factors (e.g., traffic conditions, gap availability, advisory timing, and HMI design). Understanding these factors is essential for evaluating how COBRA advisories may affect operational safety and efficiency.

The review is structured into five parts. Section II-A introduces the COBRA concept and its operational principles, outlining its relevance to driver compliance and behavioural responses. Section II-B examines human-related factors such as personality traits, cognitive and affective states, and socio-economic characteristics, and discusses their potential influence on advisory adherence. Section II-C addresses external factors, including road characteristics and HMI modalities, which can be manipulated or observed in experimental settings. Section II-D summarises representative experimental designs from the literature, illustrating how driving simulators are used to replicate traffic conditions and measure driver reactions. Section II-E reviews common evaluation methods and key performance indicators (KPIs) for assessing both safety- and efficiency-related outcomes.

A. COBRA as a speed advisory system

The COoperative Bottleneck Reduction Algorithm (COBRA) is a proactive traffic control strategy to prevent traffic breakdowns before they occur [4]. Unlike conventional measures such as Variable Speed Limits (VSL) or Ramp Metering, COBRA leverages connected vehicles and Cooperative Intelligent Transport Systems (C-ITS) to dynamically adjust vehicle speeds near bottlenecks. By sending individualised speed advisory signals, COBRA aims to maintain smooth flow and reduce the probability of congestion-induced breakdowns.

The operational effectiveness of COBRA ultimately depends on how drivers respond to these advisories. This study therefore focuses on understanding human driving behaviour when receiving COBRA's recommendations, with the aim of evaluating the system's potential for real-world application and its implications for traffic safety and efficiency.

1) Operational flow: COBRA continuously monitors traffic conditions, detects high-flow clusters, and applies targeted control to stabilise traffic. First, it tracks vehicle trajectories in real time, using speed, headway, and density data to group vehicles into clusters. If the flow in a cluster exceeds a predefined threshold, the system predicts a risk of breakdown and prepares to intervene. A desired speed–density combination is then selected so that, if achieved, a stabilising shockwave will propagate upstream of the bottleneck. Each vehicle in the affected cluster is assigned a target trajectory, and a deceleration advisory is issued. The system monitors driver compliance and adjusts the target trajectory if deviations occur, before finally releasing control once vehicles have passed the bottleneck or when no further deceleration is needed.

2) Driving modes: COBRA employs three driving modes to structure its control actions. In Mode N (Normal mode), no control signal is applied and the vehicle follows its own driving rules. In Mode H (Holding mode), the vehicle has a target trajectory but has not yet received a deceleration advisory. In Mode A (Advised mode), the vehicle receives a deceleration advisory intended to bring it toward the computed target speed.

3) Relevance to driver behaviour: While COBRA assumes compliance, real drivers may be influenced by a combination of traffic cues, cognitive workload, emotional state, and trust in the system. If congestion is not visible, drivers may doubt the need to slow down; if a lane change appears advantageous, they may prioritise it over deceleration. This underlines the importance of studying driver behaviour in controlled scenarios that manipulate adjacent-lane conditions.

B. Human driver-related factors

Previous studies group human factors influencing driving behaviour into four categories [5]: personality traits, affective–cognitive–psychomotor functions, acceptance and trust, and socio-economic characteristics.

Personality traits strongly affect compliance. Aggressive drivers tend to change lanes more frequently, accept shorter gaps, and brake later [6], [7], making them less likely to follow speed advisories. Affective, cognitive, and psychomotor functions also play a role: drivers with faster reaction times respond more promptly to advisories [8], [9], while emotions such as anger increase crash risk and lead to more violations [10], [11]. Perceived headway affects decision-making; for instance, drivers tend to maintain larger gaps behind trucks than behind cars. Distraction, whether visual, manual, or cognitive, can further impair compliance. Common distractions include mobile phone use, conversation with passengers, and in-vehicle infotainment interaction, all of which have been shown to increase crash risk [12]–[15]. Acceptance and trust also matter: observing non-compliance from surrounding vehicles can undermine belief in the system's reliability [16]. Finally, socio-economic characteristics influence behaviour: age, gender, driving experience, and education affect reaction times, braking strategies, and crash risk [17]–[22].

C. External factors

External factors encompass road characteristics, traffic conditions, and the behaviour of surrounding vehicles. Inconsistent geometric design, such as sudden lane drops, curves, or gradient changes, can increase cognitive load and encourage risky manoeuvres [23], [24]. High traffic density intensifies vehicle–vehicle interactions, requiring shorter reaction times and increasing the likelihood of abrupt actions [25]. Drivers often adapt to the prevailing traffic state, for example by maintaining smaller headways in dense conditions or accelerating when adjacent lanes flow faster.

The human–machine interface (HMI) is another critical factor. Visual HMIs, which can be static or dynamic, provide precise speed information but may divert gaze from the road [26], [27]. Auditory HMIs enable eyes-free interaction but can increase cognitive load in complex environments. Combined audio–visual formats leverage both channels to improve comprehension and compliance [28], [29]. The placement, timing, and clarity of HMI messages are integral to system effectiveness.

D. Reference experimental designs

Experimental design choices strongly influence observed compliance. Ramanathan et al. [30] found that flashing alerts positioned in the mid-peripheral visual field reduced speeding duration more effectively than steady alerts or those placed in less conspicuous locations. Yadav et al. [31] showed that rural environments with low traffic density and open roads encouraged speeding, while urban conditions with dense traffic and structured intersections promoted compliance. In connected-vehicle contexts, Sharma et al. [32] demonstrated that V2V information led to more consistent headway and speed adjustments, enabling calibration of compliance-sensitive trajectory models. These findings emphasise the need to reproduce realistic situational factors—such as traffic flow, lane configuration, and communication type—in experimental setups.

E. Evaluation methods of driving behaviour

Evaluation of driver behaviour under speed advisory conditions requires both clear key performance indicators (KPIs) and robust analytical frameworks. Common KPIs include the period of incursion, which measures how long a vehicle remains above a specified speed threshold; the percentage of driving time spent speeding; the frequency of speeding episodes; and safety-related indicators such as time-to-collision (TTC) and time headway (THW). These indicators allow quantitative assessment of both compliance and safety margins.

Analytically, Generalized Linear Models (GLMs) have been used to examine the influence of multiple variables on compliance behaviour, accommodating non-normal data [31]. Theoretical models, such as prospect theory [32], interpret driver compliance in terms of perceived gains and losses relative to a reference state. Combining quantitative KPIs with behavioural theory enables a richer understanding of the mechanisms behind advisory compliance.

F. Summary and refinement of study focus

The literature highlights numerous factors influencing compliance with speed advisories. For the present study, focus is narrowed to adjacent-lane traffic conditions, visible deceleration cues, and advisory timing. Other variables, such as weather and complex road geometries, are excluded due to simulator constraints.

TABLE I: Factors identified from literature that may influence driver response to cooperative speed advisories

Category	**Factors**
External factors	Weather conditions
	Traffic-related factors
	Road design
	Surrounding traffic behaviour
Personal characteristics	Cognitive state
	Emotional state
	Driving styles
	Socio-economic characteristics
System-related factors	HMI type
	Perceived system reliability
	Advisory content

III. Experimental Design

A. Overview and Scope

The experiment aimed to investigate driver responses to a vehicle-based cooperative speed advisory system based on the COBRA algorithm, under controlled yet realistic highway bottleneck conditions. The focus was on two independent variables: (1) the relative position to adjacent-lane deceleration; and (2) the relative position to a gap in the adjacent lane.

A fixed-base driving simulator provided a consistent experimental environment, ensuring repeatable conditions while varying only the two factors. Twelve scenarios were constructed by combining the levels of both variables. Environmental conditions such as weather, lighting, and road geometry were kept constant to eliminate confounding effects.

B. Scenario design

Two spatial dimensions of adjacent-lane influence were systematically varied: (1) the **relative position to adjacent-lane deceleration**; (2) the **relative position to a gap in the adjacent lane**. All other road geometry and traffic parameters were held constant to isolate the effects of these variables.

1) Target state selection through shockwave theory: COBRA selects a **target state** in the fundamental diagram (FD) to generate a stabilising upstream shockwave and prevent capacity drop. The target state lies to the right of the uncontrolled state, reducing speed and increasing density to avoid breakdown.

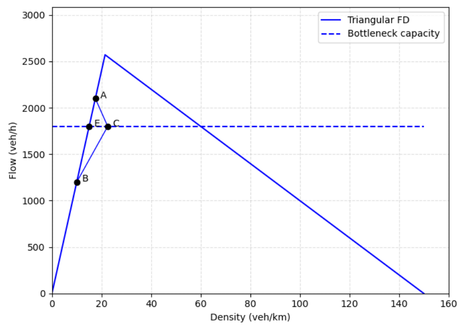


Fig. 1: Fundamental diagram illustrating target state selection.

2) Scenario reference state computation: The deceleration timing and location for each vehicle are first determined by computing the required deceleration duration, the corresponding distance, and the discrete-time start position. These are calculated as

$$t_{i,j}^{\text{dec}}(k) = \frac{v^{\text{target}} - v_{i,j}(k)}{a}, \quad a < 0, \tag{1}$$

$$d_{i,j}^{\text{dec}}(k) = v_{i,j}(k) t_{i,j}^{\text{dec}}(k) + \frac{1}{2} a \left[t_{i,j}^{\text{dec}}(k)\right]^2, \tag{2}$$

$$t_{i,j}^{\text{start}}(k) = \left\lceil \frac{t_{i,j}^{\text{startC}}(k)}{\tau^{\text{ctrlr}}} \right\rceil \tau^{\text{ctrlr}}, \tag{3}$$

$$x_{i,j}^{\text{start}}(k) = x_{i,j}(k) + v_{i,j}(k) t_{i,j}^{\text{start}}(k). \tag{4}$$

After the start of deceleration has been determined, the vehicle trajectory is generated in three sequential phases. In the first phase, the vehicle travels at a constant speed before deceleration begins, with the position at time step k given by

$$x_{i,j}(k) = x_{i,j}(k) + v_{i,j}(k) \cdot (t_{i,j}^{\text{start}} - t_k). \tag{5}$$

In the second phase, discrete deceleration is applied until the target speed is reached. The speed and position are updated at each control step as

$$v_{i,j}(k+1) = \max\left(v_{i,j}(k) + a\tau^{\text{ctrlr}},\ v^{\text{target}}\right), \tag{6}$$

$$x_{i,j}(k+1) = x_{i,j}(k) + v_{i,j}(k)\tau^{\text{ctrlr}} + \frac{1}{2}a(\tau^{\text{ctrlr}})^2. \tag{7}$$

In the final phase, once the target speed is reached, the vehicle maintains this constant speed until arriving at the bottleneck. The position update in this phase is given by

$$x_{i,j}(k+1) = x_{i,j}(k) + v^{\text{target}}\tau^{\text{ctrlr}}. \tag{8}$$

3) Relative position to adjacent-lane deceleration: Three categories are defined: upstream, same position, and downstream, representing whether deceleration in the adjacent lane is visible to the ego vehicle at the onset of the advisory.

4) Relative position within adjacent lane gap: The adjacent lane gap is the longitudinal space between lead and lag vehicles. Four discrete positions are defined by dividing the gap into equal segments from the lead vehicle.

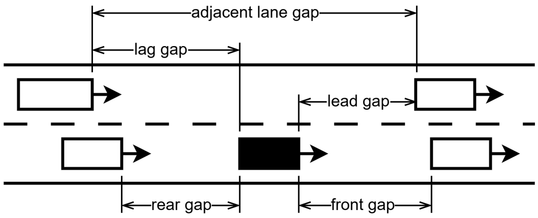


Fig. 2: Adjacent lane gap definition

C. Experimental platform and environment setup

This subsection describes the physical and virtual setup used in the experiment, covering the driving simulator hardware, road network design, and the human–machine interface (HMI) for delivering COBRA advisories.

1) Driving simulator hardware: The driving simulator software used for this research is SCANeR (v1.9) by AV Simulation. The simulator consists of a fixed-base seat with three 4K high-resolution screens providing a 180-degree field of view, combined with a Fanatec steering wheel and pedals. This mid-level simulator allows participants to experience immersive driving while supporting advanced features such as connected and automated driving and VMS integration in experimental designs. The simulator is located at the Faculty of Civil Engineering and Geosciences, Delft University of Technology, as shown in Figure 3.

2) Road network design: The experimental road layout was designed to simulate a realistic but controlled highway environment suitable for investigating driver responses to COBRA speed advisories. The virtual road is a straight, one-directional, two-lane highway segment with a total length of 2000 m. Each lane has a width of 3.5 m, reflecting typical European highway design guidelines. Rows of trees are placed uniformly along the roadside at 12 m intervals to provide visual cues that support longitudinal speed estimation in the simulator. A fixed bottleneck is implemented at 1500 m from the starting point of the road, serving as the trigger location for speed advisories and ensuring sufficient distance for informed deceleration or lane-changing decisions.

Fig. 3: Driving simulator used in the experiment.

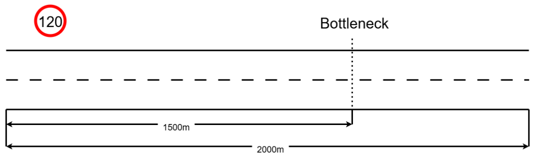


Fig. 4: Schematic layout of the experimental road.

3) HMI design: The advisory was presented as a speed limit symbol styled to resemble a regulatory road sign, displayed at the top of the simulated instrument cluster in a position corresponding to a head-up display in real vehicles, thereby aligning with the driver's natural line of sight. Auditory feedback was provided simultaneously with the visual advisory. When a deceleration instruction was issued, the icon with "80" appeared, accompanied by the spoken message *"Slow down to 80."* Upon entering the bottleneck zone, an additional auditory cue *"Keep to 80"* reinforced the target speed. In automated driving segments preceding manual takeover, a textual message *"Take control in* x *seconds"* with a countdown appeared centrally on the screen, providing clear temporal information to ensure a timely and predictable transition.

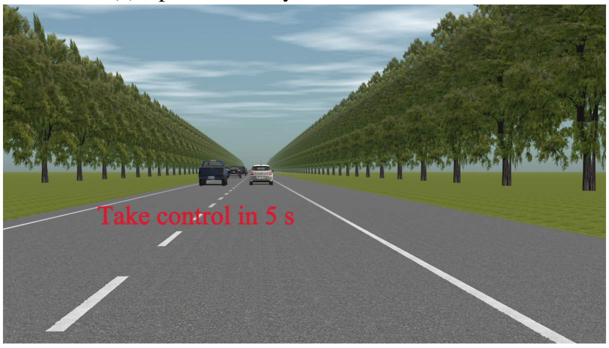
D. Questionnaire design

Two structured questionnaires were administered to complement the objective driving behaviour data by capturing participants' background characteristics, subjective perceptions, and self-reported responses related to the cooperative speed advisory system.

Before the main driving scenarios, participants completed a pre-experiment questionnaire to collect demographic details such as gender, year of birth, and highest educational level, along with driving experience including years holding a license, average weekly highway driving hours, and prior simulator experience. They were also asked about their typical speed limit adherence and general attitude towards in-car speed advice systems.

After completing all scenarios, participants filled out a post-experiment questionnaire reflecting on their experiences. This included items assessing clarity, timing, and perceived

(a) Speed advisory: 80 km/h visual cue



(b) Manual takeover countdown display

Fig. 5: Visual HMI elements presented to the driver.

relevance of the advisories, as well as overall trust in the system. Participants also reported on their perceived mental workload, stress levels, and the reasons behind their decisions to slow down or change lanes. Questions on acceptance and perceived safety gauged their willingness to use such a system in everyday driving and its perceived contribution to traffic safety. Open-ended feedback invited comments on moments when the advisory system was particularly helpful, confusing, or in need of improvement.

E. Pilot test and adjustments

A pilot test was conducted to validate scenario feasibility, confirm technical stability, and assess participant comprehension of the advisory system. Several refinements were made as a result. To improve the transition from automated to manual driving, an additional familiarisation drive was introduced before the main trials so that participants could experience the handover process in advance. The road design was modified to include two 120 km/h speed limit signs, aligning the virtual environment more closely with real-world driving conditions. The HMI presentation was revised by moving the advisory to the height of the instrument cluster and replacing lengthy text with a simple visual icon plus an auditory cue. To avoid biasing driver behaviour, the scenario termination condition was changed to occur 5 seconds after a lane change rather than immediately. Finally, the advisory reaction time parameter was increased from 2.0 s to 2.5 s to better reflect natural driver responses observed during the pilot.

IV. RESULTS

This section presents the experimental results obtained from the driving simulator study on driver responses to a vehicle-based cooperative speed advisory system. The focus is on the objective measurement of driving behaviour and the corresponding subjective perceptions reported by participants. Quantitative indicators were derived from processed simulator trajectory data, while qualitative insights were obtained from the post-experiment questionnaire to provide complementary user-centred perspectives.

The results are organised into subsections covering longitudinal behaviour, reaction times, efficiency-related indicators, safety-related indicators, lateral behaviour, and subjective questionnaire responses. Within each subsection, numerical results are presented alongside descriptive observations of the patterns identified in the data, without in-depth interpretation or theoretical comparison.

The dataset used corresponds to the processed outputs were transformed into structured indicators for each participant–scenario combination. Unless otherwise specified, results are grouped by the relative position of advisory message delivery (Downstream, Same Position, and Upstream) and, where applicable, by lane-change status (lane-changing versus non-lane-changing drivers).

A. Longitudinal behaviour indicators

1) Speed profile – lane-changing drivers: The speed–time profiles for lane-changing drivers (Figure 6) show consistent acceleration before the advisory ($t < t_{msg}$) from approximately 100 km/h to over 110 km/h in all three timing groups: Downstream (Figure 6a), Same Position (Figure 6b), and Upstream (Figure 6c). This acceleration coincided with higher speeds observed in the adjacent lane.

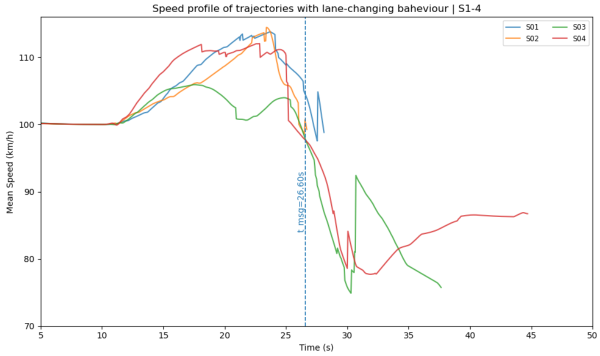
For the Downstream group (Figure 6a), the mean RT_{decel} was -2.30 s, with deceleration starting slightly before t_{msg} and coinciding with adjacent-lane deceleration.

In the Same Position group (Figure 6b), the mean RT_{decel} was 3.08 s. Deceleration commenced almost immediately after t_{msg}, with a sharp speed drop within seconds, coinciding with the onset of adjacent-lane deceleration.

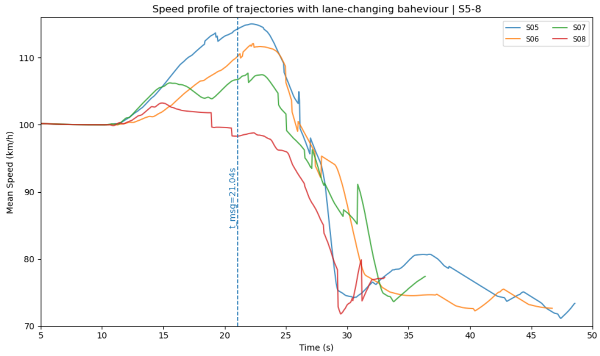
For the Upstream group (Figure 6c), the mean RT_{decel} was 3.66 s. Despite an earlier t_{msg} (15.2 s), drivers delayed deceleration, and some accelerated briefly after the message before slowing down.

In the Downstream condition, earlier lane changes often occurred before the advisory and coincided with adjacent-lane slowing. In the Same Position condition, lane changes typically occurred shortly after the advisory and the onset of adjacent-lane deceleration. In the Upstream condition, lane changes were generally delayed, with some trajectories showing continued travel at or above pre-advisory speeds before slowing down and changing lanes once larger forward gaps appeared (Figure 6c).

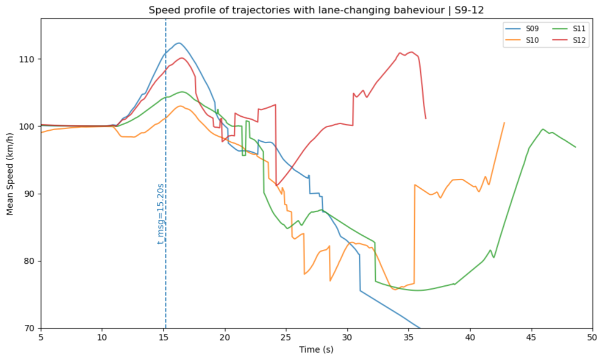
A truncation in the speed curves is visible because the scenario ended exactly 5 s after the lane change was detected as completed. Post–lane-change behaviour was outside the study scope and is not analysed further here.



(a) Downstream scenarios S1–4



(b) Same Position scenarios S5–8



(c) Upstream scenarios S9–12

Fig. 6: Speed profile of trajectories with lane-changing behaviour

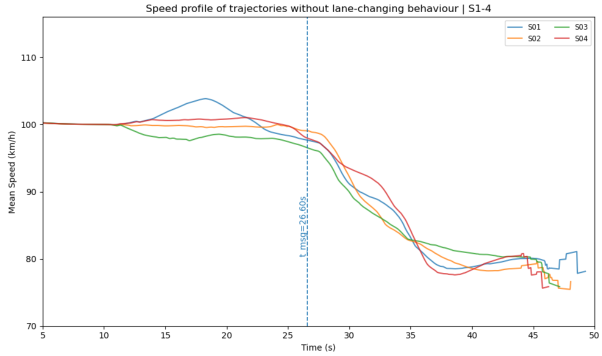
2) Speed profile – non-lane-changing drivers: For non-lane-changing drivers (Figure 7), pre-advisory speeds remained near 100 km/h, with slight acceleration to around 105 km/h in some cases after manual control.

The Downstream group (Figure 7a) had a mean RT_{decel} of 3.24 s, with deceleration typically beginning just after t_{msg}, corresponding with changes in the speed of the in-lane lead vehicle.

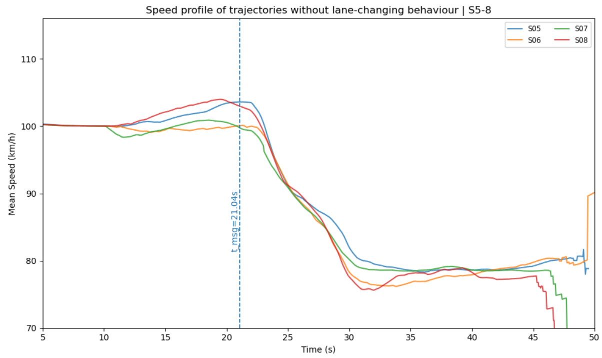
In the Same Position group (Figure 7b), the mean RT_{decel} was 2.94 s, showing a prompt and consistent reaction.

For the Upstream group (Figure 7c), the mean RT_{decel} was 4.37 s, significantly later than Same Position ($p = 0.02$). Speeds stabilised around 78–80 km/h after 30 s.

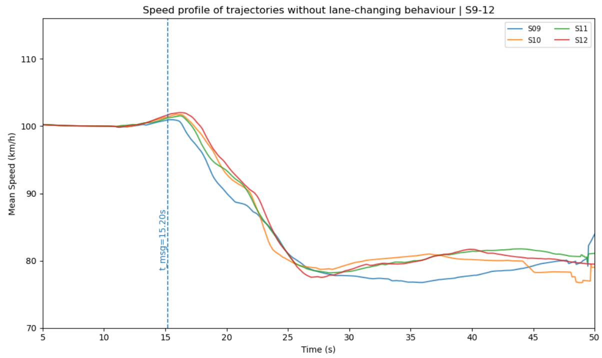
Across all timing groups, non-lane-changing speed trajectories displayed smooth patterns with gradual accelerations and decelerations.



(a) Downstream scenarios S1–4



(b) Same Position scenarios S5–8



(c) Upstream scenarios S9–12

Fig. 7: Speed profile of trajectories without lane-changing behaviour

3) Reaction time for deceleration: Table II summarises the mean RT_{decel} for each scenario, separated by lane-changing and non-lane-changing drivers.

For interpretation, scenarios are grouped into three timing categories in Table III: Downstream (1–4), Same Position (5–8), and Upstream (9–12).

In the lane-changing group, Downstream scenarios produced the earliest deceleration (−2.30 s), significantly earlier than Same Position and Upstream ($p < 0.001$). Same Position and Upstream did not differ significantly ($p = 0.329$); in the Upstream condition, no adjacent-lane deceleration was observed before the advisory.

In the non-lane-changing group, Same Position drivers decelerated significantly earlier than Upstream ($p = 0.020$). Downstream and Same Position did not differ significantly.

TABLE II: Mean RT_{decel} by Scenario ID for lane-changing and non-lane-changing drivers

Scenario ID	Lane-change	Non lane-change
1	-1.32	1.59
2	-2.66	2.63
3	-3.08	4.19
4	-0.55	4.87
5	3.08	3.48
6	4.76	3.48
7	2.28	1.69
8	3.05	3.11
9	3.74	4.37
10	4.58	3.63
11	3.45	4.10
12	2.39	5.23

TABLE III: Mean RT_{decel} by Scenario Group for lane-changing and non-lane-changing drivers

Scenario Group	Lane-change	Non lane-change
Downstream (1–4)	-2.30	3.24
Same Position (5–8)	3.08	2.94
Upstream (9–12)	3.66	4.37

The reference reaction time in the experimental design was 2.5 s. Except for the Downstream group with early deceleration, RT_{decel} in all other scenarios exceeded this reference.

The statistical results for group means and one-sided pairwise t-tests are presented in Table IV.

TABLE IV: Group means, sample sizes, and one-sided pairwise t-tests for RT_{decel}

Group / Comparison	Mean	n	t / p
Non-lane-changing			
Downstream (1–4)	3.24	34	G1 $<$ G2: $t = 0.35$, $p = 0.636$
Same Position (5–8)	2.94	38	G1 $<$ G3: $t = -1.50$, $p = 0.070$
Upstream (9–12)	4.37	41	G2 $<$ G3: $t = -2.10$, $p = 0.020$
Lane-changing			
Downstream (1–4)	-2.30	19	G1 $<$ G2: $t = -4.18$, $p < 0.001$
Same Position (5–8)	3.08	20	G1 $<$ G3: $t = -4.81$, $p < 0.001$
Upstream (9–12)	3.66	22	G2 $<$ G3: $t = -0.45$, $p = 0.329$

4) Final speed and mean deceleration rate: Table V summarises the mean final speed and mean deceleration for each scenario.

One-sample t-tests were performed for both final speed and mean deceleration (Table VI).

Across all scenarios, the mean final speed was 80.04 km/h, not significantly different from the target ($p = 0.92$). The mean deceleration was -1.74 m/s^2, significantly less severe than the target of -2.00 m/s^2 ($p = 0.00003$).

TABLE V: Final speed and mean deceleration by scenario

Scenario ID	Final speed (km/h)	Mean deceleration (m/s^2)
1	79.68	-1.59
2	79.63	-1.59
3	79.70	-1.74
4	80.22	-1.53
5	80.18	-2.05
6	81.18	-1.65
7	81.16	-1.94
8	78.60	-1.94
9	80.54	-1.63
10	78.22	-1.68
11	80.71	-1.79
12	80.68	-1.73

TABLE VI: One-sample t-tests for overall means vs. targets

Metric	Mean	Target	t	p	N
Final speed (km/h)	80.04	80.00	0.10	0.92	12
Mean deceleration (m/s^2)	-1.74	-2.00	4.35	0.00003	12

5) Time to collision: All mean TTC values were above 6 s. For lane-changing drivers, mean TTC values were similar across groups (7.3–7.6 s) with no statistically significant differences. In the non-lane-changing group, Downstream scenarios had the highest mean TTC (9.276 s), significantly greater than Same Position and Upstream.

B. Lateral behaviour indicators

The lateral behaviour indicators in Table VIII summarise lane-changing dynamics across scenarios.

A univariate linear regression of lane-change ratio on gap position yielded a coefficient of -0.0010 ($p = 0.406$), with $R^2 = 0.070$, indicating no significant relationship.

When grouped by longitudinal timing (Table IX), Downstream drivers initiated lane changes 6.54 s before t_{msg}, Same Position at -0.24 s, and Upstream $+4.79$ s. All pairwise differences were significant ($p \leq 0.001$).

C. Questionnaire results

The pre-experiment survey ($n = 21$) showed a mean age of 28.0 years (SD $= 8.0$), mean driving experience of 8.3 years

TABLE VII: Minimum and mean TTC by scenario for non lane-changing and lane-changing drivers

Scenario ID	Non lane-change		Lane-change	
	Minimum TTC (s)	Mean TTC (s)	Minimum TTC (s)	Mean TTC (s)
1	8.13	8.89	4.93	7.73
2	9.16	9.46	–	7.24
3	–	–	6.35	7.63
4	9.45	9.60	6.20	6.96
5	6.17	7.57	6.43	7.70
6	6.12	7.79	6.80	8.06
7	7.26	8.49	7.49	7.50
8	7.52	8.19	4.43	6.97
9	8.51	8.94	5.44	7.27
10	6.19	7.83	7.30	7.65
11	8.50	9.01	8.68	8.27
12	6.82	8.00	5.69	6.50

TABLE VIII: Lateral behaviour indicators by scenario

Scenario ID	RT_{lc} (s)	d_{lead} (m)	d_{lag} (m)	Lane change ratio
1	-8.56	27.43	50.78	0.52
2	-8.31	12.83	65.35	0.33
3	-3.72	20.53	52.41	0.62
4	-6.74	26.89	35.10	0.52
5	-0.50	31.02	42.92	0.57
6	-1.06	22.17	53.89	0.57
7	0.68	28.08	42.96	0.48
8	0.24	19.99	50.26	0.38
9	6.13	22.84	45.46	0.43
10	6.51	22.85	49.61	0.52
11	4.12	24.11	49.46	0.48
12	2.08	38.06	35.04	0.43

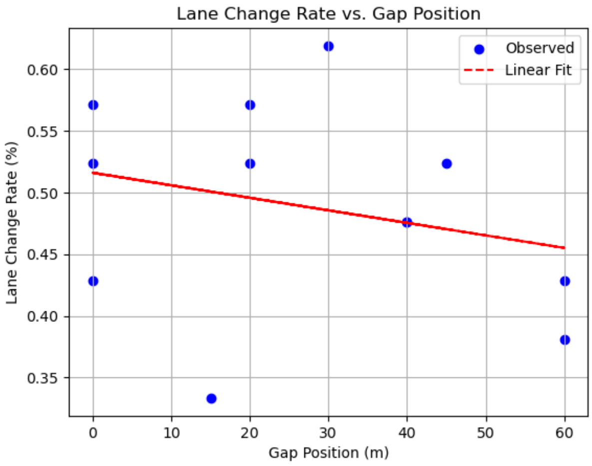


Fig. 8: Lane-change ratio vs. gap position with linear regression fit

(SD = 9.4), 60.9% male and 39.1% female, mostly calm or neutral driving styles, and generally positive attitudes toward speed advisory systems.

Post-experiment, *system information and trust* scored 4.02 ± 0.86, *acceptance* 4.32 ± 0.48, *behavioural response* 3.24 ± 0.69, *perceived safety* 2.68 ± 1.03, and *personal state* 2.54 ± 1.24. Open-ended comments highlighted a preference for earlier advisory timing, improved visibility, and adaptive guidance.

D. Summary

Driver responses varied with advisory timing, visual traffic cues, and lane-change intentions. Safety (TTC) was maintained above 6 s in all conditions. Final speed targets were met, though deceleration rates were generally less than the nominal -2.0 m/s^2. Subjective responses indicated high trust and acceptance, moderate behavioural alignment, and some safety concerns, particularly in upstream scenarios without visible adjacent-lane deceleration.

TABLE IX: Reaction time for lane change and gap acceptance by longitudinal timing group

Group	RT_{lc} Mean (s)	d_{lead} Mean (m)	d_{lag} Mean (m)
Downstream (1–4)	-6.54	22.72	49.60
Same Position (5–8)	-0.24	25.69	47.46
Upstream (9–12)	4.79	26.68	45.25

V. Discussion

This section interprets the behavioural patterns integrating objective performance indicators with subjective evaluations to explain how advisory timing and visual traffic cues influenced driver responses. The discussion follows the main result categories—longitudinal behaviour, system efficiency and safety, lateral behaviour, and questionnaire outcomes—and concludes with methodological limitations that define the scope of applicability.

A. Longitudinal behaviour

For lane-changing drivers, the relative timing of the advisory strongly shaped deceleration initiation. In **Downstream** scenarios, where participants could fully observe adjacent-lane deceleration before receiving the advisory, the mean RT_{decel} was negative (-2.30 s), indicating pre-emptive braking triggered by visual cues. In **Same Position** scenarios, the advisory coincided with visible deceleration, producing rapid compliance ($RT_{\text{decel}} = 3.08$ s) and sharp speed reductions. In **Upstream** scenarios, the advisory preceded any observable adjacent-lane deceleration, leading to the latest responses (3.66 s) and, in some cases, brief acceleration post-advisory. This delay suggests that drivers relied on surrounding traffic speed as an implicit confirmation cue before slowing down.

Non-lane-changing drivers displayed smoother and later decelerations, particularly in the Downstream condition (3.24 s), where braking followed the lead vehicle's behaviour. Reaction times were shortest in the Same Position condition (2.94 s) and longest in the Upstream condition (4.37 s). Across all groups, absence of visible external cues in the Upstream condition contributed to delayed action.

B. System efficiency and safety

Across all scenarios, final speeds closely matched the target of 80 km/h ($p = 0.92$), confirming that the efficiency goal was met. However, the average deceleration magnitude (-1.74 m/s^2) was significantly milder than the nominal -2.0 m/s^2 ($p < 0.001$), consistent with drivers moderating braking for comfort [6]. Such under-deceleration concentrates part of the speed reduction closer to the bottleneck, potentially weakening COBRA's intended smoothing effect in mixed-traffic conditions unless the advisory algorithm adapts trigger points or recommended deceleration rates.

Safety, measured by time-to-collision (TTC), remained well above conservative thresholds (minimum and mean values $>$ 6 s) in all cases. Non-lane-changing drivers in the Downstream group achieved the highest mean TTC (9.28 s), reflecting earlier braking. Among lane-changing drivers, TTC values were stable across timing conditions, suggesting consistent gap acceptance strategies. However, subjective safety ratings were lower in scenarios without visible adjacent-lane deceleration, echoing findings from [16] that mismatches between advisories and observable traffic behaviour can erode trust even when objective safety is uncompromised.

C. Lateral behaviour

Lane-change ratios and timing confirmed that dynamic traffic cues outweighed absolute gap position in predicting manoeuvre initiation. Downstream drivers changed lanes earliest (mean $RT_{\text{lc}} = -6.54$ s), while Upstream drivers delayed by $+4.79$ s on average.

Gap acceptance analysis showed the largest forward gaps (d_{lead}) in the 45/60 m group and the smallest rear gaps (d_{lag}) in the 0 m group, a result of drivers adjusting their manoeuvre timing relative to actual in-traffic conditions rather than the scenario's initial gap configuration.

D. Subjective evaluation

Participants rated *system information and trust* (4.02) and *acceptance* (4.32) highly, indicating clear understanding of the advisories and willingness to adopt the system. Lower *perceived safety* scores (2.68) reflected concerns about rear-end and side-collision risk in conditions lacking visible deceleration cues. The moderate *behavioural response* score (3.24) and milder-than-prescribed decelerations suggest that drivers balanced compliance with comfort and situational judgement. Low *personal state* scores (2.54) indicate minimal additional workload or stress, consistent with the smooth longitudinal profiles observed.

E. Methodological limitations

While the controlled simulator environment ensured repeatability and precise measurement, several limitations affect the generalisability of the results:

- **Experimental scope:** The study was restricted to a straight, two-lane highway segment under controlled conditions, omitting more complex road geometries and varied environmental settings. Broader testing could reveal additional context-specific effects.
- **Traffic and system modelling:** Surrounding vehicles followed static, pre-defined trajectories with 100% compliance to the advisory. The COBRA algorithm did not adapt in real time to lane changes or manual driver interventions. Real-world mixed traffic, with heterogeneous compliance, could produce different outcomes.
- **Interface configuration:** The HMI was deliberately simple, using only visual and auditory cues. More advanced interfaces might alter trust, timing, or compliance, as suggested by prior studies.
- **Participant factors:** The sample was relatively small, skewed toward younger, tech-familiar drivers. Behaviour in older or less technology-oriented populations may differ.
- **Questionnaire design:** Post-experiment surveys captured overall impressions, not scenario-specific perceptions, limiting the resolution of subjective analysis.
- **Data processing:** The analysis relied on scenario-level averages, which may smooth over short-term fluctuations or individual extremes that could be relevant to risk assessment.

These constraints define the scope within which the findings are valid and highlight the need for further work in more varied, adaptive, and realistic conditions, including on-road trials that account for environmental variability and driver heterogeneity.

VI. Conclusion

This chapter summarises the key findings of the study, answers the main research question and its sub-questions, and provides recommendations for future research and development of cooperative speed advisory systems based on the COBRA concept. The conclusions are derived from a controlled driving simulator experiment involving 12 scenarios and 21 participants, combining objective behavioural analysis with subjective evaluations.

A. Conclusions

The main research question asked how drivers respond to a vehicle-based cooperative speed advisory system in simulated real-world conditions, and how such a system can be evaluated for its operational safety and efficiency. The results show that driver responses were shaped by the timing of the advisory relative to the bottleneck, the presence of visible decelerating traffic in the adjacent lane, and lane-change intentions. Safety margins, as measured by minimum time-to-collision, remained above conservative thresholds in all scenarios. Efficiency objectives were generally met, with final speeds stabilising near the target of 80 km/h, although decelerations were typically milder than the nominal -2.0 m/s^2. Subjective evaluations reflected high clarity and acceptance ratings but lower perceived safety in conditions without adjacent-lane deceleration cues.

Regarding Sub-question 1, the findings, supported by literature, confirm that driver responses are influenced by a combination of external driving conditions, system-related aspects, and driver characteristics. External factors include traffic density, adjacent-lane speed patterns, and road geometry. System-related aspects concern the content, modality, and display location of the advisory. Driver characteristics encompass risk perception, driving style, and prior experience with similar systems. In this study, the experimental focus was placed on controllable factors such as advisory timing (Downstream, Same Position, and Upstream) and the ego vehicle's relative position to an adjacent-lane gap, both of which were found to have a direct impact on response timing and manoeuvre decisions.

For Sub-question 2, the results indicate that different traffic conditions significantly influenced behavioural responses. Downstream advisory timing encouraged earlier deceleration and more lane keeping, whereas Upstream timing often coincided with delayed deceleration and a higher proportion of lane changes. Scenarios in which decelerating vehicles were visible in the adjacent lane generally showed higher advisory compliance, suggesting that visual traffic cues play an important role in facilitating system acceptance. Smaller following gaps from vehicles in the target lane were often linked to delayed deceleration or lane changes, possibly due to perceived rearward pressure in the manoeuvre decision.

In answering Sub-question 3, safety was evaluated primarily using time-to-collision measurements and lane-change gap analysis. All scenarios maintained TTC values above conservative thresholds, although a small number of lane changes occurred with relatively short gaps. Efficiency was evaluated by measuring the extent to which drivers reached and maintained the target speed, as well as by analysing deceleration profiles. While most participants achieved the target speed, the majority decelerated less aggressively than the system's nominal recommendation, indicating a preference for smoother braking. Subjective ratings confirmed system clarity, trust, and acceptance, but also revealed reduced perceived safety when advisory messages were not supported by visible traffic behaviour.

For Sub-question 4, the study suggests that for real-world deployment, COBRA should evolve from an open-loop control strategy to a dynamic closed-loop system capable of recalculating target speeds and trigger points in real time, especially following driver interventions such as lane changes. The system should integrate multi-lane traffic modelling to predict cross-lane interactions, coordinate advisories across lanes, and anticipate the impact of lane-changing vehicles on target arrival times. It should also account for heterogeneous driver compliance and reaction times, adapting advisory parameters to current traffic compositions. Furthermore, effective deployment would require validation under partial penetration rates, supported by connected vehicle data integration, to ensure operational effectiveness in mixed traffic environments.

B. Recommendations

Future experiments should incorporate a wider range of road geometries, including curves, ramps, and gradients, as well as varied environmental conditions such as different weather, lighting, and road surface states. Traffic diversity should be increased by including a broader range of vehicle types and varying penetration rates of connected and automated vehicles. Collecting subjective driver perceptions during specific experimental conditions, and linking them to objective behavioural metrics, would provide richer insights into compliance mechanisms.

The participant pool should be expanded to cover a broader demographic range in terms of age, gender, driving experience, and familiarity with in-vehicle technologies. Including professional drivers could offer valuable comparisons between trained and general populations. Future research should also evaluate COBRA performance under mixed penetration rates and different levels of compliance, extend its application to multi-lane traffic environments, and investigate its effects on platoon control and traffic flow stability in human-in-the-loop contexts. These steps would improve the robustness, generalisability, and practical applicability of the system for real-world deployment.

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