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Understanding Drivers' Lane Choice Behavior at Pre-Signalized Intersections

Examining Implications for Efficiency and Applicability of Pre-Signal Use for Regular Traffic

R.C. van Rooijen

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Colophon

Author	R. C. van Rooijen
Graduation Committee	Dr. V. L. Knoop Chairman TU Delft, CiTG, Transport & Planning
	Dr. ir. A. M. Salomons Daily supervisor TU Delft TU Delft, CiTG, Transport & Planning
	Dr. ir. H. Taale Daily supervisor RWS Rijkswaterstaat, section WVL TU Delft, CiTG, Transport & Planning
	Dr. ir. H. Farah Third member TU Delft, CiTG, Transport & Planning
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Information	Robbin van Rooijen
Telephone	+31 6 306 236 80

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Preface

As I stand on the threshold of completing my Master of Science in Transport & Planning at the Faculty of Civil Engineering and Geosciences of the TU Delft, I am filled with a profound sense of accomplishment and gratitude. This thesis represents the culmination of a journey that has expanded my horizons, challenged my intellect, and deepened my passion for the field of choice modeling and traffic management.

The creation of this thesis would not have been possible without the guidance and support of many individuals, and I would like to take this opportunity to express my appreciation to each of them.

First and foremost, I extend my gratitude to my daily thesis advisor, Maria Salomons, whose expertise, and constructive feedback were instrumental in turning the unforeseen in the foreseen. The bi-weekly meetings really pushed me into the right direction whenever I got a bit off track. It is a great honor and appreciation of my work that based on this research Maria initiated research proposals for my follow-up graduation students.

I am also thankful for my daily company advisor, Henk Taale, for joining the bi-weekly meetings, and for giving me the opportunity to join the ITS Edulab, which is a cooperation between Rijkswaterstaat and the TU Delft. I am grateful to the colleagues at Rijkswaterstaat, who always were interested in my progress, and were undoubtedly the reason for the astonishing 1000+ respondents to the questionnaire.

Last but not least, I want to acknowledge the numerous participants and organizations that contributed to help achieving the required respondents to the questionnaire. Your willingness to collaborate and share insights was essential in gathering the data required for this research.

As I embark on the next phase of my professional journey, I carry with me the knowledge and experiences gained during the pursuit of this Master's degree. The skills and insights acquired in the Transport & Planning program, internships, and side jobs have equipped me to tackle the complex challenges of our dynamic and interconnected world. It is my hope that the findings and insights presented within these pages will contribute to the field of traffic management and inspire further research and innovation.

Robbin van Rooijen
Delft, November 2023

Summary

Recently, the proposed pre-signal strategy of Li *et al.* (2014) has emerged as a promising new measure to mitigate the impact of heavy left-turn volumes at intersections within the boundaries of the current infrastructure. The pre-signal is an additional traffic light (i.e. stop line) upstream of the main coordinated intersection that separates directional traffic flows upfront. The pre-signal allows vehicles with the same direction to proceed and the vehicles will utilize the entire cross-section of the main intersection while discharging the main intersection during its green phase, as visualized in Figure 1.

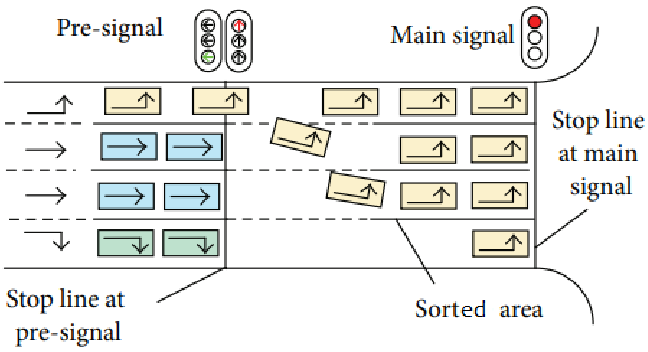


Figure 1. – Example of the Pre-Signal's Working Mechanism (Li et al., 2019)

That pre-signals can yield a higher intersection capacity is undoubtedly proven in literature by many simulation studies. However, behavioral assumptions in those studies regarding the spread behavior of drivers in the sorted area were not based on validated findings from behavioral science, and were to the researcher's opinion optimistic in the sense of a perfectly equal spread of drivers in the sorted area. This questions the validity of these promising findings. Therefore, this research tries to investigate the spread behavior of drivers, with the objective of reflecting these findings against potential implications for the applicability and efficiency of pre-signals for regular traffic. The main research question reads: How does drivers' lane selection downstream of pre-signals impact the efficacy of pre-signal implementation for regular traffic? This more general main research question was split into two sub-main research questions: (1) How do drivers choose their preferred lanes downstream of pre-signals?, and (2) To what extent do drivers' lane choice strategies affect the efficiency and applicability of pre-signals for regular traffic?

To gain insight in the spread behavior of drivers and their underlying choice strategy, a stated-choice experiment has been executed in which respondents were repeatedly asked to state their preferred lane choice. Respondents were exposed to a variety of traffic situations, which varied in traffic crowdedness, turning directions, and number of spread opportunities. Through videos and static images from the driver's perspective, which were extracted from a 3D visualization model, respondents had to imagine them being the driver of the car.

The stated-choice experiment was part of an overarching questionnaire, which also gathered some respondents' characteristics in terms of driving experience, driving frequency, driving style, and the plan-ahead potential. The questionnaire was conducted by well over 1000 respondents of which approximately 600 respondents completed it. As a result, the final data set contained 8864 preferred lane choices along with their respondent' characteristics. The respondents' preferred lane choices were processed in a MultiNominal Logit (MNL) choice model under an efficient design strategy. The latter strategy was adopted to increase the reliability of estimates, and the validity of more realistic traffic conditions by balancing utilities among choice alternatives. Nevertheless, a hypothetical bias is present due to the expected gap between revealed-preference and stated-choice behavior, and readers must be aware of the strengths & weaknesses of such an MNL model. A total of ten choice scenarios were defined, which together captured the variety in turning directions, and spread opportunities in terms the number of lanes in the sorted area. Among which two were dedicated to traffic situations without pre-signals. Attributes predominately described traffic crowdedness, respondent characteristics, and alternative specific characteristics. A cross-scenario analysis of the obtained model estimations provided a profound insight in the attribute valuation differences that were present within-and between choice scenarios. These insights were reflected in potential implications for the applicability and efficiency of pre-signals.

The results have shown that pre-signals do not affect drivers in their appreciation of traffic crowdedness. In general, drivers account for heavy good vehicles more than twice as heavily than for cars. Besides that, the discomfort for heavy good vehicles increases whenever it concerns the trailing vehicle, and when these vehicles are positioned in lanes closer to the driver. This further emphasizes the tendency to avoid heavy good vehicles. Regarding the discomfort for cars, drivers account about twice as heavily whenever there is no option to avoid heavy good vehicles. Although it was found that pre-signals do not affect drivers in their appreciation of traffic crowdedness, substantiation differences have been found in the discomfort associated with lane changing. This led to the lane-changing aspect being the predominant factor to assess potential implications for the pre-signals' efficiency and applicability for regular traffic. Drivers maintain a high-keep right desire when they are positioned in the most left lane of the sorted area, and this slightly moderates when drivers are positioned more centrally. This was the result of a much lower discomfort for right lane changes than for left lane changes, and an increase of this gap increases whenever the target lane of the driver equals the most left lane of the sorted area. In addition, drivers are the most hesitated to execute multiple left lane changes. This together does not withhold drivers from spreading left-wise in the sorted area, it just requires the driver's right side being more crowded with respect to its left side.

The results have shown that only three out of the ten choice scenarios contributed to an equal spread in the sorted area. The underlying reason for the success of these choice scenarios was the absence of multiple lane changes to reach the outer lanes of the sorted area. This critical bottleneck lies at the heart of the entire pre-signal paradigm, imposing a barrier that

significantly obstructs the equal spread of drivers and eventually the efficiency of the system. Those particular choice scenarios succeeded in this, either because of a central starting position of the driver, or due to a limited sorted area size of two lanes. Although the latter seems to be rather arbitrary, it contradicts with some of the core elements of pre-signals, i.e. to provide traffic downstream the pre-signal with more pre-sorting lanes than upstream of the pre-signal. Then, it is questionable whether pre-signals can improve the capacity of the main intersection, because literature has only provided evidence for this to increase with at least three lanes included in the sorted area for all traffic directions. These results emphasize the limited support for the behavioral assumption that previous researchers incorporated in their simulation studies to highlight the potential of pre-signals to increase the intersection's capacity significantly. Although this research did not explicitly test the consequences of the obtained driving behavior with respect to the intersection's capacity, such previous statements about the potential of pre-signals should be questioned at this point.

This research revealed a scarcity of evidence supporting the efficacy of pre-signals, yet it unveiled opportunities for traffic engineers to make informed decisions regarding their implementation. Two distinct options emerged:

- In option 1, all traffic directions must use the entire sorted area. Despite literature support for an increased intersection capacity with at least three lanes in the sorted area, achieving an equal spread under this option poses challenges, even for a relative small pre-signal design with 3 lanes in the sorted area. Multiple lane changes for turning directions hinder the spatial utilization of the outer lanes. Hence, being less efficient than literature argued.
- Conversely, in option 2, parts of the sorted area can be dedicated to a particular traffic direction. This option yields an equal spread in the sorted area by avoiding the need of multiple lane changes, but introduces increased costs and safety concerns. These arise from the need of dynamic road signing, a lack of predictability in pre-signal design, and an increased driving task. Although option 2 is expected to be the most efficient, option 1 is recommended due to the absence of such secondary implications.

Unfortunately, the design of a pre-signal system that achieves both an equal spread and uses the entire sorted area for all traffic directions proves unfeasible.

This research addressed a critical gap in pre-signal studies, emphasizing the necessity of integrating behavioral science before passing judgment on this innovation. Future research should incorporate the estimated utility functions into a new simulation model for a quantitative analysis of intersection performance. Additionally, investigating the impact of driver characteristics, learning curves, sorted area lengths, part-utilization pre-signal types, and the influence of different pre-signal controllers on driver behavior is essential. Notably, literature currently overlooks implementation risks, urging future research to explore aspects such as traffic safety, cost efficiency, connectivity, and human factors. This study lays the groundwork for understanding pre-signals, highlighting the imperative for further research and a holistic approach to their implementation.

Contents

Lists of figures and tables

List of Figures

List of Tables

1. Introduction

Considering the ongoing urbanization and the scarcity of residual space, traffic engineers face a growing challenge in managing traffic through tight saturated urban networks. This emphasizes the need for traffic management strategies that achieve more throughput on the current infrastructure without the utilization of any additional scarce urban space. Heavy left-turn volumes significantly reduce the capacity of conventional signalized intersections and often form the bottleneck in the traffic network due to a separate green phase allocation (Ghanim and Abu-Lebdeh, 2016). Previously, researchers proposed some unconventional measures to prohibit and re-allocate left-turn traffic from the signalized intersection, such as median U-turns, jughandles, superstreets, continuous flow intersections, and bowtie intersections. Although these methods are demonstrated to be effective in increasing the intersection's capacity (Autey *et al.* (2013); Esawey and Sayed (2013)), they require additional infrastructure, which again may be scarce. Recently, the proposed pre-signal strategy of Li *et al.* (2014) has emerged as a promising new measure to mitigate the impact of heavy left-turn volumes within the boundaries of the current infrastructure.

The pre-signal is an additional traffic light (i.e. stop line) upstream of the main coordinated intersection that separates directional traffic flows upfront. The area between the stop lines of the pre-signal and main intersection is called the 'sorted area'. This area can consist of all lanes between the two stop lines, or just some of them. The pre-signal allows vehicles with the same direction to proceed and the vehicles will distribute themselves laterally across the intersection cross-section (i.e. all available entry lanes of the main intersection). By doing so, vehicles utilize the entire cross-section of the main intersection while discharging the main intersection during its green phase, as visualized in Figure 1.1. As a result, the duration of all phases, including the problematic left-turn phase, can be shortened due to a decrease in the required green time for vehicles to discharge the main intersection.

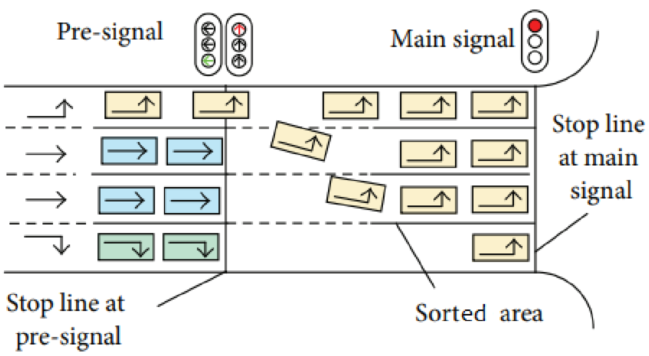


Figure 1.1. – Example of the Pre-Signal's Working Mechanism (Li et al., 2019)

Many simulation studies, among which Xie and Ma (2012); Zhao *et al.* (2013); Yan *et al.* (2014); Vieira *et al.* (2019); Yao *et al.* (2020), showed that when the pre-signal is well configured the system can increase the intersection's capacity significantly by up to 50%. Despite all the previous effort, pre-signals present-day have not seen any implementations for regular traffic yet, but for transit priority only. This is expected given the knowledge that no studies have exclusively tested the validity of the simulation studies' findings regarding the implications of human involvement. Drivers are most likely inexperienced with any kind of pre-signal system, and they will be confronted with an unfamiliar lane choice in the sorted area. Not knowing what driving behavior is expected, questions the validity of the statements made about the pre-signals being able to significantly increase the intersection's capacity. This study will contribute to the process of validating these by reflecting these against findings from behavior research.

1.1. Research objective

The research objective of the study is split into two parts. First, it will define a problem statement which is central throughout the research. Then, the problem statement will be reformulated to a general main research question, which will be split into two sub-main research questions and several sub research questions. The latter is done after the formulation of the research methodology. The answers to the sub research questions together enable the possibility to provide an answer to the main research question.

1.1.1. Problem statement

The main problem of not knowing the driving behavior that is expected at pre-signalized intersections can be further peeled off to a more detailed specification of that knowledge gap. Driving behavior can be expressed as lateral and longitudinal actions, of which the latter refers to the well-known car-following model. In this case, the missing piece of the puzzle concerns the lateral pre-sorting driving behavior that is currently unknown. Drivers in the sorted area are confronted with an unfamiliar lane choice (i.e. choosing their preferred lane in the sorted area for discharging the main intersection), which has not been researched yet. Although some conventional signalized intersections also incorporate similar actions, they are still not representative for the lane choice behavior at pre-signals, because of differences in lane-change opportunities -and dimensions. Since the effectiveness of the pre-signal is dependent on the distribution of drivers in the sorted area, knowledge about this lane-choice behavior is crucial for the validation of the simulation studies' findings.

The preferred lane-choice of drivers is expected to be influenced by traffic conditions in the sorted area and the pre-signal's system size in terms of its n.o. lanes the sorted area includes. While the former is arbitrary, the latter follows from the reasoning of a turning point where an increase in the n.o. lanes in the sorted area will no longer gain additional efficiency. Understanding this underlying choice process can help to define in which conditions pre-signals might be helpful to implement and what design strategies help accompany this. Thus, the main problem statement can be defined as the lack of knowledge about the preferred lane choice strategy of drivers in the sorted area under various traffic conditions and its interaction with pre-signal designs.

1.1.2. Main research question

To gain more insight in the decision-making process of human drivers for the preferred lane choice downstream the pre-signal, and the way how this may questions the credibility of previous findings, this study aims at answering the following main research questions:

General main research question:

How does drivers' lane selection downstream of pre-signals impact the efficacy of pre-signal implementation for regular traffic?

Sub-main research questions:

How do drivers choose their preferred lanes downstream of pre-signals?

To what extent do drivers' lane choice strategies affect the efficiency and applicability of pre-signals for regular traffic?

In this study, efficacy refers to the ability of a system, method, or intervention to produce the desired results or outcomes under specific conditions. It measures the effectiveness and success of a particular approach in achieving its intended goals or objectives. In essence, efficacy reflects how well something works in practical terms and how closely it aligns with its intended purpose.

1.2. Research methodologies

Since pre-signals have not been implemented for regular traffic in practice, the research topic has an innovative character. Revealed preferences or observations from practice are not available, therefore it is important to select a research methodology that can deal with this problem. In the research of Glendon (2007), an overview of empirical methods is given that are suitable for studying driving behavior. This overview is given in Figure 1.2. Research methods are ranked from high to low ecological validity, which measures the ability to generalize experimental findings to the real world. As can be noticed, on-road & in-vehicle observations obtain the highest ecological validity, while those are not applicable to pre-signals. Methods that can provide a more moderate ecological validity are indirect post hoc analyses and a driving simulator. They are considered as potential research methodologies, because those methods allow for an analysis of driving behavior in an innovative field, and obtain the highest ecological validity possible. An indirect post hoc method consist of a statistical analysis after the data have been collected, as is the case by questionnaires and interviews. These three research methods will be discussed further with the objective to select a proper research methodology for this study.

1.2.1. Indirect post hoc methods

Questionnaires and interviews share most of their features, because they both belong to the group of self-report instruments (Lajunen and Ozkan, 2011). In these research methodologies, participants are asked to answer structured questions, which are assumed to reflect low ← ecological validity → high

On-road & in-vehicle observation (direct)	Naturalistic observations: actual road, standard circuit
On-road & in-vehicle observation (indirect)	Instrumented: vehicle, driver, video/still recordings
Indirect (post hoc)	Crash data (police, other) Questionnaires Interviews/focus groups
Simulation	Driving simulator
Experimental and quasi-experimental / before-after studies	Small scale Field or Laboratory Compare experimental and control groups

Figure 1.2. – Methods to Study Driving Behavior from Glendon (2007)

their reality. Furthermore, only the answers themselves are taken into account, and the participants are aware that they are part of a research. Questionnaires and interviews can be used to study driving behavior in both a concrete and a more abstract manner. The latter approach would imply more freedom to answer questions, while the concrete approach only let the participant choose from a limited set of options. This is mainly the field where questionnaires and interview differ form each other. The questions in a questionnaire can be designed both concrete- and abstract-wise, while an interview with questions based on a pre-defined choice set would not have any additional value compared to a questionnaire.

The main advantages of questionnaires and interviews are based on costs, data collection, and statistical possibilities. Compared to for instance a driving simulator or a small case study, the costs of these methodologies are by far less expensive. Moreover, a lot of respondents can be reached within a limited time frame. Since the questions and context can be steered, questionnaires and interviews can study driving behavior on road environments which are hard or not feasible to conduct in practice. If the questions and body structure of the experiment are well designed, these methods can be very efficient and statistically tested. Mainly questionnaires support statistical analysis on the sample representativeness and the reliability of the outcomes, by making use of confidence intervals and standard errors respectively. Statistical analysis on interview outcomes can become rather vague due to the freedom participants have to answer questions. Because of this shortcoming, a questionnaire is preferred above a interview. Besides that, with the same effort a lot more respondents can be reached with a questionnaire instead of conducting interviews. However, an interview can be a helpful tool to validate the findings from the questionnaire.

Questionnaires also have some disadvantages that the researcher must be aware of. First, drivers may not be known to the things they consider while driving, while such decisions will be estimated based on their answers in the experiment. Moreover, validity issues arise in the domain of research on new technologies. Do stated choices obtained from a a questionnaire reflect their true behavior in real traffic situations? This refers to the hypothetical bias and is argued in literature constantly. Although there is evidence that stated-choice preference -and revealed-preference data produce fairly comparable parameters, and especially ratios, researchers argue that drivers behave differently compared to real world driving. This phenomenon is known as the stated-preference paradox:

> *"We particularly use stated-choice experiments when we wish to examine preferences for new alternatives or attribute values beyond current ranges, however, the less familiar respondents are with the alternatives, the less valid their responses."(E.J.E., 2022)*

1.2.2. Driving simulator

A driving simulator is a frequently used tool for investigating driving behavior in new technologies. Simulators vary from a simple road environment display on a computer screen controlled by a joystick or keyboard to full-size vehicles mounted on motion systems controlled by a steering wheel, pedals, and a gearshift from a real car. A standard definition of a driving simulator is, therefore, hard to obtain. One of its major advantages is the controllability of the experiment in terms of repeatable situations, scenes, and scenarios. This implies experimental power and efficiency since the control element reduces random extraneous effects in the data and the experiment can be steered towards the researcher's needs. Software and electronic interfaces form the road environment and the control systems. By steering those inputs, it is possible to conduct behavioral studies on road environments which are hard or not feasible to conduct in practice. However, this virtual world induces also its limitations in terms of validation and authenticity issues. Researchers argue that drivers behave differently compared to real world driving, because of a lack of time-pressure (e.g. delayed by traffic lights) drivers encounter in the simulator experiment and the fact that participants feel observed (Carsten and Jamson, 2011). Again, they may obey the experiment and steer towards desired behavior for the researcher, yielding biased outcomes.

Probably the main reason not to choose for a driving simulator in this research is the challenge to obtain a sufficient amount of participants and to include the dynamics of the pre-signal system into the simulator environment. A sufficient amount of participants is required to ensure a high level of reliability and to allow for a cross-scenario analysis in terms of varying traffic conditions and pre-signal designs. Reaching participants through a questionnaire requires significantly less effort, therefore it has a major advantage compared to the driving simulator.

1.2.3. Research methodology

Section 1.2.1 & 1.2.2 discussed the strengths and weaknesses of the questionnaire, an interview and a driving simulator as potential research methodologies to capture the preferred lane choice of drivers. Since pre-signals have not been used for regular traffic, the research methodologies that can be applied in this study are minimal, and biased outcomes of the experiment are unavoidable. A questionnaire and interview are preferred above a driving simulator based on the ability to reach more participants, the support of empirical analysis, and the design flexibility of the experiment, whereby the questionnaire is preferred on both fronts above the interview.

Thus, the research methodology that will be used in this study is a questionnaire. To gain insight in how drivers are affected in their preferred lane choice downstream the pre-signal, participants will be asked to do a stated-choice experiment. In a stated-choice experiment, participants are asked to choose a preferred alternative out of a set pre-defined alternatives. The drivers' choice strategy can then be withdrawn from the choices made by the participants, and a cross-scenario analysis enables the possibility to get insight in the preference differences across various traffic conditions and pre-signals designs. This obtained behavior can then be reflected on the applicability and efficiency of pre-signals in general.

1.3. Research approach

The research approach contains four consecutive parts: I literature review, II experiment design, III data generation & model estimation, and IV discussion & conclusion. The research framework in Figure 1.3 represents a schematic flow diagram of work packages and forms the path towards the answer of the research question. The objective of the individual parts and their related sub-research questions will be discussed further in detail.

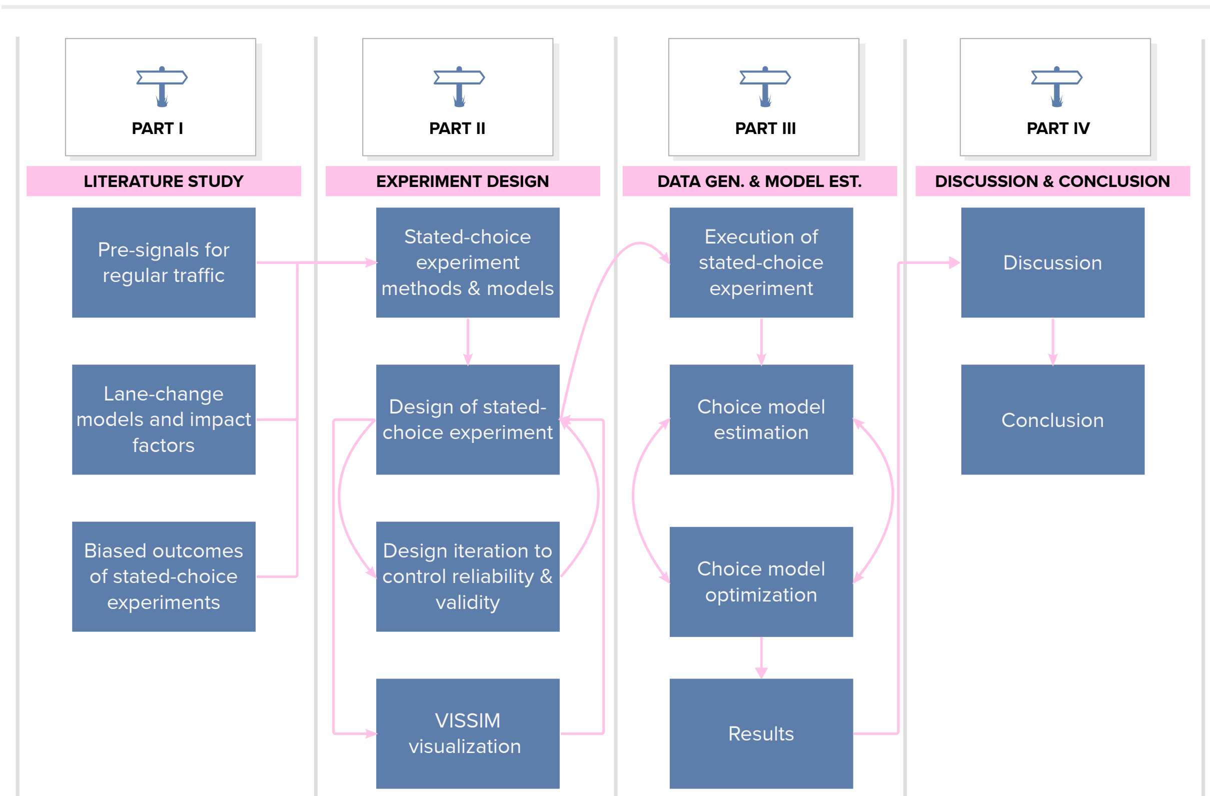


Figure 1.3. – Research Approach Framework

1.3.1. Part I Literature review

The objective of the literature review is to further specify the knowledge gap around pre-signals, and to provide the theoretical background that is needed for the design of the stated-choice experiment in Part II. Hereby, it tries to answer the following sub-research questions.

1. What knowledge is currently missing that caused pre-signals not being implemented for regular traffic yet?
2. Which part of that knowledge gap can be filled by this research?
3. What factors influence lane-choice behavior at intersections?
4. How have researchers previously coped with biased outcomes of stated-choice experiments in hypothetical traffic environments?

The literature review consist of three main subjects of which each is defined as a separate work package. First, research on the system dynamics of pre-signals and its current constraints help to identify the current challenges and the knowledge gap pre-signals face when it comes to implementing these systems for regular traffic. Besides that, it elaborates on the scientific contribution of the study with respect to filling that knowledge gap. Second, a review on existing lane-change models and lane-change classifications helps to define a set of factors that influence the desired lane choice of drivers. These insights will be used in Part II to make a selection of relevant factors to include in the design of the SC experiment. Third, a review on the sources and mitigation of the hypothetical bias, which is most likely inherent to SC experiments, helps to define strategies to mitigate the presence of it. Besides that, it helps to understand how valid research outcomes will be, and how it can be controlled.

1.3.2. Part II Experimental design

The second part of the research has the objective to design a stated-choice experiment in such a way that it can extract the respondents' trade-offs between the relevant factors across pre-defined scenarios under low uncertainty and model inconsistencies. A review of the existing SC experiment methods & models will lead to the decision to choose for a specific model strategy that suits the research the most. This is formulated in a fifth sub-research questions.

5. What methods and models exist in the field of stated-choice experiments, and which is recommended for this research?

Additional effort on model development is needed to control the reliability and validity of the experiment. This effort is translated into design iterations, in which the main focus will be on creating realistic traffic situations, minimizing the standard error of the model, and to minimize the required number of respondents. A 3D traffic environment in VISSIM will be designed with the aim to visualize the hypothetical traffic situations participants encounter in the SC experiment. How this 3D environment relates to the extraction of trade-offs is elaborated upon in section 5.4.

1.3.3. Part III Data generation & model estimation

After Part II has been completed, the stated-choice experiment is ready for distribution and execution. The objective of this part is to collect data from the stated-choice experiment and to estimate scenario dependent choice models that reflect how drivers are affected in their preferred lane choice downstream the pre-signal across pre-defined traffic environments. After the model estimation, explanatory variables that have been found relevant to lane-choice behavior will be tested for significance and model performance optimization. A cross-scenario comparison of these results will reveal how drivers are affected in their preferred lane choice downstream the pre-signal, and what trade-offs they make in a particular traffic condition. Three sub-research questions are defined to structure this process.

6. What trade-offs between the relevant lane-changing factors make human drivers in their desired lane choice downstream the pre-signal?
7. How are these trade-offs affected by the driver's intended turning direction and the number of lanes in the sorted area?
8. To what extent does the drivers' preferred lane choice downstream the pre-signal differ from one of a conventional signalized intersection without a pre-signal, and what are the implications of these differences for the applicability and efficiency of pre-signals in general?

The answers to these questions can be tied together to comment on the applicability and efficiency of pre-signals. As a result, the main research question can be answered.

1.3.4. Part IV Discussion & conclusion

The objective of the discussion & conclusion is to answer the research question and to reflect upon the limitations of the chosen research methodology. To conclude, any advise on future research will be given.

1.4. Relevance of the research

That previous research effort on pre-signals has not resulted in any implementations for regular traffic is not a coincidence. In fact, no research has been dedicated to study the implications of human involvement into these hypothetical traffic situations. Without any confirmation of the credibility of the promising results from simulation studies, researchers must be critical and skeptical against the added value of pre-signals. This study will contribute to the process of validating the added value of pre-signals by testing the underlying assumptions and statements from the promising looking simulation studies. Although this study might not be able to test all findings from previous research, it still provides an excellent basis for the first insights in how human drivers deal with such unfamiliar traffic situations. Besides that, it can serve as a source of inspiration for future research directions. Looking more closely to the pure outcomes of the research questions, this study contributes to help defining when pre-signals might be helpful to implement and to identify design strategies for pre-signals. This is done through a comparison of the choice preferences under varying traffic conditions and pre-signal designs, given that the preferred lane distribution is closely related to the efficiency of pre-signals.

1.5. Thesis outline

The structure of the report corresponds with the four parts that have been defined in the research approach. Figure 1.4 schematically represents how the chapters in the report are related to the research approach. The first part consist of three chapters, which together form the conceptual basis for the next part of the report. Chapter 2 includes the literature review on the system dynamics of pre-signals and its current challenges that prevent the technology from a successful implementation in practice. Chapter 3 works towards a set of impact factors that human drivers consider while making a lane choice through a systematic review of lane-change classifications and lane-change models. Chapter 4 develops a framework that combines multiple sources and mitigation strategies of the hypothetical bias. Throughout the following parts of the report, there will be extensively referred to this prior knowledge of the first part. Within Part II, Chapter 5 defines the design choices for the stated-choice experiment that will be designed in Chapter 6. Chapter 7 includes the data generation and the model estimation of the stated-choice experiment. Part III includes just one chapter, which will present the results of the stated-choice experiment. The design choices and assumptions from Part II form the basis for the discussion in Part IV. Finally, the main research question will be answered in the conclusion.

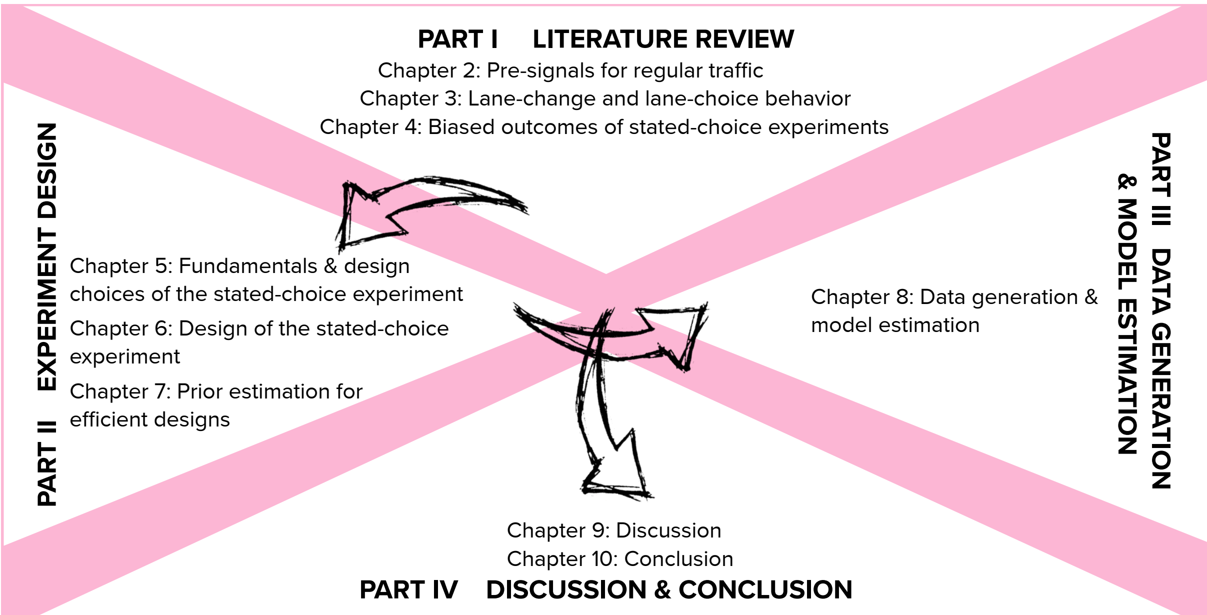


Figure 1.4. – Structure of the Report

Part I. Literature Review

2. Pre-signals for regular traffic

This chapter represents the first out of three parts of the literature review and it concerns the literature review of pre-signals for regular traffic. The sub research questions that will be answered in this chapter are as follows:

- What knowledge is currently missing that caused pre-signals not being implemented for regular traffic yet?
- Which part of that knowledge gap can be filled by this research?

The answer to the first sub question helps to identify the current challenges and knowledge gap pre-signals face when it comes to implementing these systems for regular traffic. This will be covered in Section 2.2, after a brief introduction to pre-signals in Section 2.1.

The answer to the second sub question specifies the scientific contribution of the study with respect to filling that knowledge gap. This will be elaborated upon in Section 2.3.

2.1. Introduction to pre-signals

The pre-signal is an additional traffic light (i.e. stop line) upstream of the main coordinated intersection that separates directional traffic flows upfront. The area between the stop lines of the pre-signal and main intersection is called the 'sorted area'. This area can consist of all lanes between the two stop lines or just some of them. The pre-signal allows vehicles with the same direction to proceed and the vehicles will distribute themselves laterally across the intersection cross-section (i.e. all available entry lanes of the main intersection). By doing so, vehicles utilize the entire cross-section of the main intersection while discharging the main intersection during its green phase. Figure 2.1 illustrates an example of the two different types of pre-signal systems that exist: single-movement (SM) and multi-movement (MM). Those systems differ in sorted area usage. The SM system only allows one conflicting directional traffic flow in the sorted area, whilst the MM system, as the name implies, deals with multiple.

This study will be mostly focused on the SM pre-signal systems, because traffic safety issues arise with the MM systems as the workload for human drivers drastically increases. This is mainly due to the complexity of the task demand that increases when multiple directional traffic flows have to interact in the sorted area. An example of such an internal conflict can be found in Figure 2.1.II, in which the left turning vehicles in the third lane will have a conflict with the through going vehicles in the fourth lanes. Literature argued that based of these reasons the SM pre-signal system should be implemented first (Li *et al.*, 2014); (Li *et al.*, 2019). They also acknowledged that under saturated traffic conditions the differences in effectiveness of both systems in terms of required green time are negligible. So, by focusing on the SM pre-signal system instead of the MM system, the research outcomes will be more steered towards the current needs of the literature.

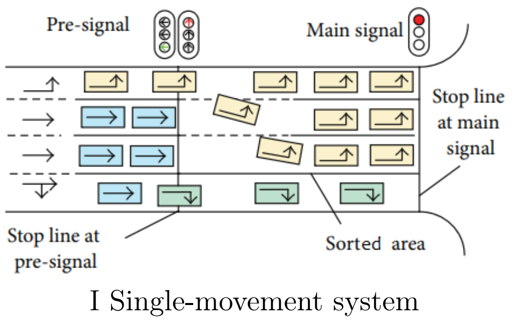


Figure 2.1. – Pre-Signal Classification Based on Traffic Movements, Adapted from (Li et al., 2014)

Based on the design of the sorted area, another classification of pre-signals can be made. The pre-signal system is of full-utilization (FU) type if all lanes between the pre-signal and main signal are considered to be part of the sorted area. If not all lanes have been included in the sorted area, the pre-signal system is of part-utilization (PU) type.

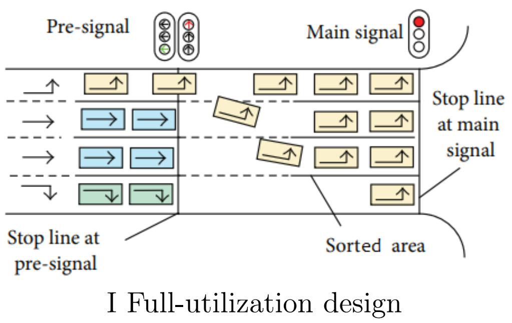


Figure 2.2. – Pre-Signal Classification Based on Sorted Area Utilization, Adapted from (Li et al., 2014)

2.2. The stage in the process of pre-signals for regular traffic

The idea of pre-signals was first documented in 1991 by the U.K. in the Department of Transport (Oakes *et al.*, 1994). The initial purpose of the pre-signal was to provide priority to transit with the aim to jump over the car queue of the signalized intersection (Wu and Hounsell, 1998), and now they are increasingly employed across Europe and beyond (Sun *et al.*, 2021). Nowadays research has extended the application of pre-signals to regular traffic with the main objective to increase the capacity of the main intersection. Literature first focused solely on pre-signal use for separate left turn phases, after which the focus has shifted towards pre-signal use for all phases of the main intersection. The latter being the focus of this research. When it comes to pre-signals for regular traffic, previous research effort has not resulted in an implementation of the system yet. A brief summary of literature about the current knowledge of pre-signals helps to gain insight in why pre-signals have not been implemented for regular traffic, and can specify its stage in the process of achieving a potential application.

Intuitively, adding an extra stop line may decrease the capacity of an saturated intersection. However, many modeling studies, among which Xie and Ma (2012); Zhao *et al.* (2013); Yan *et al.* (2014); Vieira *et al.* (2019); Yao *et al.* (2020), showed that when the pre-signal is well configured, the system can increase the intersection's capacity significantly by up to 50%. Intersections with heavy left turns often facilitate a separate phase for it, yielding a waste of capacity, because some entry-lanes cannot discharge during its green phase. The pre-signal can eliminate this problem by redistributing traffic to all available entry-lanes of the main intersection. Research from Xuan *et al.* (2011); Xie and Ma (2012); Ma *et al.* (2013); Li *et al.* (2014); Vieira *et al.* (2014); Li *et al.* (2019); Vieira *et al.* (2019); Xia *et al.* (2019) also acknowledged that the efficiency of the system is constrained by the design and type of the system, the degree of saturation, and the control structure with its interaction between the two signals. Their findings will be elaborated upon greater in-depth to find out if researcher are on the same page regarding how these aspects impact the pre-signal's efficiency.

2.2.1. Findings from literature about the single-movement system

The phase swap sorting strategy from Li *et al.* (2019), as shown in Figure 2.3, provides an excellent example of the working of the SM pre-signal system. The main green phase will be swapped between the directions of the intersection. All vehicles in the sorted area must be discharged at the end of each main green phase stage to ensure that vehicles of the next main green phase stage can enter the sorted area during the main green phase stage of their conflicting directions of the main intersection. The pre-signal green duration is equal to the main green plus an additional prior time variable and minus a posterior time variable. The prior time ensures that discharging vehicles from the pre-signal arrive at the main stop line on the desired time. If the prior time is too high, vehicles will arrive at the main intersection in red, and thus need to slow down or even stop. Conversely, the prior time cannot be too low, since the pre-signal then would not serve its purpose to reduce the impact of the reaction time and start-up acceleration of drivers, and to use the main green efficiently as vehicles would not have sufficient time to reach the stop line of the main intersection before the start of its green. Regarding the posterior time, if set too low, vehicles queued before the pre-signal would not have sufficient time to pass its stop line, while if set too high, pre-signal green relative to main green would be too high and not all vehicles are able to discharge the main intersection, yielding residual vehicles in the sorted area. This suggest that the efficiency and safety of the pre-signal system is closely related to its design.

Li *et al.* (2014) was one of the first who did research on the effectiveness of the pre-signal in relation to its design. He argued that the sorted area must be of sufficient length to facilitate enough space to ensure drivers from their desired lane change. Insufficient length of the sorted area will block other vehicles from their desired lane change, which could easily

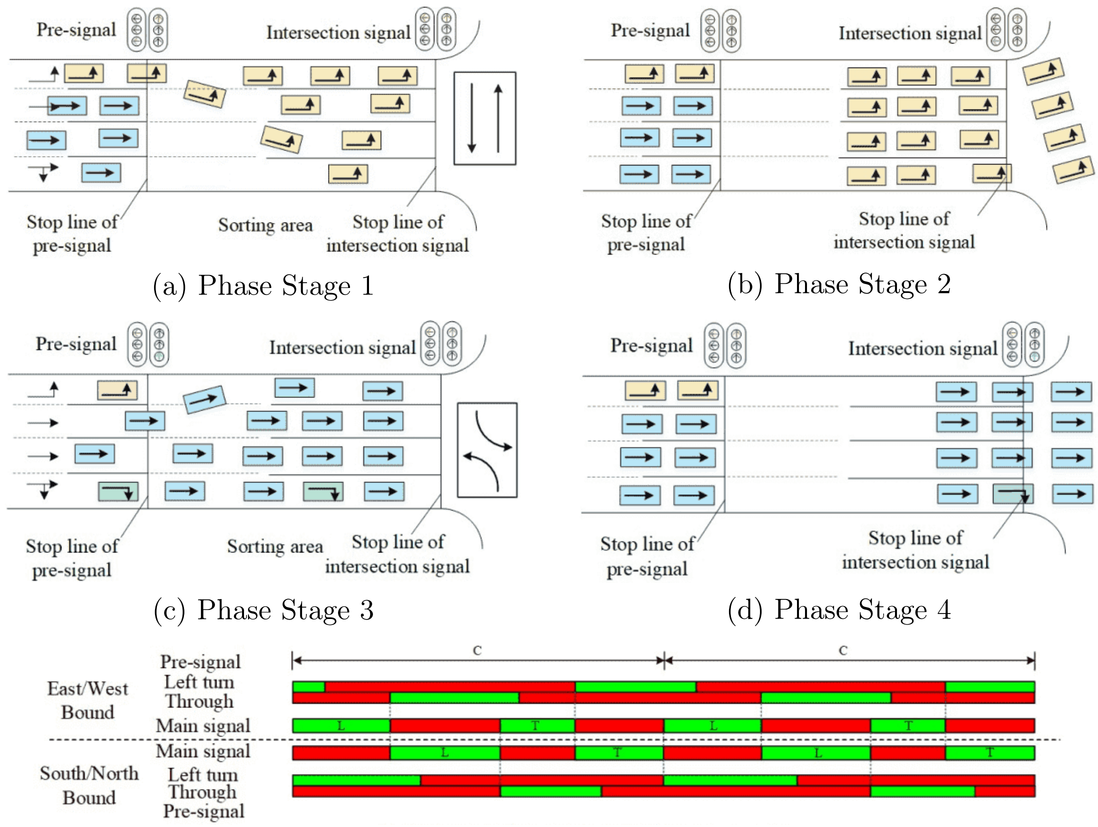


Figure 2.3. – Components and Operation of the Single-Movement Pre-Signal System (Li et al., 2019)

cause a storage blocking or an upstream spillback. Hence, he argued that the optimization of the sorted area is one of the most important tasks when it comes to pre-signal design. Not only the length of the sorted area plays a role, but also the signal time planning, lane allocations, and traffic demand. The main findings of his research are:

- the longer the sorted area, the more main green is required to solve the queue, and the more pre-signal green in advance of the start of the main green must be given;
- the longer the sorted area, the more total main green can be saved with respect to the total pre-signal green and total green of an intersection without a pre-signal;
- the longer the sorted area, the less influence it has on the traffic flow at the pre-signal;
- there will be an optimal length of the sorted area for each pre-signal with a specific traffic demand, signal timing, and intersection configuration;
- if the length of the sorted area is insufficient, the required main green may be higher for pre-signals with respect to an intersection without a pre-signal;
- if the length of the sorted area is insufficient, the difference in number of lanes before and after the pre-signal can affect the relative green of the pre-signal;

- in oversaturated conditions of the sorted area, the required main green is linear to the length of the sorted area, but in undersaturated conditions, the required main green is linear to the traffic demand;
- the minimum length of the sorted area is advised to be 120 m;
- the n.o. exit lanes should be equal to or greater than the n.o. lanes in the sorted area.

Vieira *et al.* (2014) and Vieira *et al.* (2019) agree with Li *et al.* (2014) that there will be an optimal design of the pre-signal system, and which is dependent on the traffic demand, signal timing and intersection configuration. He argues that pre-signals are able to maintain a constant flow irrespective of the main green length and traffic intensity, so even under high traffic demand and low main green time the pre-signal system is able to operate on that constant flow. An intersection without a pre-signal would need higher main green times to improve traffic flow under high traffic demand. Since higher green times result in excessive high average waiting times for other vehicles in the system, high green times should be avoided. Therefore, the pre-signal system has a major advantage, since it can facilitate high traffic flow and low average waiting times under high traffic demand conditions, by making use of low main green time intervals. Moreover, Vieira *et al.* (2014) confirmed that for pre-signals the average waiting time continuous to decrease when lower green times are being used till a minimum green time of 20 seconds. Regarding the sorted area, he agrees with Li *et al.* (2014) that the longer the sorted area, the more effective the pre-signal system becomes. However, he argues that limiting the length of the sorted area is desirable since it it would increase safety levels (e.g. vehicles cannot over speed due to less space) and reduces the space required for implementing the system. Besides that, they disagree in the minimum length of the sorted area: 40m and 120m according to Vieira *et al.* (2014) and Li *et al.* (2014) respectively. This significant difference may be the result of Li *et al.* (2014) who explicitly implemented lane-changing constraints obtained from real observed behavior to facilitate enough space to ensure drivers from their desired lane change.

Research of Xia *et al.* (2019) also acknowledged the same fundamentals as discussed above, but he also made a distinction between a FU and PU type of pre-signal system, in which the latter involved a separate lane in the sorted area for right-turning vehicles. Since the efficiency of the pre-signal system increases with lower main green time intervals, i.e. lower cycle times for the main intersection, he argues that a high relative share of right-turning vehicles requires longer main green, and therefore makes the system less efficient. Besides that, he found that as traffic volume increases, the importance of the design of the pre-signal system increases along, since the effect of it on decreasing the intersection delay will be even greater.

Li *et al.* (2019) criticized previous recommendations on the fact that they were mostly based on the expected traffic demand, which may obtain a shorter sorted area length. This starting point may fail to serve parts of the traffic demand in this stochastic arrival process, yielding spillbacks further upstream of the pre-signal. Conversely, the efficiency of the pre-signal system will suffer from the starting point of a longer sorted area length due to a low spatial utilization with higher delay and lower capacity. Li *et al.* (2019) developed a method that designed the geometric design and signal timing collaboratively. By making use of shockwave theory while keeping in mind the stochasticity of traffic arrival patterns, he determined the furthest point a queue in the sorted area could reach and its probability that the queue will be longer than the selected length. Furthermore, he developed a formula which is able to calculate the minimal required length of the sorted area for optimal flow rate, which is based on the corresponding traffic conditions, red duration, and available lanes in the sorted area. Note that traffic engineers themselves should consider any additional length and a keep clear area must be integrated as well. This area should be located between the sorted area and the stop line of the pre-signal as illustrated in Figure 2.4. The keep clear area must be of sufficient length to provide drivers enough time to read the pre-signal indications and finish their lane-change process. According to Li *et al.* (2019) this area must be no less than 50 meters and should be designed based on the number of lanes before and after the pre-signal.

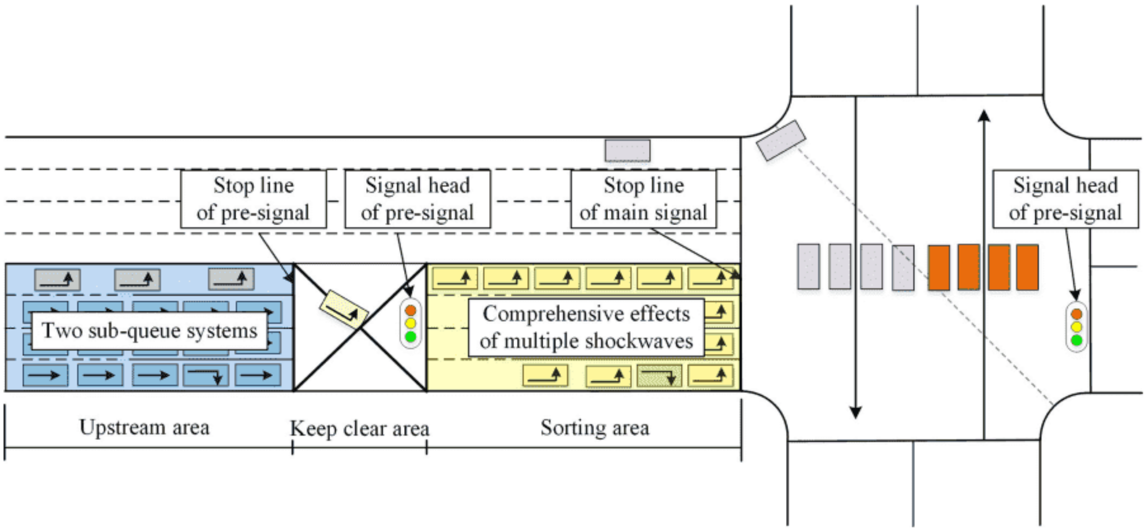


Figure 2.4. – Pre-Signal Layout and Traffic Dynamics With a Keep-Clear Area Included (Li et al., 2019)

2.2.2. Putting things into perspective

From the literature review in Section 2.2.1, it can be derived that researchers are on the same page regarding the optimization of the design of the pre-signal system, and thus not disagree on each other. An overall agreement can be found in the acknowledgment that there will be an optimal length of the sorted area for each pre-signal system with a specific traffic demand, signal timing, and intersection configuration. Moreover, they all agree with the fundamental relationships behind these design characteristics how they lead to such an optimal design. Although researchers agree on the fundamental impacts behind design choices, there also can be found some disagreements in literature about the exact configuration of these choices. Examples of such disagreements are the formulation of the minimum length of the sorted area, the implementation of stochasticity in traffic arrival patterns, and the design of the sorted area about whether or not to implement a separate keep clear area. It was remarkable that all researchers formulated their own starting points, and that non of them elaborated further upon findings of other studies. Moreover, research outcomes were mostly reflected on a single-case study with a specific intersection design and traffic demand schemes and, therefore, are hard to compare. This explains the disagreements in literature findings, but it also strengthens the reliability and validity of the fundamental relationships behind design choices and the efficiency of the pre-signal system, since the same fundamentals have been found across studies with different starting points.

Li *et al.* (2019) did an excellent job in capturing these fundamental relationships into one single formula that produces the minimum length of the sorted area for an optimal efficiency of the pre-signal system. With this formula he assists traffic engineers with a general design guideline for the pre-signal system. The formulation of the keep clear area in his study as shown in Figure 2.4 area remains rather vague and should be studied more in-depth before such a system can be realized in practice. Moreover, the validity of the formula can be criticized due to a lack of validation of the assumed queuing behavior in the sorted area. The formula is based on an optimization of the density in the sorted area, i.e. drivers are evenly distributed, while in real traffic drivers may not distribute themselves evenly in the sorted area, as criticized in this research.

Bie *et al.* (2017) developed a real-time adaptive traffic control method for pre-signal systems. By setting three groups of loop detectors as shown in Figure 2.5, the green phase of the main intersection can be controlled dynamically. The most upstream group of loop detectors monitors the arrival of vehicles to the pre-signal. The second group just upstream the pre-signal counts the number of vehicles entering the sorted area in each cycle. The third group just upstream the main signal counts the number of vehicles that leave the sorted area in each cycle. The main green phase will end if and only if the counted vehicles of the second group equals the third. Thus, the end of the main green phase depends on the clearance time of vehicles in the sorted area. This ensures that delayed vehicles will not get stuck in the sorted area and, therefore, they will not block an entire lane in the next phase(s), with the result of a temporary capacity drop of the system and rather unsafe traffic situations in the sorted area. In fixed-time control this phenomenon is tackled by setting a large enough offset between the main signal and pre-signal. If set too high, the main green phase may not be fully used. So, real-time adaptive control can avoid the waste of green time as well as secure a safe and efficient clearance of the sorted area. The offset between the two signals equals the sum of the green and yellow times of the previous main signal. The longer the pre-signal green the higher the capacity of the current phase, since more vehicles can enter the sorted area. However, this may lead to excessive waiting times for other phases. Therefore, the end of the pre-signal green is based on a real-time optimization of the total vehicle delay of the intersection.

Although such a real-time adaptive traffic control method could solve the problems regarding the uncertainty of the queuing process, the stochasticity of traffic arrival patterns, and the clearance of the sorted area, it still might not be the preferred system in all situations. The geometric design parameters of the system are determined by the use of the maximum vehicles that can be discharged by the pre-signal during its maximum green, which is longer then the length needed, since long pre-signal green times are avoided through the vehicle delay optimizer. This system also requires the installation of 36 loop detectors for a tandem intersection as shown in Figure 2.5. Thus, the real-time adaptive traffic control pre-signal system increases the required space and overall costs.

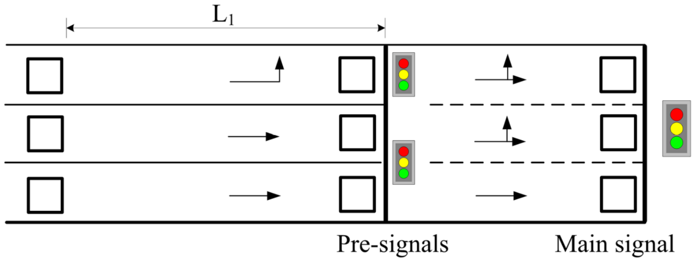


Figure 2.5. – Layout Scheme of Loop Detectors for the Pre-Signal System (Bie et al., 2017)

2.2.3. Knowledge gaps to be filled

Throughout literature, researchers recommended some future works to be done, which concerned the following fields: safety, design variants, and empirical validation.

- **Safety**: Fixed time pre-signal controllers run a cycle with pre-defined green times. Safety concerns are involved when it comes to the potential of vehicles being stuck in the sorted area. If the purpose of the pre-signal is to let vehicles discharge the main intersection closely to vehicles of the previous main phase, any green time waste disfavors the use of pre-signals. However, sufficient green time must be given to allow all vehicles to leave the sorted in time, which may reduce the efficiency of fixed-time pre-signals. Further research on this signal interaction is needed to ensure a safe design and efficient design of the pre-signal system.
- **Design variants**: Most of the research in literature reflects upon a single case-study or is limited to a set of design variants, and research outcomes are hard to compare or to combine given the variety in the starting points of each research. Thus, there is a need for a full design variant analysis that compares the efficiency and geometric design parameters of all full-utilization and part-utilization types across the range of unsaturated to saturated traffic conditions. This will help traffic engineers to judge whether some kind of pre-signal system can be effective in their case.
- **Empirical validation**: There is an urgent need for empirical validation of the queuing behavior in the sorted area to validate the findings of the model studies as discussed in Section 2.2. When such knowledge can be implemented in the current models, research outcomes become more concrete and powerful with the back support of empirical validation from e.g. SC experiments, driving simulators, or a real implementation of the system in practice.

2.3. Conclusion

This chapter discussed the classification of pre-signal systems and guided through the process of how literature developed and assessed the SM pre-signal systems in terms of their efficiency and geometric design parameters. It also specified the challenges that pre-signal systems face and the knowledge that is currently missing. Based on these findings, an answer can be given to the first two sub research questions: *What knowledge is currently missing* *that caused pre-signals not being implemented for regular traffic yet?*; *Which part of that knowledge gap can be filled by this research?*.

The main reason why pre-signals have not been implemented for regular traffic yet is the absence of a design guideline for traffic engineers that provides traffic engineers with a full overview of the design variants of pre-signal systems accompanied with its efficiency (e.g. vehicle delays or capacity) and geometric design characteristics (e.g. sorted area length and signal timing) across the range of unsaturated to saturated traffic conditions. The literature review has shown that for a fixed-time control the effectiveness of the system is closely related to the length of the sorted area, the signal timing, queuing behavior, traffic demand, and their interactions. Researchers agree that under saturated traffic conditions the pre-signal system is able to operate more efficiently than under unsaturated conditions, however it remains unclear how the share of left, right turning and through going vehicles affect its performance. Currently, traffic engineers are not able to judge whether a specific system design would be better than another, or are not even guaranteed that the system would work in their specific application since research outcomes are case-specific and hard to compare.

Real-time adaptive pre-signal controller could solve the problems regarding the uncertainty of the queuing process, the stochasticity of arrival patterns, and the clearance of the sorted area. However, validation of its efficacy still plays a major role in the engineer's restraint to actually implement pre-signals. Research outcomes in literature often rely on opportunistic assumptions that drivers will spread themselves evenly, i.e. optimally, in the sorted area, while these never has been validated with behavioral research. Even if less opportunistic assumptions were used, there still remains an uncertainty about the validity of these assumptions, since these have never been validated either. The empirical validation of the behavioral queuing assumptions is the second missing piece of the puzzle that could accelerate the process of working towards a well-configured design guideline.

This knowledge gap is exactly where the research steps in. This research tries to capture the queuing behavior and trade-offs of human drivers in the sorted area across various traffic conditions. Besides that, it tries to capture the interactions between queuing behavior and the design of the sorted area in terms of its system size and lane configuration. By taking into account the fundamental relationships as defined in Section 2.2.1 that researchers all agree upon, advise can be given about when a pre-signal might be helpful, i.e. when drivers spread themselves evenly or close to even, and what the consequences are of increasing or decreasing the number of available lanes in the sorted area. Then the traffic engineer can better judge whether or not a particular pre-signal system is better than another, and is able to check the validity of current advise given in literature. Moreover, it may stimulate researchers to elaborate on this research by including empirical validated queuing behavior in their model studies.

3. Lane-change and lane-choice behavior

This chapter represents the second out of three parts of the literature review part and it concerns the review of lane-change behavior. The sub research question that will be answered in this chapter is as follows:

- What factors influence lane-choice behavior at intersections?

The answer to this question helps to determine the main things human drivers consider while making a lane-change and the factors that influence their desired lane choice. These insights can be used in Part II to select a set of relevant variables that should be integrated in the SC experiment. This chapter first elaborates on the broader perspective behind lane change behavior in terms of the classification of lane changes and existing lane-change theories. These topics will be discussed in Section 3.1 and 3.2 respectively. After that, the perspective will be narrowed down in Section 3.3 towards a concrete list of factors that influence the lane-choice of drivers at intersections.

3.1. Classification of lane changes

One of the first lane-change theories that includes the decision of a lane change is introduced by Gipps (1986). In his study, he tried to focus on the factors that influence a lane change rather, than to classify lane changes. Although Gipps distinguished route required lane changes from lane changes with the aim to maintain a desired speed, criticism on his approach has been given. Hidas (2002) argued that a lane change in some situations forces vehicles in the destination lane to adapt their speed, while Gipps' rules neglected this phenomenon. This would imply that under his theory a lane change in congested situations can never occur. Therefore, Hidas (2005) classified three lane change categories based on space gaps during the maneuver: free, forced, and cooperative lane changes. In the case of a free lane change, there is no noticeable gap change between the original follower and leader in the destination lane during the lane change of the of the subject vehicle towards that lane. This implies that there is no interference between the subject vehicle and the follower. Concerning a forced lane change on the other hand, the subject vehicle forces the follower to decrease its speed. This may occur when the subject vehicle starts moving closer to the target lane and the follower decrease its speed to avoid a collision before the subject vehicle proceed with its lane change. In the case of a cooperative lane change the follower slows down to allow the subject to execute its lane change. This is characterized by an increasing gap between the leader and follower before the lane change and a decreasing gap afterwards.

Instead of classifying lane change categories based on the gap between the leader and follower in the destination lane, literature also categorized lane changes based on their motive of execution. The majority among which (Zhang *et al.*, 1998; Wei *et al.*, 2000; Kesting *et al.*, 2007; Kordani *et al.*, 2012) distinguish two types of lane changes: mandatory and discretionary. A mandatory lane change is a maneuver that the driver has to execute in order to continue to its destination, while the goal of a discretionary lane change is to maintain favorable driving conditions for the driver themselves or others. The latter one could also be distinguished as a courtesy lane change of which the driver itself does not benefit from the lane change, but is executed with the aim to help other drivers. Besides that, Wei *et al.* (2000) also distinguishes preemptive lane changes, which are lane changes to position the driver in a favorable lane for an upcoming maneuver at intersections downstream his route (e.g. to take a position on left lanes of the road while the driver desires to turn left soon). Note that these lane changes are not mandatory for the driver to continue to his destination.

Schakel *et al.* (2012) argues that gap acceptance models fail to include car-following dynamics, such as relaxation and synchronization. Relaxation refers to the observed phenomenon that drivers temporally accept a smaller gap than most car-following models prescribe. Synchronization is another lane change aspect that can be seen as lane change preparation, in which drivers adapt their speed and align with a gap in the adjacent lane. Lane changes have been classified according to their lane-change process (i.e. the way they are prepared and executed) into three categories: free lane changes, synchronized lane changes, and cooperative lane changes. The level of desire determines the type of lane change, which is based on the desire to follow a route, to gain speed and to keep right. If there is little desire to change, no lane change or a free lane change occur for which both no preparation is required. For somewhat higher desire, the lane changer is willing to synchronize its speed with the target lane. The willingness of the potential follower to cooperate increases along with increasing desire of the lane changer. During a cooperative lane change, the potential follower cooperates with the lane changer to create a gap, which can be triggered by for instance the use of a turn indicator or a lateral in-lane position of the lane changer.

For lane changes at pre-signalized intersections, literature has only specified one classification yet. According to Li *et al.* (2014), lane change behavior can be classified based on the vehicle's location into three categories: adjustment phase, free lane-change phase, and forced-lane change phase. During the adjustment phase the drivers generally do not change lanes as they adjust themselves to the traffic environment. This phenomenon can be expected just downstream the stop line of the pre-signal. After that, drivers enter the free lane-change phase, in which they will opt for a higher speed or their target lane. A forced lane change can be described as a lane change that drivers must execute when they already entered their target lanes. The desire to changes lanes in the free lane-change phase is either based on acquiring a higher speed or the need to be in a specific lane for tuning purpose. Therefore, lane-change actions can be further classified into target type and efficiency type. The desire to change lanes for the target type increases as the vehicle approaches the stop line closer, and will continually increase until the driver changed lanes to its target lane. The probability to change lanes can increase to 1 for drivers who approach the pre-signal, however this will not hold for drivers in the sorted area since drivers downstream the pre-signal cannot opt for a different turning direction anymore. The desire to change lanes for the efficiency type remains unchanged in the free lane-change phase.

3.2. Existing lane-change theories

One of the first lane-change theories for urban driving situations that was intended to be integrated in car-following models is the one of Gipps (1986). In his view, a driver's decision to change lanes depends on three questions: is it (1) possible, (2) necessary, and (3) desirable to change lanes? The driver's goal to reach his destination timely is translated into the objective to maintain a desired speed and to be in the correct lane, of course all within safety and comfort margins. The effect of vehicle performances is only considered for heavy vehicles. The model is designed in such a way that it reflects the driver's behavior by three patterns, depending on the distance to his intended turn. These patterns entail:

1. if the turn is remote, it has no impact on lane-change behavior, and the driver focuses on maintaining his desired speed;

2. if the turn is within the middle distance, the driver starts to ignore speed improvements that require a lane-change in the direction away from the turn;

3. if the turn comes closer, the driver should be in the correct lane or the adjacent one, and the driver is solely interested in reaching the correct lane and not its desired speed.

Kesting *et al.* (2007) developed a general lane-changing model called MOBIL (*Minimizing Overall Braking Induced by Lane change*). In his view, a lane change is considered as a multi step process on a strategic, tactical, and operational level. The strategic level refers to the intended route of the driver and, therefore, to mainly mandatory lane changes. In the tactical level the driver prepares the intended lane change by cooperating with drivers in the target lane through acceleration and deceleration in advance. Finally, a gap-acceptance model in the operational stage determines if an immediate lane change is safe and desirable. The lane-change decision is based on a utility trade-off between the total acceleration (or deceleration) before and after the lane change. The driver, therefore, not only considers his own interest, but also the one of his follower and expected follower.

The main problem with the two models discussed above is the lack of a trade-off between mandatory and discretionary lane changes. Toledo *et al.* (2007) integrated both of these lane changes in a model that was based on one single utility framework. Furthermore, he integrated lane changing and car-following models in his driving behavior model framework, instead of combing models independently. As a result, driving behavior is not modeled based on current or past traffic conditions as an separate instantaneous decision anymore, but drivers anticipate via acceleration and deceleration on the behavior of other vehicles in combination with their own path plan. The integrated driving behavior model consist of four models:

1. target lane model: formulates a discrete choice problem that is based on a single utility per lane of mandatory and discretionary desire;

2. gap acceptance model; captures the decision to change lanes to the target lane if the adjacent gap is acceptable;

3. target gap model; if the adjacent gap is rejected, it captures the short term drivers' plan in terms of speed and position to accomplish the desired lane change;

4. acceleration model; consist of three sub-models which each describe acceleration behavior in different scenarios (stay in the lane, lane change, and target gap).

Schakel *et al.* (2012) criticized most of the lane change models known from literature because of their simplicity in the formulation of gap acceptance. They are either based on a distance and speed differences or on a car-following model, and fail in capturing car-following dynamics such as relaxation and synchronization. The desire to change lanes in his model is based on three incentives: to gain speed, to follow a certain route, and to keep right.

VISSIM is the word's leading microscopic traffic simulation software and is frequently used for intersection modeling. Within the VISSIM models, two types of lane change algorithms are integrated for lane assignment; a free and necessary one (PTV-Group, 2021). The latter one is based on routing decisions. For a necessary lane change, the driving behavior parameters contain the maximum acceptable deceleration for the lane changing vehicle and its follower on the new lane. The deceleration depends on the distance to the emergency stop position of the next route connector. The underlying model of free lane changes is a car-following model in which the vehicle's acceleration is predicted based on the velocity of the preceding vehicle and the distance headway on the new lane between them. If more space is available on the new lane or if longer driving at the desired speed is required, a free lane change will be executed. The algorithm checks whether on the new lane the desired safety distances between the follower and the lane changing vehicle, and the lane changing vehicle to its preceding vehicle are maintained. The algorithm could be modified such that it reflects an accurate outcome instead of simply relying on car-following models. It is possible, among others, to change the aggressiveness of drivers, the lane change function of each vehicle type, and the percentage of drivers that will attempt using each lane.

3.3. Factors that influence the lane-change decision

The goal of this section is not to capture all the factors that influence a lane-change decision, but rather to focus on the main things drivers consider during a lane-change decision and what leads up to their desired lane-choice. These will mostly follow from the discussed lane-change theories in section 3.2. Moreover, some lane-choice -and lane-utilization studies in literature have revealed the factors that human drivers consider while changing lanes. These will be elaborated upon as well.

Most of the lane-change decisions in the lane-change models are based on the utility maximization principle. The utility of a specific lane change is dependent on the classification of the lane change, and is in most cases highly influenced by route and speed incentives within safety and comfort margins. Some also include a form of politeness in lane-change behavior, such as cooperative speed adaptation and the consideration of the utility of other drivers. Several other explanatory variables that influence a lane-change decision can be withdrawn from the lane-change models as described in section 3.2: the classification of the lane change, the driver's distance to his intended turning movement, the presence of heavy and slow vehicles, the desire to keep right, vehicle performance boundaries, and the aggressiveness of drivers.

These variables already give an insight in the factors that influence a lane-change decision. However, some literature particularly focused on lane-change and lane-choice behavior at urban signalized intersection. Bugg *et al.* (2013) extended research on the VISSIM's lane-change algorithm, because it did not consider the utility of either lane for each vehicle that approaches the intersection. The goal of his research was to design a lane-choice model to gain understanding of the factors that influence each driver's lane choice when approaching an intersection, such that is could be used to modify the VISSIM's free lane change algorithm. By achieving this, vehicles can be assigned to either lane based on the probabilities of a behavioral lane choice model. In his research he estimated a Logit choice-model based on observations from practice. He found that the driver's lane choice can be represented by a function of the arrival phase and the queues in either lane, which correspond to an intuitive thought process:

- at a particular decision point, the driver checks the signal and the queues in either lane before choosing a lane;
- if a driver arrives in red, the lane choice can be modeled as either a function of the current lane queue length, the difference between the queue length of the current and adjacent lane, or with separate parameters each;
  - in the latter case, the queue length on the adjacent lane affects the lane-choice decision twice as much as the current lane queue length;
- if a driver arrives in green, the lane choice can be modeled as a function of the queue of the current lane or other lanes, in addition to the remaining green time;
- if no signal distinction was made, the lane choice was mostly based on the queues on either lane.

This finding underpins the importance of the signal phase to lane-choice behavior at signalized intersections. Moreover, Tainter *et al.* (2018) conducted a driving simulator study to investigate the lane utilization of auxiliary lanes at intersection. Auxiliary lanes at intersections can be seen as the additional lanes upstream of the intersection that sort traffic and facilitate extra vehicle storage capacity. He found that familiarity with the concept significantly impacted the lane utilization of auxiliary lanes. Note that this familiarity among participants was introduced by the researcher who specifically explained the fundamental purpose of auxiliary lanes.

Choudhury and Ben-Akiva (2008) particularly focused on lane-choice behavior at signalized intersections, and they described the intersection lane selection as a two-level decision: a choice of the target lane and a choice of the immediate lane. The target lane choice represents the tactical decision of the driver related to path plan considerations, such as the distance to the point at which the driver needs to be positioned in a specific lane and the required number of lane changes. Hereby, familiarity with the network is considered through planning capabilities of drivers. Therefore, drivers were divided into two classes based on their planning capability:

1. myopic drivers, who take into account their path plan but consider delay while making a lane selection only in their immediate subsequent section;

2. drivers who plan ahead, take into account their path plan and anticipate delay wile making a lane selection beyond their immediate subsequent section.

Situational constraints such as maneuverability considerations influence the immediate lane choice of drivers, and a maneuver to the target lane may not be possible. The immediate lane choice of drivers is the lane the driver positions after a lane change, which may not be the same as the original target lane. Changes in traffic conditions also can change the driver's target lane. Only immediate lane changes can be observed and the initial chosen target lane of the driver remain unobserved. Utility forms the basis of the choice model for target and immediate lane choices. and for each the variables that affect these decisions are summarized in Table 3.1.

Table 3.1. – Variables Likely to Influence the Target Lane and Immediate Lane Choice of Drivers (Choudhury and Ben-Akiva, 2008)

Target lane choice		**Immediate lane choice**	
Path plan variables	- n.o. lane changes - distance to next turning movement	**Current position of the driver**	- proximity of a given lane to the receiving lane close to the driver
Lane attributes	- queue lengths - average speeds - queue discharge rates	**Neighborhood variables**	- presence of other vehicles and their actions - relative position and speed - geometric elements of the roadway
Driving style and capabilities	- plan-ahead distance - aggressiveness - vehicle characteristics	**Driving style and capabilities**	- plan-ahead distance - aggressiveness - vehicle characteristics
Expected max. utility	- utility that can be derived from choosing the immediate lanes (choice of target lane is thus indirectly influenced by variables that influence the immediate lane choice given the target lane)	**Choice of target lane**	- proximity of the immediate lane to the chosen target lane

3.4. Conclusion

A lane-change decision of human drivers is hard to fully understand because of their complex decision making process. That may be the reason why researchers have developed a variety of different lane-change models. In section 3.1 and 3.2 various lane-change classifications -and models have been discussed. The discussed lane-change theories differ in the way how a lane-change decision is prescribed:

- by the reason of executing, in which most distinguish mandatory and discretionary lane changes, and some courtesy and preemptive lane changes;
- by the gap between the leader and follower in the destination lane before and after the lane change, in which Hidas (2005) distinguishes free, forced, and cooperative lane changes;

- by the lane change process in terms of preparation and execution, in which Schakel *et al.* (2012) distinguishes free, synchronized, and cooperative lane changes;
- by the target lane of the driver, in which Choudhury and Ben-Akiva (2008) distinguish target lane -and immediate lane choice, whereby the intentional lane change may differ from the executed lane change;
- by the vehicle's location, in which Li *et al.* (2014) distinguishes an adjustment phase, a free lane-change phase, and a forced-lane change phase.

The lane-change theories and lane-choice experiments revealed the main factors that influence the lane-choice decision in the lane-change process. A summary of those findings provides the answer to the third sub-question: *what factors influence lane-choice behavior at signalized intersections?* The factors as given in Table 3.2 are considered to affect lane-change behavior at intersections. These insights can be used in Part II to select a set of relevant variables that should be integrated in the stated-choice experiment to prescribe the range of traffic conditions, which will be varied throughout the experiment.

Table 3.2. – Factors that Influence Lane-Change Behavior

Lane-change factors	
Path plan	- n.o. lane changes to target lane - distance to next turning movement stop lines - distance to end of each queue - lane-change classification
Lane attributes	- queue lengths - average speeds - queue discharge rates (e.g. heavy vehicles) - relative position and speed (i.e. gap)
Driver specific	- plan-ahead distance - aggressiveness / driving style - vehicle characteristics - myopic drivers vs. drivers who plan ahead - keep right desire - familiarity with fundamental purpose
Other	- congestion level - ground marking & traffic signs - phase of traffic signal

4. Biased outcomes of stated-choice experiments

This chapter represents the third out of three parts of the literature review part and it concerns the review of biased outcomes of SC experiments in hypothetical traffic situations. The sub research question that will be answered in this chapter is as follows:

- How have researchers previously coped with biased outcomes of stated-choice experiments in hypothetical environments?

The answer to this question will help to define strategies to mitigate the hypothetical bias (HB) that is inherent to the use of a SC experiment in hypothetical traffic situations. These insights will be used in Part II to implement some strategies in the design stage of the SC experiment. This chapter first provides a brief introduction to the hypothetical bias in Section 4.1. After that, Section Section 4.2 discusses from a general perspective the sources and potential mitigation strategies of the HB. This discussion will lead up to the formulation of a framework in Section 4.3 that provides researchers with a general guide line to mitigate the magnitude of the HB. Finally, the conclusion in Section 4.4 gives the answer tot the sub research question.

4.1. Introduction to the hypothetical bias

In order to understand that there will be a HB, it is important to distinguish revealed preference (RP) from stated preference (SP). RP is grounded from an economic theory, which suggests that the best way to measure consumer preferences is by observing their revealed behavior ex-post. Conversely, SP is a way to measure consumer preferences by asking for their preferences ex-ante, which reflect their stated behavior. SP choice experiments have been frequently applied in the transportation sector for demand estimation and attribute valuation of transport services, infrastructure, facilities, travel behavior, mobility, and freight transport. Those experiments often consider the evaluation of non-existing products, services, or technologies. RP for such hypothetical innovations would not be a suitable approach, because revealed behavior cannot be observed. This is where the HB steps in, and this is exactly the reason why a HB is expected in this research. The main question that arises here is: do SPs of respondents in hypothetical choice experiments reflect their choices and behavior in real-world settings? This gap is commonly referred as the HB, and is arguably the most important aspect when it comes to the legitimacy of choice experiments and the value for policy decision-making.

4.2. The hypothetical bias in stated-choice experiments

Although the HB is most likely inherent to SC experiments, especially in the field of hypothetical situations, empirical evidence has shown that the HB presence does not withhold the SC experiment from presenting real-world preferences. While research statements about the existence, consequences and mitigation of the HB are often conflicting, it becomes impossible to concretely formulate the sources and mitigation strategies for the HB that is most likely present in the research outcomes. However, experience from previous research can be used to come up with a framework that summarizes causal relations between the sources of HB and potential effective mitigation strategies.

A meta-analysis study of Haghani *et al.* (2021a) merged findings about the HB from 300 plus studies with the aim to estimate the likely magnitude of the HB and to be better able to understand what experimental factors contribute to an increase in the HB. Moreover, the study came up with two hindering factors of choice experiments that prevented a holistic understanding of the HB problem. First, it is difficult or sometimes even impossible to empirically test the HB in many choice contexts due to the absence of RPs that reflect the true preferences. Second, empirical observations of the HB and the effectiveness of mitigation methods vastly differ across sectors (e.g. economic, transportation or health) and choice contexts. This suggests that it is necessary to study the HB in a context-specific and nuanced manner. A follow-up study of Haghani *et al.* (2021a) was executed with the aim to offer a unified definition of the HB, and to closer look into the explanations of the HB and context-dependent mitigation strategies. This will be elaborated upon in Section 4.2.1 and 4.2.2 respectively.

4.2.1. Sources of the hypothetical bias

Throughout literature there have been proposed several explanations for the emergence of the HB. Among them is *the lack of consequentiality* of hypothetical responses that reflects the believe of respondents that their response has no impact on policies and only fulfills the researcher's interest. As a result, respondents may not behave truthfully and price-sensitive or invest considerable cognitive effort into their responses. A *lack of incentive compatibility*, i.e. the respondents are no worse or better off after the completion of the experiment, between the researcher and respondent may yield the same consequences (Morkbak *et al.*, 2014). Researchers also have to deal with *deceitful strategic answers* of respondents in case they may think that revealing their true preferences puts them in an unfavorable position (Meginnis *et al.*, 2021). Respondents then can make misleading preferences in favor of themselves. An example would be to prefer existing no or low toll routes above new toll routes. Researchers are advised to cope with this strategic behavior, if such behavior is expected, by informing the respondent about the true purpose of the experiment and their contribution to it. In case of the *presence of moral or prosocial elements*, a HB may arise when respondents choose preferences that led them appear more socially desirable. This phenomenon especially concerns public goods with social implications.

Neurological studies also revealed some behavioral phenomena that, despite the effort of mitigating the HB by design, will yield undeniable factors that could introduce biased responses in stated-choice experiments. Probably the most contributing factor is the *hot-cold empathy gap phenomenon* that is described by psychologists in literature (Loewenstein, 2005; Kang and Camerer, 2013). This phenomenon suggests that humans have a cognitive bias that inherently limits them to correctly predict future choices. Moreover, Haghani *et al.* (2021a) argues that the same cognitive bias applies to choices in hypothetical situations. Besides the hot-cold empathy gap, humans also have a tendency to align preferences with past actions. Ariely *et al.* (2003) defines this as the *coherent arbitrariness*, and implies that a first choice, even if randomly chosen, will affect consecutive choices and that respondents tend to seek consistency in their choices. When making these choices, respondents are required to invest a considerable amount of cognitive effort to make a well-considered trade-off between the attributes of alternatives. According to literature, respondents may try to *minimize cognitive effort and attention* by choosing the opt-out option frequently (Wlomert and Eggers, 2016), if available, or yea-saying (Van Soest and Hurd, 2004). This may highlight the importance of information salience in the experiment design to keep the attention level of respondents on the attribute trade-off of alternatives.

Instead of explanations for the emergence of the HB, Haghani *et al.* (2021b) also came up with a set of moderators that are likely to increase or decrease the magnitude of the HB. First, *characteristics of the respondent* have been proven to influence the magnitude of the HB (Wuepper *et al.*, 2019), such as gender, personality traits, knowledge and familiarity with the product or good in question, and not observable characteristics that could be acquired by supplement questions. In the context of hypothetical traffic situation, examples of unobservable characteristics would be the driving style or aggressiveness of the driver. A frequently used driving style self-assessment in questionnaires is the the multidimensional driving style inventory of BenAri *et al.* (2004), which categorizes driving styles into four dimensions: reckless and careless, anxious, angry and hostile, and careful. Second, *characteristics of the good or service* in question may influence the magnitude of the HB, such as the good being private or public in the case on non-use values. These values occur in public goods when respondent have to value a resource apart from its use (e.g. the existence of a forest in a protected area). Third, the *stake size* of the costs involved in the cost attributes of alternatives, which is suggested to be positively correlated to the magnitude of the HB. The higher the stake size, the larger the HB is to be expected. Figure 4.1 summarizes the main sources and moderator of the HB that have been discussed in this section.

4.2.2. Mitigation strategies for the hypothetical bias

Throughout literature there have been proposed several mitigation strategies that try to limit the presence of the HB. Those strategies differ in whether they are ex-ante or ex-post measures, i.e. applied during the design stage of the experiment or after it by the implementation of follow-up questions which can be used to correct the HB in model estimation. The effectiveness of the mitigation strategies are generally either assessed via the absolute or via the relative HB. The former consist of a before-after analysis of two choice experiments of which on only one the mitigation strategy is applied. The latter consist on of an expert judgment analysis of the choice experiment itself in which the HB will be compared to previous evidence from literature or an a priori known direction of the HB. It must be

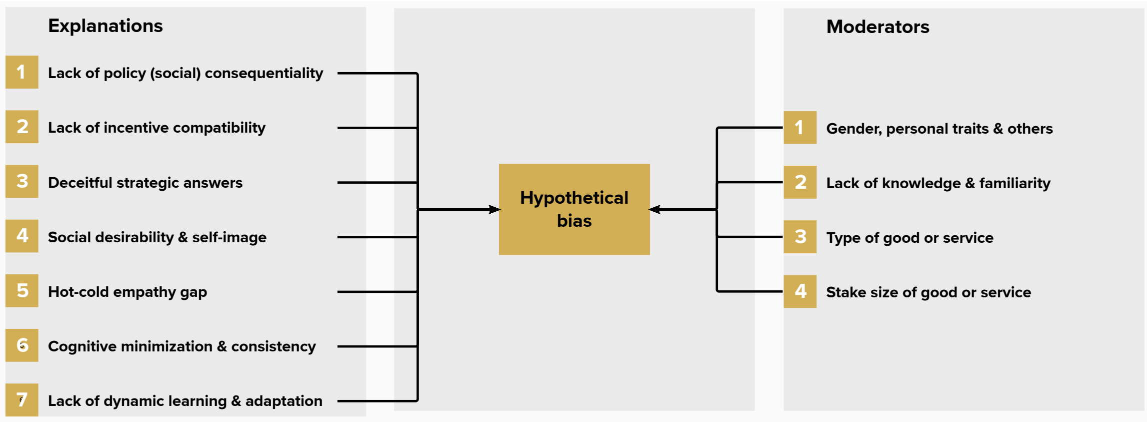


Figure 4.1. – Summary of the Main Explanations and Moderators of The Hypothetical Bias

said that HB assessment on a relative basis introduces some downsides. If a researcher fails to observe significant differences in estimates with and without the mitigation method, it is unclear whether the mitigation strategy is ineffective or there was no HB in the first place. Moreover, mitigation strategies are not mutually exclusive and are often researched in multiples, which makes it often impossible to determine the effect of a single strategy. This again stresses the difficulties around the HB and the nuanced attitude that is required when any statements on the HB are being made. Haghani *et al.* (2021b) did an excellent job in this when he executed a systematic literature review on the mitigation strategies of the HB, of which the aim was to develop a general guide for HB reduction in stated-choice experiments. The concepts and main findings about the following mitigation strategies will be briefly summarized: cheap talk, honesty priming, solemn oath, opt-out option, time-to-think, referencing and pivot designs, consequentiality scripts, real talk, choice certainty scales, RP-assisted estimations, and perceived consequentiality scales.

A. Ex-ante mitigation methods

Cheap talk:

When applied in a stated-choice experiment, cheap talk can be seen as a nonbinding communication between the researcher and the respondent before the start of the experiment. This additional communication should make the respondent aware of the existence and consequences of the HB with the aim to reduce the effects of social desirability and self-image. Cheap talk helps to remind respondents to choose their real preferences instead of some other socially more desirable answers by revealing the consequences of those actions. It usually consist of three components: (1) it describes the HB phenomenon, (2) it introduces possible explanations for the HB, and (3) it pleads to respondents that they answers the upcoming questions with this knowledge in the back of their head while treating the scenario as if they encounter them in real life. Evidence about the effectiveness of cheap talk is mixed throughout literature and suggestions are made that this strategy would be more effective if respondents are unfamiliar with the alternatives.

Honesty priming:
The goal of honesty priming is to unconsciously influence the perception, behavior, and decision-making of respondents. Social psychology studies have suggested that priming for honesty activates the sense of honesty without even asking them explicitly to give truthful answers. Respondents can be primed by for example by including honesty related words in a subtle matter. The aim of this strategy is to reduce deceitful strategic behavior and social desirable responses. Although literature seems to disagree on each other when it comes to the added value of honesty priming, they do agree that cheap talk have a larger effect in reducing the HB compared to honesty priming. Since only a limited amount of effort is required to implement honesty priming, researchers can argue to just apply it regardless of its effectiveness.

Solemn oath:
Unlike honesty priming, the solemn oath strategy is grounded on a direct approach for the mitigation of deceitful strategic behavior and social desirable responses. By applying the solemn oath strategy, respondents are explicitly asked to swear on their honor to give honest answers. The agreement between the researcher and respondent can be seen as an implicit contract between them that rests on the theory of commitment from social psychology. Despite its simplicity the method is relatively new compared to other ex-ante strategies and it has not been applied frequently in stated-choice experiments. Haghani *et al.* (2021b) argues that there is yet no evidence available that underpins the effectiveness of the solemn oath in stated-choice experiments, and that culture and religious backgrounds play a major role in this.

Opt-out option:
The opt-out option is a design choice of the researcher that includes a form of ″none″option among the alternatives. The respondent will be unforced to make a choice if they disagree with all of alternatives being presented, e.g. when they find all alternative too expensive. The unforced choice then would be the opt-out option or the status-quo. The aim of this strategy is to reduce the HB by discounting budget constrains and the lack of incentive compatibility. Researchers have to choose the frequency of the opt-out reminders in their experiment, but literature argues that a repeated opt-out remember increases the effectiveness of the method beyond other ex-ante strategies.

Time-to-think:
Mainly health economics have suggested a strategy to mitigate the HB that provide respondents in a stated-choice experiment more time to reflect their choices. This principle is frequently tested throughout the health sector by allowing respondents several hours up to a night to think. The aim of this strategy is to reduce the impact of the hot-cold empathy gap and to increase the cognitive effort of respondents. Although there is no strong underlying theory that formulates the impact of response time on choice behavior, there is evidence that it can effect choice behavior and attribute levels. Arana and Leon (2013) proposed this strategy with a time span from several hours to months, and in his view a stated-choice experiment is not more than a one-shot experiment in which there is no potential for respondents to re-adapt their behavior if market conditions change throughout

time. In traffic situations, drivers have to make instantaneous decisions and have no night to think about their choices. One could therefore argue if such a method would be appropriate to reveal driving behavior. However, respondents often have to deal with unfamiliar hypothetical traffic situations, so researchers could argue to implement some sort of learning curve or adaptation into their stated-choice experiments.

Referencing and pivot designs:
A lack of familiarity of the respondent with the good or service in question has been proved to be a major source in the magnitude of the HB. Intuitively, any step towards reality and reducing this unfamiliarity gap mitigates the effects of this lack. Referencing and pivoting to a real experience has been suggested as a potential strategy to reduce the HB by closing the gap between RP and SC. Instead of distributing one experiment design to all respondents, this strategy tunes the attributes of alternatives to their experience or chosen alternative in the real world, which can be gathered through additional questions a priori of the experiment. A disadvantage of the strategy is that is complicates the choice model estimations by introducing correlations within pivot designs.

Consequentiality scripts:
In the valuation of non-market goods, it is known that if respondents care about the policy and believe that their responses potentially influence the decision-making process of whether or not the policy, they are incentivised to respond truthfully and price-sensitive. Consequentiality scrips are introduced to mitigate the HB by increasing the respondents' feeling of social political consequentiality and incentive compatibility. The strategy is not more than letting respondents read the script, that assures respondents of their influence, a prior to the questions. It has been proposed that the strategy shows comparable effects to that of the cheap talk strategy.

Real talk:
As a variation of the consequentiality script, real talk scripts inform respondents before the experiment about the version of hypothetical scenarios they will encounter and emphasize that there will be another a similar version as follow-up that includes non-hypothetical scenarios. According to Alfnes *et al.* (2010) this will prompt respondents to be consistent with their real preferences, as the cognitive dissonance theory implies.

B. Ex-post mitigation methods

Choice certainty scales:
The choice certainty scale is arguably the most-established ex-post strategy for HB mitigation. Through follow-up questions, participants are asked to rate their certainty on a numerical scale about the choice they just made. By calibrating the certainty levels afterwards, Ready *et al.* (2010) suggested that it was possible to largely mitigate the HB when uncertainties were reflected as an additional error component of the utility functions. The strategy mainly compensates for the lack of familiarity phenomenon. However, Beck *et al.* (2013) warned researchers of the potential that although correction for certainty scales increase the model fit and reliability of the estimates, it may not reflect better / more truly

behavioral representation. Differences in outcomes should then be interpreted with caution, particularly when benchmark estimates are missing, since uncertainty score can significantly correlated with misleading information. A study of Beck *et al.* (2016) emphasized the carefulness that is required when correcting for certainty scales, by showing that when researchers calibrate poorly the HB may even aggravate.

RP-assisted estimations:
Instead of solely relying on hypothetical choice data, researchers can also assist this with RP data to improve the model fit and reliability of the estimates. This choice modeling strategy is common practice in the field of behavioral studies for transport and traffic. It must be said that RP-assistance is not designated as a HB mitigation strategy, but rather a method to investigate the existence of the HB by using the RP data as benchmark against the SP data (Hensher and Bradley, 1993). Currently, the view on this strategy is not to let RP and SP data compete, but it is advised to view them as complementary and to use both their strengths and weakness to achieve more reliable estimates.

Perceived consequentially scales:
This aim of this strategy is similar to that of consequentiality scripts, but the approach has an ex-post character. The approach gathers self-evaluated perceived consequentiality scales from respondents by additional follow-up questions to compensate for it during the choice model estimation process afterwards. Perceived consequentiality scales share the same difficulties as the choice certainty scales, therefore it must be implemented carefully.

4.3. Putting things into perspective

Although researchers disagree on the structural existence of the HB in SC experiments, the likelihood of its existence is undeniable high and differs across all contexts and applications. This emphasizes the importance of an efficient context specific strategy to mitigate the magnitude of the HB. The fact that this is still an ongoing discussion in literature also emphasizes the need for a nuanced view regarding statements about the mitigation of the HB. This view can be created by filtering the main causal relations between the source of the HB and the mitigation strategies that have been proposed in Section 4.2.2.

In case where the HB is suspected to arise from respondents who (semi)-consciously hide their true preferences to strategically steer the research outcomes or to look socially more desirable, it is suggested to apply ex-ante measures that encourage honesty and motivate respondents to give less-than-truthful answers. This can be done explicit by implementing cheap talk and a solemn oath or implicit trough honesty priming.

In case where the HB is suspected to arise from inexperienced respondents with the good or service in question, it is suggested to increase the ability of respondents to imagine the hypothetical environment in which they have to make choices. This can be achieved by pivoting or referencing towards a real experience or to extend the time respondents are allowed to consider their choices, i.e. by implementing pivot designs or the time-to-think strategy ex-ante receptively. Alternatively, the researcher may consider to implement choice certainty scales if an ex-post method is preferred. In case where the stake size exceeds the budget constraints of the respondent, the researcher can implement opt-out options that will let participants make unforced choices if they disagree with all alternative being presented.

In case where the HB is suspected to arise from the lack of or a mismatch in incentive compatibility, and a well-aligned incentive is not desirable, it is suggested to let the respondents feel no worse off after the completion of the experiment by introducing the incentive implicitly. This can be achieved by implementing real talk, consequentiality scripts, or perceived consequentiality. The same strategies can also be used in case where respondents feel skeptical about their social or political impact, as this can also be categorized as some sort of incentive lack.

Figure 4.2 formulates the above discussion into a summary about how HB mitigation strategies may potentially counter for certain sources of the HB. It represents a framework that serves as a general guide line to assist researchers to find their way in the ongoing discussion in literature. This framework has been particularly used in Section 5.4 & 6.3 to reflect upon the presence and mitigation of the hypothetical bias in this research.

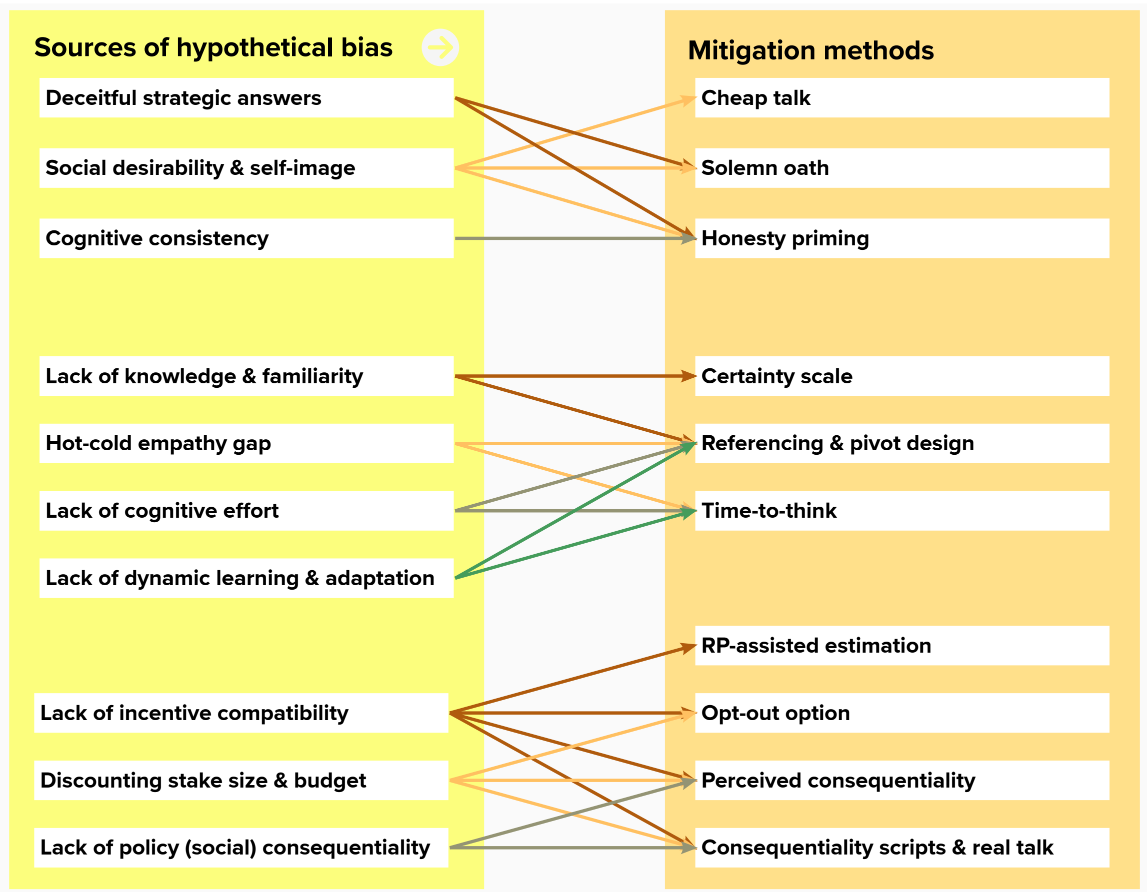


Figure 4.2. – Summary of the Potential Mitigation Strategies for Hypothetical Bias Sources

The transport sector along with health economics have only taken a moderate interest in the empirical investigations of HB mitigation strategies compared to the environmental and consumer economics sector. While cheap talk has been the overall most popular method, the transport sector invested more in RP assisted estimations and realistic designs as a way of countering for the HB. In contrast, non-transport related sectors invested a very limited effort in investigating how realistic designs can be deployed for HB mitigation (Haghani *et al.*, 2021b).

4.4. Conclusion

This chapter introduced the phenomenon of the hypothetical bias (HB) that is most likely to exist in hypothetical SP data of SC experiments. It also specified the main sources of the HB and the factors that may influence its magnitude. Furthermore, potential mitigation strategies have been defined for each source of HB, which were all captured in a framework that serves as a general guide line for HB mitigation. Based on these findings, an answer can be given to the fourth sub question: *how have researchers previously coped with biased outcomes of stated-choice experiments in hypothetical environments?*

The framework as presented in Figure 4.2 provides one part of the answer to the sub research question, as this summarizes the how researchers commonly countered for the HB. The other part consist of the warnings that have to be made about the first part. One of the main difficulties presented in this chapter was the ongoing discussion in literature about the structural existence of the HB and the effectiveness of the mitigation strategies to counter for a specific source of HB. It also emphasized the need for a nuanced view regarding the HB and the case/context-specific approach that it required to counter for the HB. The framework as provided in this chapter thus only serves as a general guide line, where additional expert judgment is needed to recognize the most likely sources of HB that arise in specific cases.

To conclude, the sources of HB are case-specific and diverse, and so should be the researcher's approach to counter for the HB. Murphy and Stevens (2005) have emphasized that: "*no single technique will be the 'magic bullet' that eliminates this bias. Ultimately, mitigating hypothetical bias will probably involve a combination of techniques, including both instrument and statistical calibration*". The insights that have been gathered in this chapter will be used in Part II to mitigate the HB in the design stage of the stated-choice experiment.

Part II. Experiment Design

5. Fundamentals & design choices of the stated-choice experiment

This chapter represents the first out of three chapters of the experiment design part and it concerns the explanation of fundamentals & design choices of the SC experiment. Besides that, an answer will be given to the following sub research question:

- What methods and models exist in the field of stated-choice experiments, and which is recommended for this research?

The answer to this research questions helps to establish a choice-modeling strategy that both complies with the needs of this research and takes into account the research feasibility. This, together with the fundamentals & design choices of the SC experiment, provides the basis for Chapter 6 in which the SC experiment will be designed by making use of the previous defined designed choices. This chapter starts with the objective description of the SC experiment in Section 5.1, and an overview of the main design steps that are required to design the SC experiment in Section 5.2. The remainder of the chapter is structured according to those defined design steps. These entail the choice model establishment in Section **??**, the case-study introduction in Section 5.3, the development of the 3D traffic environment in Section 5.4, and the conclusion in Section 5.5.

5.1. The objective of the stated-choice experiment

The aim of the SC experiment is to extract the respondent' choice strategy for their preferred lane-choice downstream the pre-signal, with the objective of reflecting these findings against potential implications for the applicability and efficiency of pre-signals for regular traffic. The SC experiment will be designed such it can extract the queuing behavior of human drivers in the sorted area while understanding their trade-offs in their thought process of choosing a desired lane. Besides that, the SC experiment tries to capture the interactions between queuing behavior and the design of the sorted area in terms of its system size and lane configuration. This is done through asking respondents their preferred lane choice in a variety of traffic situations, which vary in traffic crowdedness, turning directions, and n.o. lanes that are included in the sorted area. Given the variety in pre-signal systems, the traffic situations they can be applied in, and the underlying traffic conditions, it is desirable to design the SC experiment such that it fulfills the needs for the majority of these traffic environments. A traffic environment can be seen as an environment that is shaped by the type of pre-signal system, the traffic situations they are applied in (e.g. right turning, left turning, urban, highway, etc), and the underlying traffic conditions (e.g. heavy vehicles, traffic intensity, etc). Although it is unfeasible to include all traffic environments that literature specified, the goal of the SC experiment is set to generalize as much as possible (i.e. to avoid highly context specific traffic environments) and to steer towards the most common environments. Hereby, it is crucial to clearly describe the traffic environments that will be covered by this SC experiment. The precise details of these will be elaborated upon in the next two chapters.

5.2. An overview of the main design steps

The design of a SC experiment generally consist of two parts: the establishment of a proper choice model, and the construction of the SC experiment. These steps have to be executed consecutively since the selected type of choice model affects the way how the SC experiment should be constructed. A choice model is a model that tries to capture context dependent decision processes of individuals by making use of revealed preference (RP) or stated preference (SP) data. They often make use of discrete choices to determine their relevance on a latent scale against other available options. Since there are many choice models available, a proper choice model has to be established that fulfills the needs of this experiment. After that, the SC experiment can be constructed according to the underlying choice model. Figure 5.1 represents a schematic framework of the SC experiment design process, in which the required design steps are set in chronological order. Note that the design steps correspond with the structure of the Chapter 5 & 6.

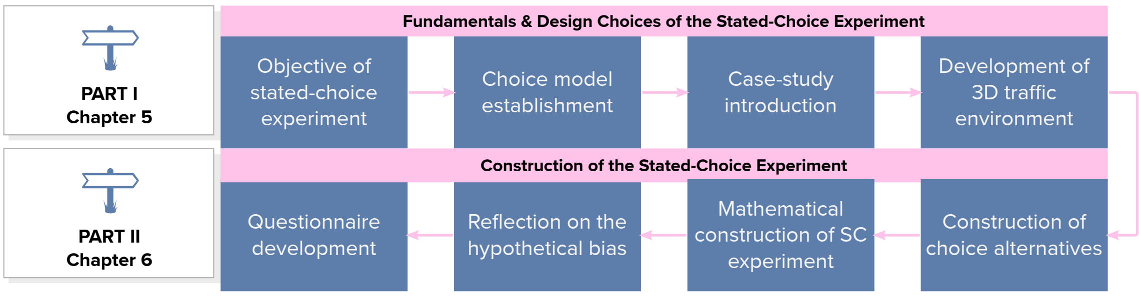


Figure 5.1. – Design framework of the stated-choice experiment

5.2.1. An introduction to choice modeling

The basic idea behind choice modeling is to observe people's choices in either real life or experiments (e.g. which car to buy: EV vs. ICE). From these choices, preferences and trade-offs can be inferred (e.g. range anxiety, price sensitivity, etc). Based on these trade-offs, future choices can be predicted (e.g. demand for EVs, charging behavior, effects of policies, etc). This predictive nature behind choice modeling is the reason that it is often used to assess the impact of future policies. One could argue: why not ask for trade-offs directly? People simply do not know and in many cases they hesitate to give true trade-off information. Judgment is also known to be more susceptible to bias than choices (Chorus, 2022).

Throughout history three researchers are acknowledged to be the founders of some underlying economical theories that together formed the revolutionary perspective of choice modeling. The revealed preference axiom of Samuelson in 1948 stated that a choice is a signal of underlying preference. The probabilistic decision-making theory of Luce in 1959 observed that choices are partly random due to noisy signals. Finally, the multi-attribute consumer theory of Lancaster in 1966 described an alternative as a bundle of attributes. Given these previous insights while contemplating the terminology as presented in Table 5.1, the following revolutionary perspective of choice modeling was formed:

> *"A choice for a multi-attribute alternative from a multinomial choice set can be conceptualized as a noisy multi-dimensional signal of the weights attached by a decision maker to the alternative´s attributes."(Chorus, 2022)*

Table 5.1. – Terminology in Choice Modeling

Terminology	**Explanation**	**Examples**
Attribute	Characteristic of the choice alternative	Cost, time, distance
Attribute level	Particular values of the attribute	10 euro, 15 min., 2 km.
Choice alternative	Choice option with score (levels) on attributes	Train
Choice set	The group of choice alternatives that can be chosen at a particular moment in time	{Train, Car, Bike}
Choice scenario	Describes the context in which the choice is made	commute, weather

A SC experiment can then be seen as an a priori designed experiment by the researcher that asks participants to complete a set of choice sets. These choice sets consist of alternatives, each described by their attributes and varying attribute levels. The choice scenario provides the context in which the choice is made. The underlying choice model can be reformulated as a mathematical model that allows for decision maker's heterogeneity and inconsistency, is economically rigorous, and is flexible and practical in multi-attribute and multinomial choice situations.

The aim of this research is to extract the queuing behavior of human drivers in the sorted area, to gain insights in the trade-offs they make while choosing a desired lane, and to capture the interactions between queuing behavior and the design of the sorted area in terms of its system size and lane configuration. This is done through asking participants of the SC experiment to select their desired lane in a variety of traffic conditions, which vary in traffic crowdedness, turning directions, and n.o. lanes that are included in the sorted area. Traffic conditions can be steered by design through varying attribute levels for each lane i.e. alternative. Turning-directions and pre-signal designs can be steered by setting up multiple choice contexts. The choice model is able to withdraw the weights of different attributes in respect to the respondents' subjective lane preference. Context dependent queuing behavior can be obtained by calculating the percentage split of lane preferences in a specific choice context. The underlying trade-offs in this thought process is then captured in the choice models' output and can be obtained by comparing relative weights of attributes in a cross-context analysis.

Choice models differ in their processing mechanism of withdrawing the attributes weights due to the implementation of various economical theories and mathematical structures. Since there have been numerous choice models proposed in literature, only a subset of these models will be discussed in the next sections, among which two most known and applied ones: Multinomial Logit model and Mixed Logit model.

5.2.2. Economic appraisal theories

The foundation of a choice model is characterized by its underlying economic theory that forms the fundamental basis of the data processing mechanism. The Random Utility Maximization (RUM) theory of McFadden arguably is the most known and applied theory in choice modeling. The theory is based on the assumption that when participants are asked to choose their preferred alternative, they will opt for the one that maximizes their own interest (McFadden, 1981). Nowadays, state-of-the art theories are on the rise in behavioral economics, of which the Random Regret Minimization (RRM) theory of Chorus receives the most attention (Chorus *et al.*, 2008). In contrast to RUM, this theory is based on the assumption that participants choose the preferred alternative based on their minimum regret that is associated with the alternative. Regret associated with a considered alternative equals the sum of regrets associated with binary comparisons of their attributes with all other alternatives in the choice set. Unlike RUM where the utility of an alternative does not and can not depend on reference levels, nor on what the choice set looks like (i.e. how the competition performs), RRM incorporates this reference-dependency and choice set-dependency. Although such dependencies might seem attractive for this research, the fact that a preferred lane choice has no serious regret associated with it, debunks the suitability of the RRM theory. This is more prevalent in risky, uncertain and taboo-related choices such as questions in which participants are asked to choose between options that could impact their live or that of others, hence not prevalent in the desired lane choice of drivers. In this kind of trade-offs, RRM offers the possibility to model a choice based on the avoidance of negative emotions instead of some payoff maximization. In contract, RUM is able to provide insights in the willingness to avoid loss, or the readiness to do effort for interest maximization. Examples of such insights would be the participant's willingness to change lanes in the sorted area to avoid queuing up behind a long queue or the readiness to change lanes for a strategic position in the network). Since these questions are of exact interest in this research, RUM-based choice models will form a proper economical foundation for choice modeling.

A linear adaptive RUM-based choice model is a representation of the choice process for individual n based on the utility maximization principle. The mathematical formulation of its utility function and maximization principle is as follows (Chorus, 2022):

n's utility of alternative i:

$$U_{in} = V_i + \varepsilon_{in} = \sum_m \beta_m \cdot x_{im} + \varepsilon_{in} \tag{5.1}$$

i is chosen by n if:

$$\sum_m \beta_m \cdot x_{im} + \varepsilon_{in} > \sum_m \beta_m \cdot x_{jm} + \varepsilon_{jn}, \forall j \neq i \tag{5.2}$$

Where:
V = Systematic utility
i, j = Alternative subscripts
m = Attribute subscripts
x = Attribute values
β = Tastes / weights for attributes - to be estimated
ε = Randomness

The utility of an alternative as described in Eq. 5.1 contains a systematic utility part and an error term. The systematic utility is a sample-specific summary of all that can be related to observed factors, while the error term captures everything else that governs the individual's choice (e.g. unobserved factors, heterogeneity in tastes, and randomness in choices). Thus, even when the systematic utility is the highest, the corresponding alternative may still not be chosen by an individual in a particular choice situation. In other words, it is only possible to predict choices up to a probability. The higher the systematic utility, the lower the error term, the higher this probability becomes. Thus, minimizing the error term is a central objective throughout the design of the SC experiment.

5.2.3. Multinomial Logit model vs. Mixed Logit model

Within discrete RUM-based choice modeling, the logit model is the most common method for the estimation of attribute tastes / weights. This parameter estimation is based on the Maximum Likelihood-principle that will find the set of parameters that makes the sample data the most likely. McFadden provided the foundation of the logit model after he was the first who combined logit to discrete choice theory from the perspective of mathematical psychology (Cramer, 2002). What initially started with the Multinomial Logit model (MNL), extensions to the standard model have been developed for more advanced applications of discrete choice modeling. Since the MNL model has been the basis for other logit models, it suggests its relative ease compared those extensions. The MNL model is easy to estimate, straightforward to interpret, and requires minimal computational effort. Because of this elegance it is the most commonly applied regression model in the space of discrete choice modeling. The probability of alternative i under the MNL model is calculated by the following formula:

$$P(i) = P(V_i + \varepsilon_i > V_j + \varepsilon_j, \forall j \neq i) = \frac{\exp(V_i)}{\sum_{j=1...J} exp(V_j)} = \frac{\exp(\sum_m \beta_m x_{im})}{\sum_{j=1...J} exp(\sum_m \beta_m x_{jm})} \quad (5.3)$$

A core assumption of the MNL model is the error component being independent and identical distributed (IID) from a distribution with the same variance across alternatives and observations. The error term is supposed to follow an Extreme Value Type I distribution, which is very similar to the normal distribution, except from the former being able to obtain a closed-form expression for the likelihood function in utility maximization. The IID assumption might be unrealistic due to taste heterogeneities that potentially exist within and between socio-demographic subsets of the respondents (e.g. gender, driving style, etc). Discarding this may lead to not fully capturing the variation across individuals of the utility associated with unobserved factors that are shared by (a subset) of alternatives, then it is captured in the randomness (i.e. unobserved utility) instead in the systematic utility V.

Another concern is the assumption of independence of irrelevant alternatives (IIA) that is inherent to the MNL model. It is the result of the assumption that the variance of the error terms equal $\pi^2/6$, which makes the MNL model mathematically elegant and analytically manageable (Ye *et al.*, 2017). IIA states that a respondent's choice is unaffected by other alternatives present in the choice set (Cheng and Long, 2007). An example of pre-signals can illustrate how the IIA property can affect the outcomes in a somewhat unrealistic manner. Suppose a sorted area size of two lanes, i.e. two alternatives in the choice set, with all having the same utility. The MNL model will assign equal probabilities to both alternatives ($P_{right} = \frac{1}{2}, P_{left} = \frac{1}{2}$). Now suppose that an extra alternative enters the choice set with again equal utilities, representing a sorted area size of three lanes. In reality it is expected that drivers who initially opted for the most right lane are not as affected by the additional lane on the left side compared to drivers who already opted for the most left lane. Although the IIA property assures an equal probability for both left lane alternatives, it achieves this by evenly 'eating up' the shares of the initial right and left lane alternatives ($P_{right} = \frac{1}{3}, P_{left,1} = \frac{1}{3}, P_{left,2} = \frac{1}{3}$), while it would have been more realistic if the MNL model obtained a share such as $P_{right} = \frac{4}{10}, P_{left,1} = \frac{3}{10}, P_{left,2} = \frac{3}{10}$.

Besides failing to capture correlations between unobserved utilities, there is another type of utility-correlation that the MNL model does not capture. It assumes that unobserved utilities of alternatives evaluated by the same individual are uncorrelated, and therefore that choices made by the same individual are uncorrelated. In fact, every observed choice is independent of all others, even if the choice is made by the same individual. Behavioral consistency is predominant in the decision-making of humans and states that when they are expected to execute a sequence of similar actions, it is easier to make one decision, and to stay with it, rather than to make a new decision every single time (Fessenden, 2018). Psychologist Cialdini stated, “Once we have made a choice or taken a stand, we will encounter personal and interpersonal pressure to behave consistently with that commitment” (Cialdini, 2009). Considering this phenomenon, not every observed choice by the same individual should be valued evenly. Thus, when using the MNL model, the model thinks that it contains more information that it actually does, yielding that it will assign too much certainty to the estimated parameters. Statistically, this implies that the model will underestimate the standard error of the parameters. So by ignoring the panel structure of the SC experiment, parameter estimates will be biased and truly insignificant parameters might become significant.

A commonly used extension that has numerous advantages against the MNL model is the Mixed Logit (ML) model. This model relaxes the IID assumption through the introduction of attribute specific taste parameters of distribution type that are able to capture unobserved taste heterogeneities between and within segments of the population by allowing them to vary randomly across individuals. By doing so, it creates correlations between the choices made by the same type of individual. For the sake of this research, this could be useful if it is expected to find taste heterogeneities between certain subsets of the respondents, such as the correlation between a more aggressive driving style and the willingness to change lanes, or the correlation between being a traffic engineer who understand the true objective of the pre-signal and the willingness to change lanes. If these type of correlations exists, then the ML model is able to capture a larger portion of data into the systemic utility part, therefore reducing the standard error of the model. The ML model allows for individual taste heterogeneity in the following way:

$$\begin{aligned}
U_{n,lane_{right}} &= \beta_{n,CAR} \cdot CAR_{lane_{right}} + \beta_{HGV} \cdot HGV_{lane_{right}} + \varepsilon_{n,lane_{right}} \\
U_{n,lane_{left1}} &= \beta_{n,CAR} \cdot CAR_{lane_{left1}} + \beta_{HGV} \cdot HGV_{lane_{left1}} + \varepsilon_{n,lane_{left1}} \\
U_{n,lane_{left2}} &= \beta_{n,CAR} \cdot CAR_{lane_{left2}} + \varepsilon_{n,lane_{left2}}
\end{aligned} \tag{5.4}$$

$$\beta_{n,CAR} \sim N(\beta_{CAR}, \sigma_\beta)$$

Where:

$U_{n,i}$ = n's utility of alternative i

$\beta_{n,CAR}$ = n's attribute specific taste parameter for the amount of cars

β_{HGV} = Taste parameter for the amount of heavy good vehicles

CAR_i = Amount of cars in alternative i

HGV_i = Amount of heavy good vehicles in alternative i

$\varepsilon_{n,i}$ = n's randomness / error term of alternative i

The ML model also relaxes the IIA assumption of the MNL model. This is done through the introduction of group alternative error terms of distribution type that are able to capture unobserved preference heterogeneities between groups of alternatives (beyond observed factors) by allowing them to vary randomly across individuals. A group of alternatives beyond observed factors can be seen as a subset of alternatives within the choice set that share common features which have not been prescribed by model parameter. By doing so, it creates correlations between the unobserved utilities of similar alternatives. For the sake of this research, this could be useful if it is expected to find groups of alternatives within the choice set beyond observed factors that may lead to unrealistic behavioral modeling. An example of such preference heterogeneity within a group of alternatives could be the presence of a dislike for the outer lanes in the sorted area that area opposite to the turning direction (e.g. a dislike for the most left lanes when traffic turns right). The ML model captures this directly with a group alternative specific parameter, while such correlations are not captured in a MNL model. As a result, the ML model corrects for behavioral aspects that were neglected in the MNL model, therefore describing driving behavior more truly. Relaxing the IIA assumption is of more value to the research than relaxing the IID assumption, since the latter only provides a more profound insight beyond the average queuing behavior and the former is crucial in obtaining that average behavior unbiased. The ML model allows for group alternative preference heterogeneity in the was as described in Equation 5.5.

Furthermore, the ML model is able to correct for panel effects. The ML model incorporates this by making preferences and tastes time-invariant, or in other words individual-specific, instead of observation specific. In fact, the unit of observation becomes the sequence of choices that is made by the same individual. By doing so, the model acknowledges that a specific preference / taste is represent in all choices made by a particular individual.

$$
\begin{aligned}
U_{n,lane_{right}} &= \beta_{CAR} \cdot CAR_{lane_{right}} + \beta_{HGV} \cdot HGV_{lane_{right}} & & + \varepsilon_{n,lane_{right}} \\
U_{n,lane_{left1}} &= \beta_{CAR} \cdot CAR_{lane_{left1}} + \beta_{HGV} \cdot HGV_{lane_{left1}} & + \upsilon_{n,left} & + \varepsilon_{n,lane_{left1}} \\
U_{n,lane_{left2}} &= \beta_{CAR} \cdot CAR_{lane_{left2}} + \beta_{HGV} \cdot HGV_{lane_{left2}} & + \upsilon_{n,left} & + \varepsilon_{n,lane_{left2}}
\end{aligned}
\tag{5.5}
$$

$$\upsilon_{n,left} \sim N(0,\, \sigma_{\upsilon})$$

Where:

$\upsilon_{n,left}$ = n's additional group alternative error term of left lane alternatives i

The ML model seems to be the solution to all the problems related to the MNL model. Although this is true to a certain extent, applying the ML model also faces some drawbacks. Where a MNL model is easy, elegant, well known and quick to estimate model, the ML on the other hand is more complex and a lot harder to estimate. Despite progress in computer power, runtime remains an issue. The runtime of a MNL model takes seconds, while a similar ML model can take up to minutes or hours. Since choice modeling requires a lot of experimenting with attribute combinations in utility functions, ML might not be the ultimate solution.

5.2.4. The choice model to adopt

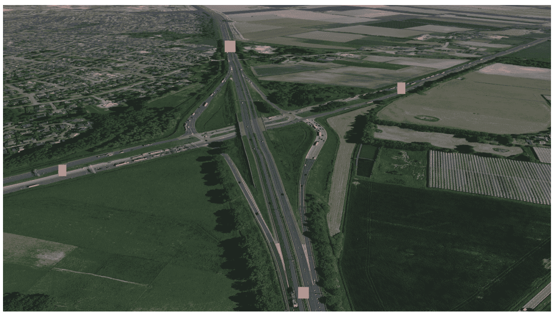
This section touched upon the strengths and weaknesses of both the MNL and ML model. Neither of them seem te be a straightforward choice if considered against the feasibility and credibility of the research. The variety of choice scenarios that are expected to be compared in the cross-scenario analysis, yield a hesitant attitude towards the implementation of ML models. A separate choice model has to be estimated for each choice scenario, and even worse, attribute combinations in these choice model's utility functions must be tested separately as well. Therefore, it is not feasible if a single ML model estimation would take minutes, instead of a MNL model estimation of seconds. Besides that, ML increases the experimental flexibility with attributes, therefore further increasing the total time demand of model estimation. This construction led to the decision to incorporate the MNL model instead of the ML model, or a combination of both.

5.3. Case-study interchange Hooipolder

One of the design choices is the implementation of a case-study throughout the SC experiment. The case-study is an example of a traffic environment from practice and will serve in the SC experiment as a bridge towards the hypothetical traffic environments of the pre-signal system. It also enables the possibilities to reflect research outcomes to specific traffic environments that everyone is familiar with, and to clearly describe the set of traffic environments to which the research outcomes can be applied to. Besides that, it supports the researcher in concretely substantiating design choices throughout the design process of the SC experiment.

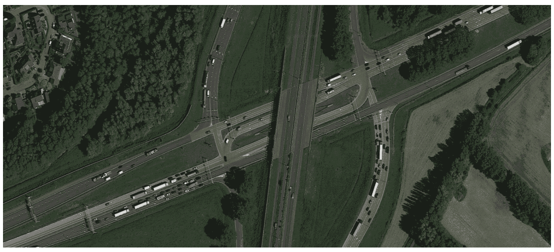
5.3.1. The project A27 Houten-Hooipolder

The case-study that will form the basis of the SC experiment design is interchange Hooipolder. This interchange is the only highway interchange in the Netherlands that is fully coordinated through traffic lights. Traffic flows to and from the A59 experience flow stagnation and inconvenient delays due to traffic jams that arise at the signalized intersection of the highways A27 and A59. In December 2018, the Dutch Ministry of Infrastructure and Water Management agreed upon a reconstruction of the interchange as part of the road widening project A27 between Houten and Hooipolder (Management, 2022). The reconstruction of interchange Hooipolder mainly focuses on improving traffic flow on the A59 by excluding North-West, East-North, -and West-North bounded traffic from the coordinated intersection through (semi-)indirect connection roads. Figure 5.2 visualizes the reconstructing of interchange Hooipolder as agreed by the ministry. According to Vervoer hart Brabant (2016), the best solution to minimize congestion issues was to reconstruct the interchange to a full cloverleaf interchange. The ministry rejected this design proposal bases on its disproportionate costs.

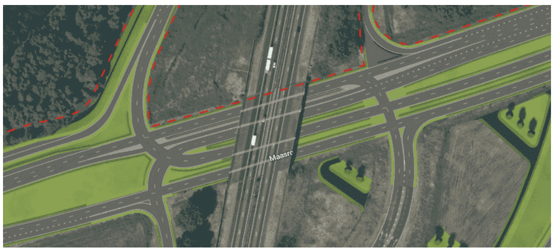


(a) Top view before

(b) Top view after



(c) Intersection close-up before



(d) Intersection close-up after

Figure 5.2. – Visualization of Reconstruction Interchange Hooipolder (Management, 2022)

5.3.2. Why interchange Hooipolder as case-study?

Introducing pre-signals at the signalized intersection of the interchange might help further improve the traffic flow on the A59, and it may deduct the need for any additional costly connection roads as proposed in the project A27 Houten-Hooipolder (see Figure 5.2.b.). Although this opportunity is not part of the research scope, and the reconstruction project has already been approved, the application of pre-signals to this case-study can still be of value. Interchange Hooipolder maintains the connection between the innovative design of the pre-signal system and real traffic environments from practice. Besides that, interchange Hooipolder being a signalized intersection of relatively large scale enables the possibility to also include pre-signal systems of larger size, i.e. with more lanes in the sorted area, yielding a wider range of traffic environments that the SC experiment can deal with. Please note that within a sorted area size of X lanes, there always remains the possibility to decrease that size for specific traffic movements to Y lanes (where X > Y), by closing lanes for those corresponding pre-signal phases (e.g. accommodate 4 lanes for through going traffic, while only serve left-turning traffic with 3 lanes). Thus, being able to include a large pre-signal system size offers the researcher flexibility in setting up traffic environments in the SC experiment form large to small scale. Finally, the widely stretched design of the interchange provides the advantage above tight urban intersection designs to implement the pre-signal system without any major complications to the surrounding traffic environment.

5.3.3. Pre-signal allocation

Concerning the implementation of pre-signals into the design of interchange Hooipolder, two scenarios can serve as the basis for pre-signal allocation, which are distinctive in the consideration of the connection roads as proposed in the project A27 Houten-Hooipolder.

Scenario 1: with connection roads
The starting point of the first scenario is the full reconstruction design of interchange Hooipolder as approved by the Dutch ministry (Figure 5.2.b & d). This design facilitates non-signalized connections for the two most crowded turning movements of the interchange to and from the direction of Utrecht. The semi-direct non-signalized connection road on the A59 in the direction of Utrecht relieves the intersection from heavy left-turn traffic, while the main strengths of the pre-signal system is to deal with such heavy left-turn traffic. Implementing pre-signals on the remainder turning movements of the intersection is likely to be less effective compared to the a pre-signal allocation of scenarios that do not consider these non-signalized connection roads, such as scenario 2.

Scenario 2: without connection roads
Given the sub-optimal pre-signal application of pre-signals as suggested in scenario 1, scenario 2 overcomes this complication by adapting the first scenario in favor of the pre-signal's application. Instead of considering the full reconstruction design of interchange Hooipolder, the second scenario takes as starting point the reconstruction design without any non-signalized connection roads. It pretends that those connection roads do not exist, while the original intersection design is considered to form the basis. Remainder characteristics of the construction design such as the project boundary and any additional road widenings are included in that intersection design of scenario 2. Thus, it can be seen as a mix of the original design and the construction design. By considering the interchange design as given in Figure 5.3 (note that the interchange is designed such that it allows for a pre-signal allocation to all four arms of the signalized intersection), the signalized intersection will not be relieved from certain traffic streams and pre-signals can serve their initial purpose effectively. Besides that, additional advantages arise when using this approach.

Figure 5.3. – Design of Interchange Hooipolder as Considered in Scenario 2

First, the road widening of the East-bounded A59 from 2 to 4 lanes enables the possibility to materialize a pre-signal system size of 4 lanes in the sorted area instead of only 2. In the original intersection design, the 2-lane A59 downstream the main intersection restricted the sorted area size to those 2 lanes only. Considering the road widenings of the construction design, the downstream A59 now includes 4 lanes that enables the possibility to materialize a sorted area size of 4 lanes upstream of the main intersection, as shown in Figure 5.4.

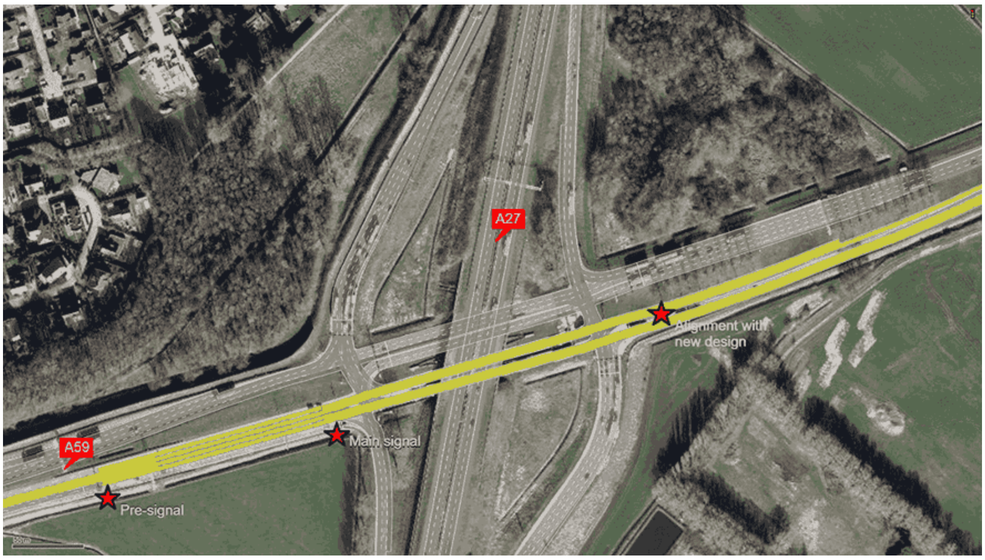
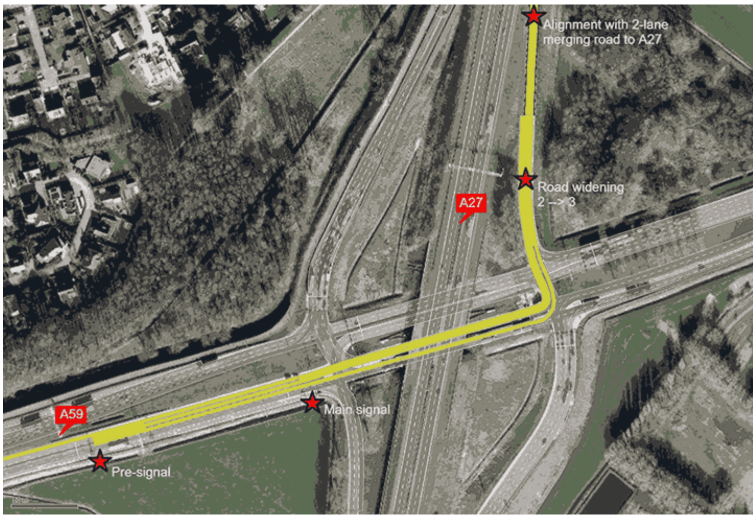


Figure 5.4. – Road Section That Facilitates a Pre-Signal System Size of 4 Lanes in Through-Going Direction

Although this can also be achieved in scenario 1, the major advantage compared to the first scenario is the possibility to also facilitate a 3-lane left turn from the A59 to the A27 by allocating the initial space for that connection road differently. Instead of allocating the space to the initial connection road, the space will be allocated to a road widening of the merging road between the main intersection and the A27 highway in the direction of Utrecht. The road widening consist of an increase in the n.o. lanes from 2 to 3 lanes. The excessive space, derived from omitting the connection roads, serves as turbulence buffer for a lane drop from 3 to 2 lanes after which it will align with the new construction design of the interchange. Figure 5.5 visualizes these design choices for the 3-lane left turn from the A59 to the A27.



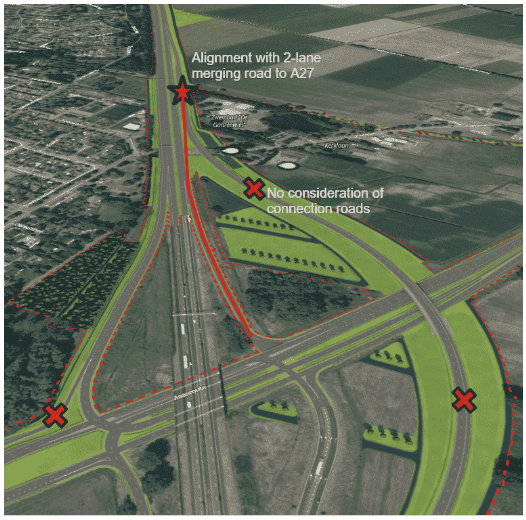


Figure 5.5. – Road Section That Facilitates a Pre-Signal System Size of 3 Lanes in Left-Turning Direction (left) and Alignment With Construction Design (right)

Second, this further enables the possibility to materialize a 3-lane right turn from the A59 to the A27 in the direction of Utrecht, as shown in Figure 5.6. The pre-signal of the 3-lane right turn is unlike the 4-lane trough direction and the 3-lane left turn active on the East-West direction of the A59 instead of its West-East direction.

For modeling purposes, a design choice is made to allocate an additional hypothetical 3-lane right turn to the pre-signal on the West-East direction of the A59, as shown in Figure 5.7. Although the latter will not be feasible in practice due to turbulence restrictions, it represents the exact opposite of the 3-lane right turn on the East-West direction of the A59. This hypothetical design choice will decrease the modeling effort without changing any of the traffic environments, i.e. the validity of the research outcomes. Since now just one pre-signal includes all intersection directions at their maximum size (3-lanes for turning directions and 4-lanes for through going directions), the required modeling effort will be minimized to only one arm of the signalized intersection instead of multiple. Figure 5.8 highlights the range of traffic directions that the West-East pre-signal on the A59 is able to accommodate. Regarding the SC experiment, this yield to a favorable situation in which all traffic environment can be researched from the perspective of just one pre-signal. Besides the reduced modeling effort, this also secures consistency throughout the SC experiment and it avoids that inconsistencies in traffic environments may influence research outcomes in an undesirable fashion.

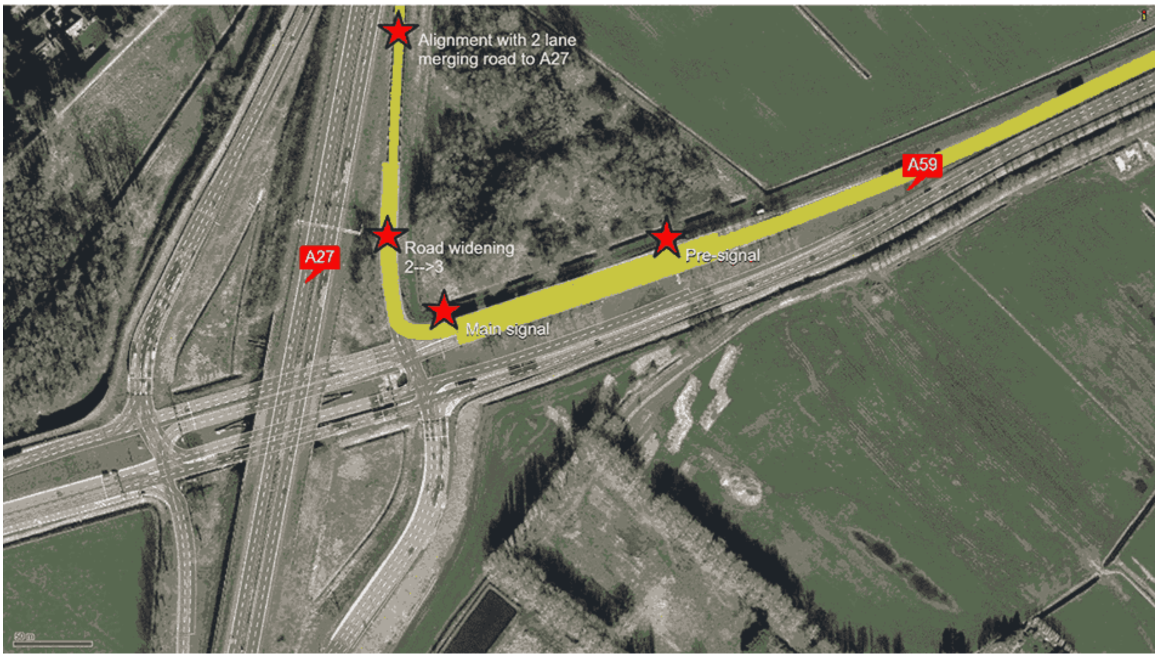


Figure 5.6. – Road Section That Facilitates a Pre-Signal System Size of 3 Lanes in Right-Turning Direction

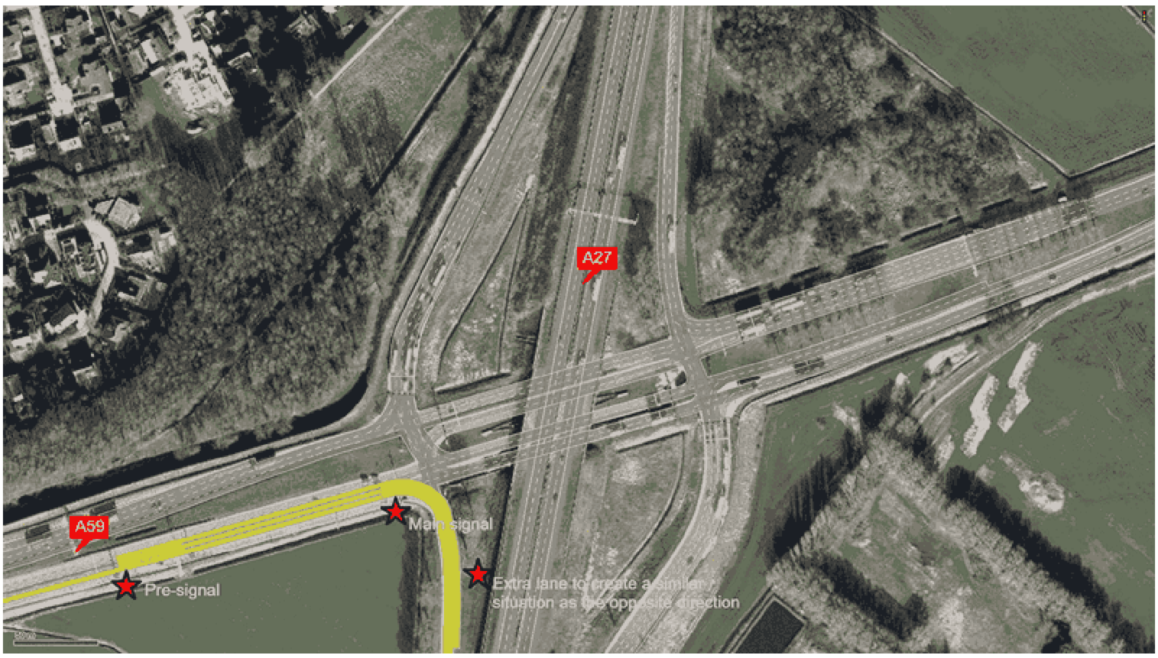
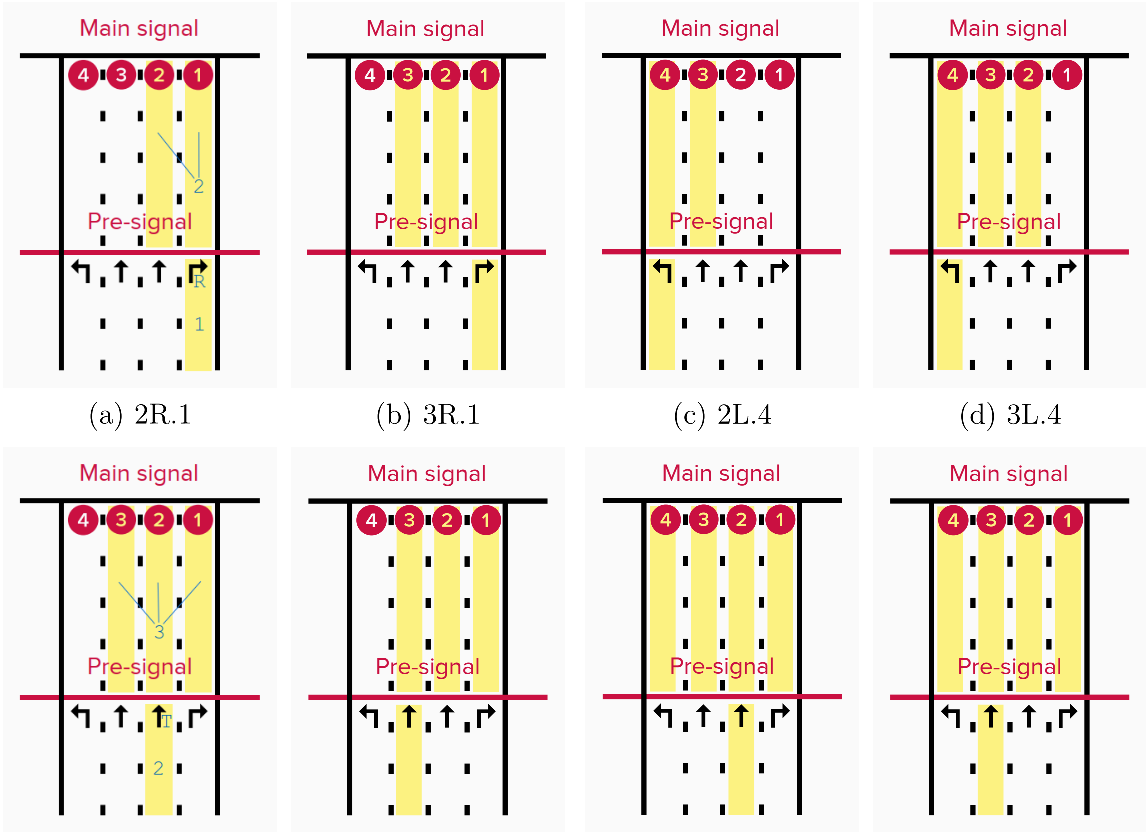


Figure 5.7. – Hypothetical Road Section in Model For Nesting Purposes

Figure 5.8. – Range of Traffic Directions for the West-East A59 Pre-Signal

5.3.4. Traffic environment research opportunities

Following from the pre-signal allocation as discussed above, the intersection design of interchange Hooipolder as considered in Figure 5.8 defines the boundary of traffic environments that can be included in the SC experiment. Within this design, the pre-signal on the West-East direction of the A59 is able to facilitate 3 sorted area lanes for turning traffic and 4 sorted area lanes for through traffic. Since a pre-signal system is only effective when the n.o lanes for direction x before the pre-signal is smaller than the number of lanes for direction x in the sorted area, not all combinations of a particular sorted area lane utilization will be of interest. The traffic environments that are considered to be the research opportunities are the ones that materialize an effective pre-signal system. An overview of these research opportunities are presented in Figure 5.9. The first component of their names corresponds to the n.o. available lanes in the sorted area (2, 3, 4) and the traffic direction (R: right, L: left, T: through), and the second component corresponds to the original number of the lane on which the vehicle is positioned upstream of the pre-signal (1: most right lane, 2: second lane from the right, 3: third lane from the right, 4: most left lane). To illustrate this, Figure 5.9.(a) & 5.9.(e) are provided with additional explanation.



(a) 2R.1 (b) 3R.1 (c) 2L.4 (d) 3L.4

(e) 3T.2 (f) 3T.3 (g) 4T.2 (h) 4T.3

Figure 5.9. – Overview of Traffic Environments That Are Considered as Research Opportunities for Interchange Hooipolder

5.4. Hypothetical 3D traffic environment

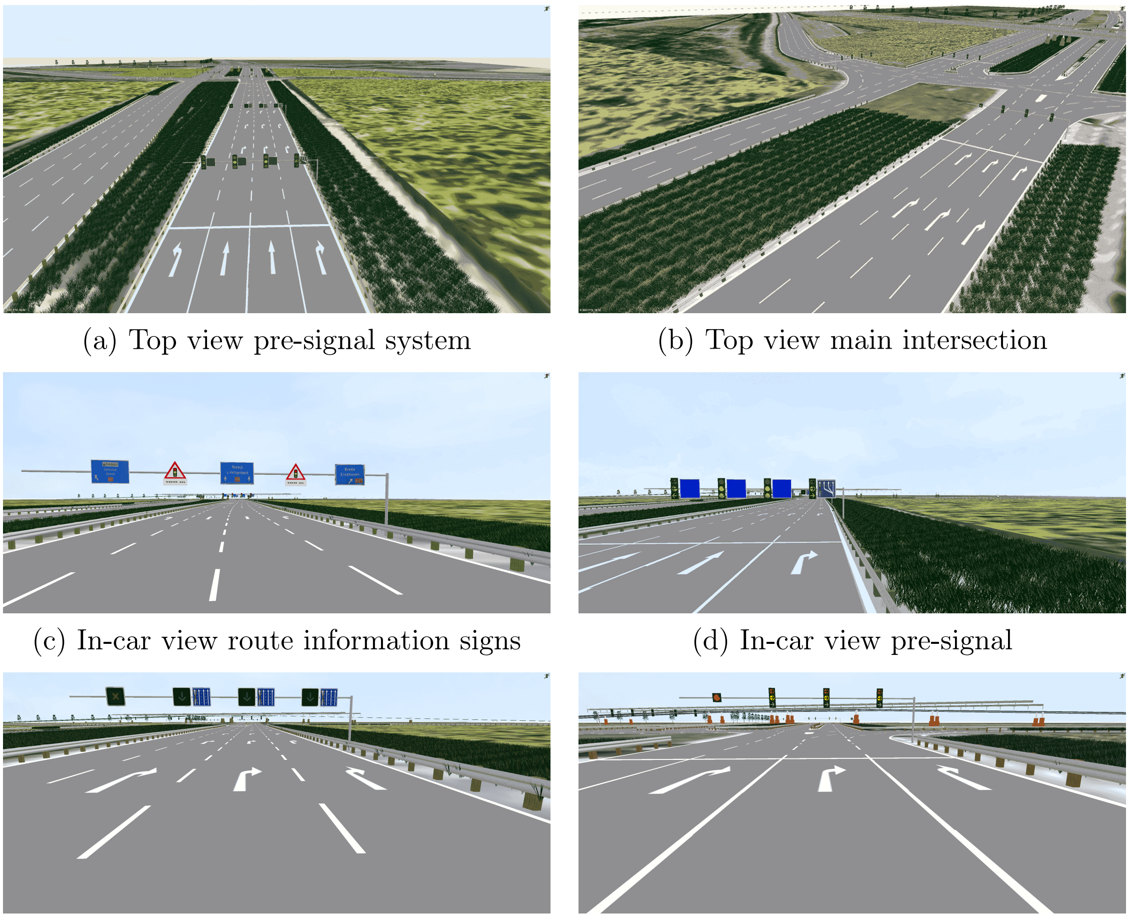
Respondents of the SC experiment are asked to reveal their driving behavior through answering questions about how they would react in certain traffic situations as presented in the questionnaire. Since respondents are inexperienced with any kind of pre-signal environment, they will be presented with a hypothetical traffic environment. In order to let respondents be able to truly reflect their driving behavior as they would have done in a real traffic situation, it is crucial to increase their ability to imagine the hypothetical environment in which they have to make choices. This is particularly discussed in Section 4.2.2, which covered the he hypothetical bias (HB) mitigation strategies, but it also introduced a phenomenon known as the stated-preference paradox:

> *"We particularly use stated-choice experiments when we wish to examine preferences for new alternatives or attribute values beyond current ranges, however, the less familiar respondents are with the alternatives, the less valid their responses."(E.J.E., 2022)*

A 3D hypothetical traffic environment is designed with the aim to provide respondents a realistic feeling and clear visualization of the traffic situation they participating in. Unlike driving simulators and VR environments, participants will not get a full 3D experience, because they will absorb information from a plane surface. The model is developed in VISSIM, a traffic simulation software with a built in scenario manager that allows to simulate traffic in a self-built traffic environment. Regarding the model's development and its implementation in the SC experiment, several design choices have been made that affect the validity of the research outcomes. These will be elaborated upon in this section.

5.4.1. An impression of the 3D traffic environment

The 3D visualization model is developed from the perspective of just one pre-signal, the pre-signal on the West-East direction of the A59. The previous section explained the range of traffic environments that can be created with the possible turning directions of its corresponding main signal. The VISSIM 3D visualization model consist of a base network and scenario steered modifications that together are able to simulate those traffic environments. Figure 5.10 provides impressions of the 3D traffic environment in VISSIM from the perspective of the 3-lane right-turn traffic environment, which is sketched in Figure 5.9.b.



(a) Top view pre-signal system

(b) Top view main intersection

(c) In-car view route information signs

(d) In-car view pre-signal

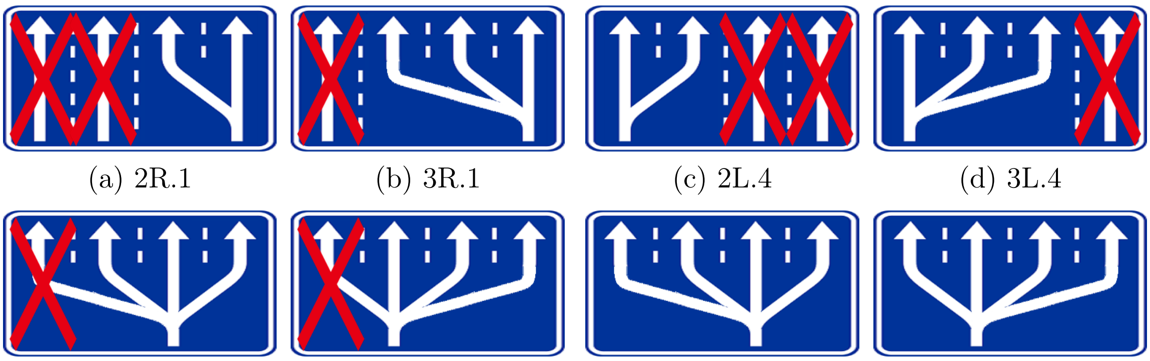
(e) In-car view lane information signs

(f) In-car view main intersection

Figure 5.10. – Impressions From 3D VISSIM Traffic Environment for the 3-Lane Right-Turn Scenario

The VISSIM model translates the hypothetical nature to somewhat tangible traffic environments. However, VISSIM lacks in achieving a similar quality in-car view that respondents would have experienced while driving on a real road. Mainly depth-seeing and the ability to look through car windows decreased respondents in their ability to make a proper judgment of the traffic situation. This emphasizes the need to also provide respondents with a birds eye-view of the traffic environment they participating in. Besides a proper overview, this will also clarify to respondents where in the pre-signal system they precisely are. Although this might not be truly representative for the real environment, it certainly benefits the choice model estimation process. This is based on the following reasoning: if respondents are not able to properly overview the traffic conditions of each alternative, they will base their preferred lane choice on only a part of the alternatives' characteristics (i.e. the ones they can overview), hence the choice model may assign relevant attributes as not significantly different from zero.

Within the visualization model, there have been several measures implemented to inform the driver about the working of the pre-signal system. Probably the most challenging is to inform drivers about when they are allowed to use which lanes in the sorted area. This is done through the implementation of additional scenario dependent lane marking and lane availability information signs. The model will adjust the lane marking arrows depending on the phase of the pre-signal and the n.o. lanes in the sorted area that are open for traffic. As can be seen in Figure 5.10.a & b, the model projects right-turning arrows on the three available lanes after the pre-signal. Besides that, the model projects a lane availability information sign next to the pre-signal that informs drivers about the lanes after the pre-signal on which they are allowed to spread themselves, as can be seen in Figure 5.10.d. This information sign differs for each turning direction of the pre-signal. A complete overview of these additional lane availability information signs, with respect to their corresponding choice scenario, is given in Figure 5.11. Finally, drivers are reminded about any lane closures downstream the pre-signal, as can be seen in Figure 5.10.e.



(a) 2R.1 (b) 3R.1 (c) 2L.4 (d) 3L.4

(a) 3T.2 (b) 3T.3 (c) 4T.2 (d) 4T.3

Figure 5.11. – Overview of Lane Availability Signs Per Scenario

5.4.2. Image versus video questioning

The 3D VISSIM model allows to either question participants through the use of images or videos extracted from the model. Mathews *et al.* (2007) found that visualizations such as photographs, maps and diagrams in many studies helped to both standardize and aid the respondent's comprehension. A video is more immersive than static visualizations because visual fields are generated dynamically depending on the simulated viewpoint. The research of Galilea and Hurtubia (2020) tested the validity of implementing videos in SC experiments against static images, and he found that videos are recommended above static images in cases where perceptions plays a role. Think of perceived safety or traffic interactions that are more dependent on visuals cues to judge it. As discussed in the literature review, it is suggested to increase the ability of respondents to imagine the hypothetical traffic environment in case where the HB is suspected to arise form inexperienced respondents with the good or service. Using videos instead of images will help respondents to get a more immersive feeling of the hypothetical traffic environment they participate in, and will increase their ability to process visual cues in the judgment about their preferred lane. Therefore, the video bases questioning approach will be implemented in the SC experiment.

Cherchi and Hensher (2015) warned that applying images and videos in a SC experiment compared to the traditional textual format, can cause confounding outcomes with risk of ambiguity in the interpretation of the choice process. This follows from the viewpoint that images and videos can convey too much information, and if not controlled, responses might be generated that cannot be associated with the attributes of the choice model. The effect of such side affects can be minimized by eliminating all elements that distract the respondents from the main focus. Since it is not possible to solely develop the 3D model by attribute elements, a balance must be found between the information richness of the video and the respondents' ability to understand the hypothetical traffic environment.

5.4.3. Static versus dynamic traffic modeling

While considering the design choice to adopt a video based questioning approach, another design choice emerges, namely the choice to either model traffic statically or dynamically. The difference between the two modeling strategies is the way how the traffic downstream the respondent, i.e. the traffic that will form the queues on each lane in the sorted area, is modeled in the video. If the video captures the view from the perspective of the respondent's driver seat, and the corresponding vehicle is called the Special Purpose Vehicle (SPV), then the videos will capture the following under the two modeling strategies:

- Static: (1) queued vehicles upstream of the main intersection are inserted statically as non-moving 3D objects, (2) the SPV is the first queued vehicle upstream of the pre-signal, (3) the video starts just before the SPV gets a green signal from the pre-signal, (4) the SPV and the queued vehicles behind it start driving in the direction of the main intersection, (5) the video pauses when the SPV approaches the main intersection's stop line at distance x, (6) respondents have to choose their preferred lane;

- Dynamic: (1) instead of inserting 3D static objects, the vehicles that will form the queue upstream of the main signal are positioned in front of the SPV in the queue upstream of the pre-signal (2) the SPV is therefore not the first queued vehicle upstream of the pre-signal, (3) the video starts just before the SPV gets a green signal from the pre-signal, (4) while all vehicles in the pre-signal queue start driving in the direction of the main intersection, vehicles in front of the SPV position themselves dynamically, (5) the video get paused when the SPV approaches the main intersection's stop line at distance x, (6) respondents have to choose their preferred lane.

Both modeling strategies have their own (dis)advantages. The main difficulty with dynamic modeling is that is requires considerably more modeling effort to exactly position vehicles in the right lane at the right moment in time. Since traffic conditions in the SC experiment will differ for each choice set, this process must be repeated numerous times, and is therefore time demanding unlike the relative quick and comfortable static modeling approach. The main concern of the static modeling approach is the static non-moving queue upstream of the main signal, which is a phenomenon that drivers will not experience in real traffic conditions. This eliminates traffic interactions between the SPV and the moving queue. However, this research is predominately interested in the drivers' trade-offs between traffic conditions, pre-signal design characteristics and lane choice strategies, and not in the well-known traffic interactions regarding lane-changes. Besides that, there is a risk that traffic interactions distract respondents from the focus of the research. Then responses might be generated that cannot be associated with the attributes of the choice model, with the result of a higher randomness and lower reliability of the research outcomes. Therefore, the choice is made to implement a static modeling approach.

5.5. Conclusion

This chapter discussed the main fundamentals & design choices of the SC experiment that together form the basis for its development in the next chapter. Among other things, it touched upon the choice model establishment with the aim to select a proper choice modeling strategy that would fulfill the needs of the SC experiment, as well as guarantee the feasibility of the research. Based on these findings, an answer can be given to the fifth sub question: *what methods and models exist in the field of stated-choice experiments, and which is recommended for the research?*

The establishment of the underlying economic appraisal theory provides one part of the answer to the sub research question. This chapter compared the most common Random Utility Maximization (RUM) theory of McFadden with the more state-of-the art Random Regret Minimization (RRM) theory of Chorus. Although it seemed attractive to incorporate the reference-dependencies from the RRM theory, a RUM-based choice model has been chosen to form the economical foundation for choice modeling. The fact that a preferred lane choice has no serious regret associated with it, debunked the suitability of the RRM theory. Thus, choices will be processed based on the principle that individuals maximize their own interest. The other part of the answer to the sub research question concerns the establishment of a proper parameter estimation strategy. Both the Multinomial Logit (MNL) model and the Mixed Logit (ML) model were assessed on its strengths and weaknesses. Where the

MNL model turned out to be easy, elegant, well-known and quick to estimate, unlike the ML model, the ML model included properties that were contributing in understanding the queuing behavior of drivers in the sorted area less biased from the mean. These properties included the ability to compensate for panel effects and the capturing of taste-and preference heterogeneities on an individual level. Nevertheless, ML models have been rejected on the time aspect it would demand for the numerous models that are expected to be estimated.

Other design choices that were made in this chapter concerned the implementation of the interchange Hooipolder case-study, that serves as a bridge between the hypothetical SC experiment and real traffic environments from practice. Pre-signals have been allocated to the intersection such that it offered a wide-range of traffic environments without exceeding the project boundary of its latest construction design. Furthermore, a hypothetical 3D environment has been developed in the traffic simulation software VISSIM with the aim to provide respondents a realistic feeling and clear visualization of the hypothetical traffic situation they participating in while making a preferred lane choice. A design choice has been made to question respondents by making use of extracted videos from the 3D traffic environment to help them get a more immersive feeling of the hypothetical traffic environment, and to increase their ability to process visual cues in the judgment about their preferred lane. To prevent confounding outcomes with the risk of ambiguity in the interpretation of the choice process, there have been chosen to model queuing vehicles statically. This followed from the viewpoint that videos can convey too much information, and if not controlled, responses might be generated that cannot be associated with the attributes of the choice model.

6. The design of the stated-choice experiment

This chapter represents the second out of two chapters of the experiment design part and it concerns the design of the SC experiment. Design choices that have been considered in Chapter 5 will be processed into the design of the SC experiment. Although this chapter does not involve any of the research questions, it still contributes to the overall process of answering the main research question. The objective of this chapter is to develop a questionnaire, of which the SC experiment is part of, that is able to extract the respondents' decision-making process of their preferred lane choice. Therefore, this chapter designs a data collection and data processing mechanism that gathers the needed data for answering the last three research questions:

- What trade-offs between the relevant lane-changing factors make human drivers in their desired lane choice downstream the pre-signal?
- How are these trade-offs affected by the driver's intended turning direction and the number of lanes in the sorted area?
- To what extent does the drivers' preferred lane choice downstream the pre-signal differ from one of a conventional signalized intersection without a pre-signal, and what are the implications of these differences for the applicability and efficiency of pre-signals in general?

The chapter starts with the construction of choice alternatives in Section 6.1, which includes the setup of choice scenarios, the selection of relevant attributes, and the specification of attribute levels. These inputs will be processed into a mathematical design of the SC experiment in Section 6.2. Then, there will be reflected upon the HB in Section 6.3. These previous sections serve as the input for the completion of the questionnaire design in Section 6.4.

6.1. Construction of the choice alternatives

SC experiments are usually incorporated as an element or section in a larger overarching questionnaire or survey. These are typically designed in a way that the first section is dedicated to screen-out questions to judge the respondents' eligibility and to collect additional information regarding socio-demographics, general attitudes, and perceptions. The second part is typically dedicated to the SC experiment in which respondents are asked about their expected behavior regarding the topic of interest. Although such a construction order might be common in the field of SC experiments, this approach has recently been criticized. Additional questions should be asked after the SC experiment to avoid influencing choice behavior, and to prevent respondents from not continuing the questionnaire after they might feel screened through the personal questions (Liebe *et al.*, 2021). Since the data originating from the SC experiment and additional questions can both be included in choice model estimations, they cannot be treated as two completely separate sections of the questionnaire. Given the factors in Table 3.2 that influence the drivers' lane-change behavior, and given the restriction to incorporate them all in the SC experiment, it is important to make a proper selection which to include in either section of the questionnaire.

The remainder of this section focuses on the design of the choice alternatives. This process typically entails the following steps:

I Determine whether the experiment is labeled or unlabeled;

II Determine the alternatives and select attributes to include;

III Determine the attribute levels and their coding scheme.

6.1.1. Labeled vs. unlabeled alternatives

Alternatives within the choice set may be of labeled or unlabeled type. A label can be seen as a name for the alternative that incorporates some characteristics which are not described by attributes, such as the category or type of alternative. Labeled alternatives have their own label-specific utility function, and they allow for label-specific taste parameters, while unlabeled alternatives only yield one utility function with generic taste parameters. Whether to choose (un)labeled alternatives certainly depends on the research question. While unlabeled alternatives only provide insights in the relative importance of attributes, labeled alternatives also provide the possibility to determine the market shares of labels and to compare these with a status-quo alternative. This often accompanies a more complex choice task for respondents and the estimation of a larger n.o. parameters. Therefore, labeled alternatives should not be applied if there is no reason to. This study is interested in the spread of drivers in the sorted area (i.e. the market share of each lane) as well as the relative importance of attributes within and between alternatives. As an example, this research is not solely interested in the general discomfort drivers associate with lane changing, but also in why and when differences occur in lane changing discomfort. To accomplish this, each lane in the sorted area should represent a labeled alternative, otherwise there would not exist any within choice scenario taste differences.

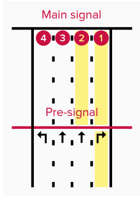
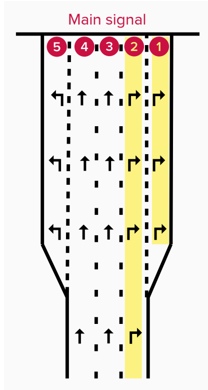
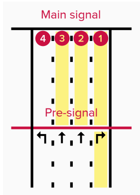
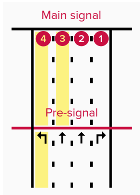
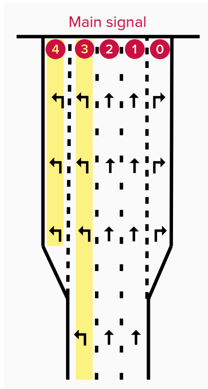
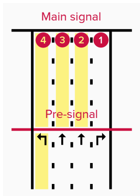
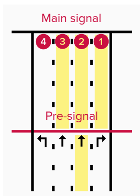
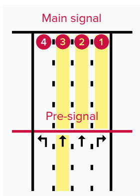
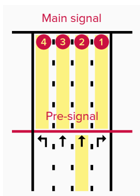
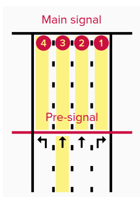
6.1.2. Scenario setup

The relative importance of attributes within and between alternatives will vary across different traffic environments. As an example, it is expected that drivers assign different weights to lane changing in situations where they turn right instead of left, or when they are allowed to spread across a different set of lanes. These kind of relations are also of interest, therefore the SC design must be steered towards the incorporation of such interactions. Interactions between attributes can be estimated with the so called full factorial design schemes. A design scheme is a table with ordered numbers that determine which attribute levels to combine into alternatives, and what choice sets to include in the choice task. The full factorial design scheme constructs alternatives that include all possible combinations of all attribute levels and is therefore able to capture attribute interaction effects. However, the main disadvantage is that full factorial designs demand an unfeasible large choice task for respondents, even when the number of attributes is low. Besides that, interaction effects between right-turning, left-turning, and through traffic cannot be captured by full factorial designs because these traffic movements cannot be described by attributes of alternatives. Therefore, another solution must be found to capture the interaction effects between traffic environments, and is elaborated upon below.

The introduction of choice scenarios reshapes the SC experiment into a set of context-dependent experiments. A choice scenario describes the context in which the choice is made and does not vary in choice sets. The context is the physical, socioemotional, and mental setting in which behavior takes place, it describes what respondents need to assume while making choices. If traffic environments are shaped by its context, interactions between them can be extracted by a comparison of the relative importance of the attribute levels in their utility functions. In order to capture interaction affects between traffic environments, which differ in the size of the pre-signal system and the intended turning direction of the driver, separate context-dependent experiments must be designed. These are formulated as choice scenarios in Table 6.1, and relate to the defined traffic environments from Figure 5.9. Please note the additional two counterpart scenarios for turning directions that are dedicated to contexts where participants imagine to be situated at conventional signalized intersections without a pre-signal. These scenarios are incorporated with the aim to be able to reflect the differences in driving behavior between the hypothetical traffic environment of pre-signals and the well-known conventional signalized intersections. Besides that, it enables the possibility to validate the outcomes of these scenarios with data from practice (e.g. comparing market shares). This gains insight in the validity of the estimated choice models and it sets the tone / attitude in answering the research questions.

The choice scenarios in Table 6.1 have been found a well-balanced selection that limits the size of the experiment to a feasible amount, while also reflecting the most common traffic environments from practice. Hence, choice scenarios such as 4R.1, 4L.4, and 5T-scenarios have not been included in the research scope. Nevertheless, it may be possible for those scenarios to sketch some hypothesis based on the research outcomes of other similar scenarios. Counterpart scenarios for through going directions have not been incorporated, since it is expected that the spread behavior will yield similar results under both signal types. This is based on the reasoning that when the n.o. through going lanes in both scenarios are equal, drivers are confronted with more or less the same dilemmas, except from the presence of an additional traffic light in pre-signal scenarios. For pre-signal choice scenarios with a left or right turn included, drivers on the main road have to spread in the opposite direction of the intended turn, while this is not the case for the corresponding counterpart scenarios. As as result, it is expected to find significant differences in spread behavior, and counterpart scenarios help to define these differences. Another reason not to incorporate counterpart scenarios for through going scenarios is to limit the n.o. choice scenarios in the SC experiment. Throughout its design stages, caution must be preserved in the expansion of choice scenarios and attributes to limit the required n.o. responses to a feasible amount. If not controlled, this amount can explode to a point where the study becomes unfeasible.

Table 6.1. – List of Choice Scenarios in the SC Experiment

A	B	C	D	E	F
2R.1	Imagine that you want to turn right to the A27 at an intersection with pre-signals and the pre-signal indicates that the two most right lanes are open		2R.1_C	Imagine that you want to turn right to the A27 at a normal signalized intersection and the two most right lanes facilitate that turn	
3R.1	Imagine that you want to turn right to the A27 at an intersection with pre-signals and the pre-signal indicates that the three most right lanes are open				
2L.4	Imagine that you want to turn left to the A27 at an intersection with pre-signals and the pre-signal indicates that the two most left lanes are open		2L.4_C	Imagine that you want to turn left to the A27 at a normal signalized intersection and the two most left lanes facilitate that turn	
3L.4	Imagine that you want to turn left to the A27 at an intersection with pre-signals and the pre-signal indicates that the three most left lanes are open				
3T.2	Imagine that you want to go straight to stay on the A59 at an intersection with pre-signals and the pre-signal indicates that the three most right lanes are open				
3T.3	Imagine that you want to go straight to stay on the A59 at an intersection with pre-signals and the pre-signal indicates that the three most right lanes are open				
4T.2	Imagine that you want to go straight to stay on the A59 at an intersection with pre-signals and the pre-signal indicates that all four lanes are open				
4T.3	Imagine that you want to go straight to stay on the A59 at an intersection with pre-signals and the pre-signal indicates that all four lanes are open				

Legend:

- **A**: Pre-signal choice scenario
- **B**: Context description
- **C**: Schematic representation
- **D**: Counterpart choice scenario
- **E**: Context description
- **F**: Schematic representation

6.1.3. Alternatives in the choice set

As mentioned before, each lane in the sorted area represents a labeled alternative. The choice set size of a particular choice scenario is then defined by the size of the pre-signal system that it prescribes. Regarding the designation of alternatives, one could easily assume a numbering from right to left. Designations such as right lane, middle right lane, middle left lane, and left lane will be avoided to prevent respondents to be influenced by the names of alternatives.

6.1.4. Attribute selection

Attributes are the building blocks of alternatives, and it is up to the researcher to select a set of attributes to describe the alternatives with. Since the objective of the study is to gain insights in the market share of labels and the relative importance of attributes, one would generally include all the attributes that are supposed relevant in the decision-making process of participants (Liebe *et al.*, 2021). However, relevance of attributes has been argued to be more important than quantity, because respondents have limitations in their ability to simultaneously process many attributes and might become tired, hence using heuristics that lead to biased outcomes (Green and Srinivasan, 1990). Another reason to be selective is that, in case of a typical online survey, participants are less engaged with the experiment and spend less time and effort on each choice task compared to for instance face-to-face interviews. Furthermore, there is a strong positive correlation between the number of attributes and the variance of the error component of estimated taste parameters. According to Caussade *et al.* (2005) it is the most influential design choice, and that even an increase from 3 to 5 attributes can increase the error variance significantly.

In the literature review part, there have been defined a set of factors that human drivers consider while making a lane-change. These are summarized in Table 3.2. A distinction can be between factors that are more tailored to the dynamics behind the execution of a lane change, and the ones that relate to the actual preferred lane choice. It is expected that, whether or not a pre-signal has been applied, traffic interactions remain roughly the same, and that the preferred lane choice of drivers is heavily affected by the type of signal. Therefore, this study is predominately interested in the factors that influence the preferred lane choice of drivers, and not that much in the ones that describe traffic dynamics. The most relevant factors from Table 3.2 have been selected to form the attributes of alternatives. The relevance and suitability of them were assessed based on the following reasoning:

- if a factor has a descriptive character that formulates the characteristics of an alternative, it must be incorporated as an attribute:
  - n.o. lane changes, queue lengths, and presence of heavy vehicles;
- if a factor is descriptive for characteristics of respondents, it may be relevant to include this in the section of additional sociodemographic questions:
  - aggressiveness / driving style, familiarity with fundamental purpose, and myopic vs. non-myopic drivers;

- if a factor satisfies one of the above, but its contribution can be extracted after the the analysis of research outcomes, it does not have to be incorporated as a separate attribute:
  - keep right desire, distance to end of each queue, and distance to next turning movement or stop line;
- if a factor relates to dynamic traffic interactions, it is assumed to be less relevant, and it most of the cases not suitable given the design choice to model traffic statically:
  - lane change classification, average speeds, relative position and speed, congestion level, plan ahead distance, and phase of traffic signal.

This already provides a clear insight in the order of magnitude of attributes that can be included in the SC experiment. Considering the line of reasoning as described above, three attributes will be included to describe differences in alternative characteristics (n.o. lane changes, queue lengths, and presence of heavy vehicles), and at least three sociodemographics will be asked to describe differences in respondent characteristics (aggressiveness / driving style, familiarity with fundamental purpose, and myopic vs. non-myopic drives). Some additional sociodemographics such as age and gender can easily be included, if desired, without any implications regarding the difficulties around too many attributes. Speaking of which, the relative low total of three attributes preserves a manageable choice task for respondents and prevents a significant increase in the variance of the error term.

Regarding the distance to the next turning movement or stop line, this predominately affects the willingness of drivers to execute (multiple) lane changes, implying that the closer the driver is to the stop line, the less tendency the driver yet feels to change lanes. This factor cannot be incorporated as an attribute of alternatives because its magnitude will be the same for every alternative, but it also cannot be overlooked. The same reasoning can be applied to the factor that describes the distance to the end of each queue. Although this varies per alternative, it still cannot be incorporated as an attribute of alternatives because its magnitude is dependent on other attributes, hence correlated. However, it is possible to assess its contribution by including the metric as an additional variable in the utility function of each alternative. To avoid respondents to be restricted from their desired lane choice, i.e. their desired lane choice is not the same as the lane they would queue up, sufficient space must be kept between the SPV and the end of the longest queue such that all lane changes can be executed. Here, it may be even valuable to ask participants if their chosen lane corresponds with their preferred lane.

6.1.5. Attribute level calibration

After the attributes have been selected, their levels can be determined, these are either qualitative or quantitative. It is straightforward that the attribute levels cannot be of qualitative data type, because neither can be described with non-numerical information. A further distinction among quantitative attributes is the measurement scale, which is either of interval or ratio type. Attributes with an interval scale are based on an order in which the absolute differences between levels are emphasized, while attributes with a ratio scale also include an absolute zero point. The latter implies that the selected attributes should have a ratio measurement scale, because they can all keep a zero value. Once the measurement scales have been defined, the attribute levels can be specified. It is advised to choose wide ranges, because all traffic conditions must be described by the same set of attribute levels. Furthermore, it increases reliability due to smaller standard errors of parameters, and it increases validity since interpolation is more reliable than extrapolation (E.J.E., 2022). However, all combinations of attribute levels should make sense and appropriate relative to other attributes, and whenever possible, equidistances must be preserved to assure orthogonality. In order to always guarantee appropriate combinations of attribute levels, they must be specified alternative specific and scenario specific. Alternative specific attributes allow for control of the traffic conditions in each lane, which are formed by the variation of attribute levels. And if the alternative specific attributes are specified per choice scenario, traffic conditions cannot only be controlled between alternatives but also between choice scenarios. This is essential given the fact that all four alternatives will not always be part of the choice set, and that for example the most right lane in scenario x might be the most left lane in scenario y. If not controlled, invalid alternatives may be created in the sense of a traffic being unrealistically distributed in the sorted area, and an incorrect pre-signal design.

The n.o. lane changes that are associated with a specific alternative is inherent to the alternative itself with respect to the overarching choice scenario, and can therefore not be further steered by design. The attribute levels of the queue length and heavy vehicle attributes on the other hand must be steered manually. This is done through varying the number and type of vehicles, together they form a set of traffic conditions for each alternative in a specific choice scenario. How these attribute levels are defined will be explained below.

When vehicles are statically inserted in the VISSIM model to form the alternatives' queues, the color and brand of each vehicle will be randomly picked, and a standstill distance of 2.00 meter will be kept according to the VISSIM's Wiedeman 74 car-following model. The average car length is 4.34 meter, which is based on a random selection of vehicles. The length of the sorted area in the model is set to 170 meters, which is based on the minimum advised length of 120 meters plus an additional keep clear area of 50 meters. Queued vehicles will be restricted from the keep clear area, yielding a residual space of 120 meters to queue up vehicles. However, sufficient space must be kept between the SPV and the end of each queue. This to avoid the feeling of respondents from being restricted to move towards their desired lane. This may reduce the residual space in the sorted area to queue up vehicles. Li *et al.* (2019) did effort in investigating the detrimental effects caused by a short sorting area, in which he was particularly interested in the unusable part of the sorted area. He observed that the majority of drivers would need a longitudinal displacement of 21 meters for a lateral displacement of 3.50 meters, while on average this relationship would be 30 and 3.50 meters respectively. The difference between them can be explained by the reasoning that drivers relax in their steering angle if traffic conditions are less crowded. Figure 6.1 shows a graphical presentation of these findings.

The keep clear area is meant to allow drivers to judge the traffic situation they are confronted with while providing sufficient space for drivers to feel able to execute their desired lane changes. The first 50 meters of the sorted area will be dedicated to the former, representing the point in the network where the video pauses, hence respondents make their

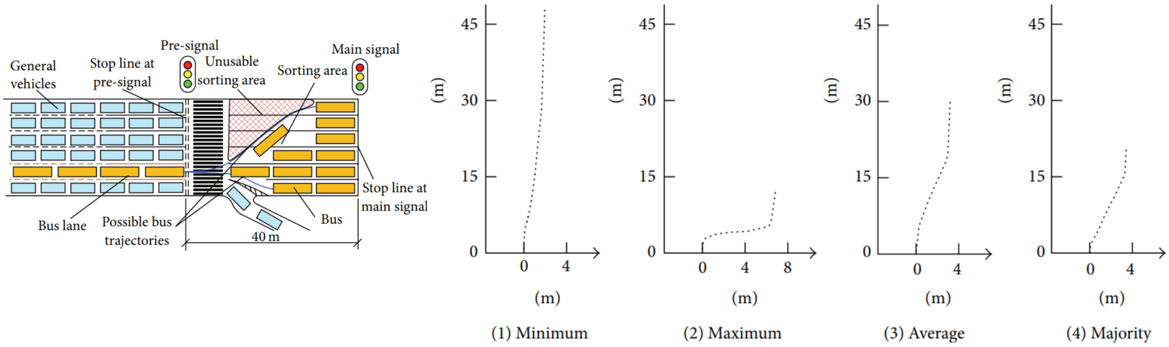
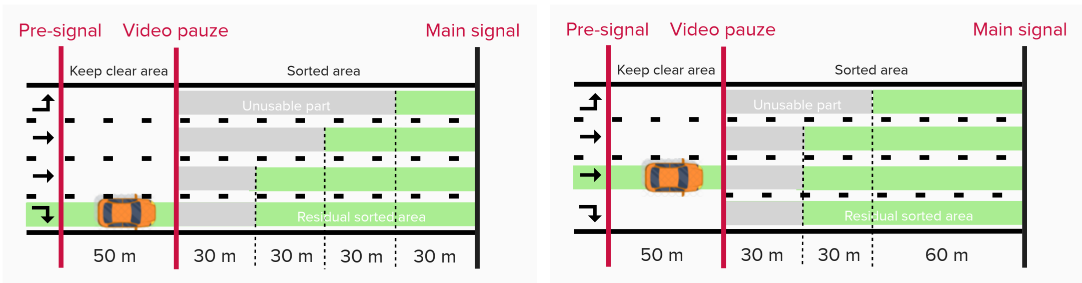


Figure 6.1. – Horizontal Displacement of Lane Changes and Their Adverse Effects on the Unusable Sorted-Area (Li et al., 2019)

desired lane choice. The latter refers to the unusable part of the sorted area. This area will be shaped by a longitudinal displacement of 30 meters for every single lane change to serve respondents with sufficient space for their desired lane changes. The ranges of the attributes must be designed such that they can define the queue for each alternative within the boundaries of the residual sorted area (RSA). Figure 6.2 shows two examples of how the unusable part of the sorted area and de RSA are shaped with respect to different choice scenarios.



I 3R.1 choice scenario II 4T.2 choice scenario

Figure 6.2. – Examples of the Unusable Part of the Sorted Area in Two Choice Scenarios

Given the average length of vehicles, the standstill distance, and the RSA, the ranges of the attributes can be specified in detail. The queue length of a specific alternative is constrained to the length of the RSA according to Equation 6.1. The maximum n.o. cars that fit in a RSE of 60 and 90 meters equals respectively 9 and 14. If 3 HGVs are part of the queue, this amount reduces to 3 and 8 respectively, representing a share of 50% and 27% HGVs in that lane. It is assumed that HGVs maintain a high keep right desire, yielding that only the two most outer right lanes contain HGVs. This is further specified in setting a maximum of 3 HGVs for the most outer right lane and a maximum of 1 HGV for the lane on the left side of it. Although a maximum share of 50% HGVs in a particular lane might feel unrealistic, the total share of HGVs of all lanes is just roughly a third or a fourth of it. This depends on the size of the sorted area that is considered in the choice scenario, but regardless of this size, these boundaries produce representative traffic type distributions and assure wide attribute ranges. Table 6.2 gives the alternative specific attribute levels per choice scenario as they follow from the above reasoning. Note that the attribute's subscripts correspond to the alternative in the choice set, i.e. the number of the lane.

$$N_{HGV} \cdot (L_{HGV} + L_{SS}) + N_{Car} \cdot (\bar{L}_{Car} + L_{SS}) \leq L_{RSA} \tag{6.1}$$

Where:

N_{HGV} = Number of heavy good vehicles in the queue

N_{Car} = Number of cars in the queue

L_{HGB} = Length of the heavy good vehicle = 10,22 m

$\bar{L}_{Car}$ = Average length of the vehicles = 4,34 m

L_{SS} = Standstill distance = 2,00 m

L_{RSA} = Length of residual sorted area

Table 6.2. – Maximum Ranges of Alternative Specific Attribute Levels per Choice Scenario

Attribute	**# Heavy good vehicles**				**# Vehicles of car type**				**# Lane changes**			
Choice Scenario	HGV_1	HGV_2	HGV_3	HGV_4	CAR_1	CAR_2	CAR_3	CAR_4	LC_1	LC_2	LC_3	LC_4
2R.1	[0, 3]	[0, 1]			[0, 8]	[0, 12]			0	1		
3R.1	[0, 3]	[0, 1]			[0, 8]	[0, 12]	[0, 9]		0	1	2	
2L.4			[0, 3]	[0, 1]			[0, 8]	[0, 12]			1	0
3L.4		[0, 3]	[0, 1]			[0, 3]	[0, 12]	[0, 14]		2	1	0
3T.2	[0, 3]	[0, 1]			[0, 8]	[0, 12]	[0, 14]		1	0	1	
3T.3	[0, 3]	[0, 1]			[0, 3]	[0, 12]	[0, 14]		2	1	0	
4T.2	[0, 3]	[0, 1]			[0, 8]	[0, 12]	[0, 14]	[0, 9]	1	0	1	2
4T.3	[0, 3]	[0, 1]			[0, 3]	[0, 12]	[0, 14]	[0, 14]	2	1	0	1
2R.1_C	[0, 3]	[0, 1]			[0, 8]	[0, 12]			1	0		
2L.4_C			[0, 3]	[0, 1]			[0, 8]	[0, 12]			0	1

Besides the amount of HGVs, it may be relevant to include an attribute of boolean type that states whether the last vehicle of the queue is of HGV or car type (0 = car type, 1 = HGV type), arguing that this might impact the desired lane choice. However, this would cause problems regarding the formulation of its attribute levels as they are dependent on other attribute levels. The levels of the CAR and HGV attributes form constraints for the levels of this additional attribute in cases when CAR_i or HGV_i obtain a level of zero. Then the level of this additional attribute is dependent on the attribute levels of those attributes. Hence, this variable is a result of, rather than a variable to be freely steered by design. To overcome this problem, one could still let it steer by design and remove incorrect defined attribute level combinations from the mathematical design of the SC experiment. Another solution would be to manually steer this attribute level based on the mathematical design, hence leaving it unchanged. The former would be inappropriate since this would let the mathematical structure collapse, therefore degrading the statistical benefits of orthogonality in the mathematical design. A choice has been made to adopt the latter strategy. This requires an additional variable to be included in the choice model without treating it as an attribute of alternatives in the mathematical design process. The name of this variable is stated as TRailing Vehicle heavy goods TRV_i and is not generic for all alternatives that consider HGVs. The ranges of the alternative specific variables are scaled relative to the range of the HGV-attribute of the corresponding alternative. To assure an equal probability of the trailing vehicle being of heavy good type, the range of TRV_i is set to [0,1] or [0,3] if the range of HGV_i equals [0,3] and [0,1] respectively. The highest value of the range is set to represent a heavy good vehicle as trailing vehicle. The main disadvantage of such a manual approach materializes itself when the variable will not be statistically significant after model estimation. Then it is unsure whether this insignificance is due to the absence of a mathematical supported configuration or a true irrelevance to the desired lane choice.

6.1.6. Variable calibration

Where attributes are particularly used to describe alternatives, there are also variables which do not rely on their own attribute, but follow directly from the interactions with attributes. In addition to the attributes, such variables can be included in the choice model as well. As discussed in Section 6.1.4, these variables included the distance to the end of each queue, and the distance to the next turning movement or stop line. While the latter expires due to a fixed video pause, the former still can be included in the choice model. This will be done with the alternative specific variable Distance Que $(DQ_1, DQ_2, DQ_3, DQ, 4)$.

Sociodemographics of respondents that have been addressed as valuable also need to be assigned to a variable. The driving styles of participants, denoted as DS_{angry}, DS_{risky}, $DS_{anxious}$, $DS_{dissociative}$, $DS_{careful}$, and $DS_{distress}$, are based on the six defined driving styles from Van Huysduynen *et al.* (2015). These were found relevant in the Netherlands and Belgium after a validation of the commonly-used multidimensional driving style inventory of BenAri *et al.* (2004). Such a driving behavior questionnaire of 44 elements is by far too complex and long-lasting to fully include in the SC experiment without exhausting any participants. Therefore, a more nuanced approach will be applied regarding the participant's self-assessment of his own driving style. Instead of asking all 44 elements, participants simply will be ask to rate all driving styles on a scale from 0 to 100 according to how these suit their driving style. Driving styles will be described with the three common characteristics which have been found to be decisive factors of that particular driving style. Table 6.3 shows how this question will be presented to respondents of the SC experiment. To eventually determine the driving style of the respondent, a data processing technique has been defined. Instead of simply looking at the maximum score a respondent has given, and therefore assuming that the driving style is a one-dimensional metric, an individual specific threshold value will be determined which sets the boundary for the respondent's driving style. This threshold is calculated by taking the sum of the mean scores of a participant and one standard deviation of the same scores. If the score on driving style x exceeds this threshold value, the driving style is coupled to that particular respondent. This is based on the approach of Van Huysduynen *et al.* (2015) who considers the driving style being a two-dimensional metric. Hence, besides the six defined driving styles, it is possible that combinations of multiple occur, which are denoted as DS_{other}.

Table 6.3. – Question to Obtain the Driving Style of Respondents in the Questionnaire

Consider the following six driving styles and their common characteristics:	
1. Angry driving - Blow my horn at others - Swear at other drivers - When a traffic light turns green and the car in front of me doesn't get going immediately, I try to urge the driver to move on	**2. Risky driving** - Enjoy the excitement of dangerous driving - Like to rake risks while driving - Enjoy the sensation of driving on the limit
3. Anxious driving - Feel nervous / uncomfortable while driving - Feel I don't have control over driving - Feel distressed while driving	**4. Dissociative driving** - Attempt to drive away from traffic lights in third gear - Plan my route badly, so that I hit traffic that I could have avoided - Distracted or preoccupied, and suddenly realize the vehicle ahead has slowed down, and have to slam on the breaks to avoid a collision
5. Careful driving - Tend to drive cautiously - Base my behavior on the motto "better safe than sorry" - On a clear freeway, I usually drive at or a little bit below the speed limit	**6. Disstress-reduction driving style** - Do relaxing activities while driving - use muscle relaxation techniques while driving - I daydream to pass the time while driving
Rate each driving style according to how they would suit your own driving style.	

Prior to the start of the SC experiment, respondents will be informed about the fundamental purpose of the pre-signal. From the literature review it was derived that this factor was an important contributor to the lane-change behavior of drivers. Respondent will not be familiar with pre-signals, but irrespective of such familiarity, there will be myopic and non-myopic drivers among the respondents, for whom it is expected that non-myopic drives take into account downstream actions into their lane-change behavior. Since respondents are provided with a context that they have to imagine while making a desired lane choice, their choice could be specifically influenced by this context if they are non-myopic classified. As an example, participants have to imagine that they make a turn at the main intersection to continue their route on another highway. Before merging into that highway, it is common practice that an onramp with multiple lanes merges to a single lane, and participants might plan ahead to avoid such additional downstream lane changes. This expresses itself in a potential higher keep right desire among non-myopic drivers. For this reason, the question will be asked: *while making a desired lane choice, did you plan ahead to potentially avoid any additional lane changes further downstream your route?*. This question may be answered with either yes or no.

Furthermore, there will also be questions asked about the participant's common driving direction, driving license, and driving experience. Although these sociodemographics have not been defined as influencing factors for their lane-change behavior, it might be interesting to test whether or not there persist significant taste or preference heterogeneities among those classifications. Of course, having a valid driving license is necessarily for participating the questionnaire. Besides that, the respondents' common driving direction may influence the desired lane choice, therefore respondents will be asked to state the driving direction they are used to (right-handed traffic, left-handed traffic, and both). It is expected that the majority of respondents is used to right-handed traffic, hence others will be removed from the data set. Last, driving experience may play a significant factor in the behavior of drivers, therefore respondents will also be asked to state their frequency of driving a motorized vehicle. Hereby, they can choose from daily, weekdays, three to four times a week, once a week, one to three times per month, and less often than once a month. In addition, participants have to state if they are in possession of a valid driving license for over or under 5 years. Table 6.4 provides a summary of how the previous discussed parameters and sociodemographics, in addition to the attributes as defined in Table 6.2, will be included in the questionnaire.

Table 6.4. – Specification of The Additional Variables and Demographics to Include in the Choice Model

Parameter	**Notation**	**Data type / measurement scale**	**Levels**	**Questionnaire**
Trailing vehicle	TRV_i	Qualitative / nominal	{yes, no}	N/A
Distance queue	DQ_i	Quantitative / interval	[32, 120]	N/A
Driving style	DS	Quantitative / nominal	{angry, risky, anxious, dissociative, careful, distress, other}	Rate each driving style according to how they suit you.
Myopic driver	MYP	Qualitative / nominal	{yes, no, other}	While making a desired lane choice, did you plan ahead to potentially avoid any additional lane changes further downstream your route?
Driving direction	DR	Qualitative / nominal	{right-handed, left-handed, both}	To what driving direction are you familiar?
Frequency of driving	FREQ	Qualitative / ordinal	{daily, weekdays, 3-4 times a week, once a week, one to three times a month, less than once a month}	How frequently do you drive a motorized vehicle?
Driving license	DL	Qualitative / ordinal	{<5 years, 5+ years}	How long have you been in possession of a valid driving license?

6.2. Mathematical design of the stated-choice experiment

This section focuses on the mathematical design of the SC experiment. This process typically entails the following two steps:

IV Determine the n.o. choice tasks in an experiment design;

V Choose an experimental design strategy.

6.2.1. The choice task size of the SC experiment

An experiment design of a specific choice scenario is a design matrix X, where each row represent a unique choice set s in choice task S, and its columns define the attributes levels of the alternatives in s. Each choice set with a specific attribute level configuration is called a profile. The total n.o. profiles $|S|$ then defines the size of X, which depends on the number of attribute taste parameters K that have to be estimated in the choice model, and the adopted design strategy. For estimating K attribute taste parameters, there have to be sufficient variation in X to preserve significance. If a choice has been made among a choice set of $|J|$ alternatives, this provides a single piece of information about the alternative being preferred above $|J|-1$ alternatives. In order to properly estimate K attribute taste parameters, there have to be more pieces of information than parameters to estimate, thus the minimum size of X can be defined by finding the smallest integer that satisfies Equation 6.2. Here, attribute level balance (ALB) may be considered, which means that all attribute levels appear equal times across all s $\in S$, and assures that all estimated parameters have an equal probability of becoming statistically significant. Although this is not a requirement, some degree of ALB is often desired to prevent imbalances in data coverage.

$$|S| \leq \frac{K}{|J|-1}. \tag{6.2}$$

Besides ALB, orthogonality must be preserved in the design since it assures that the attributes are uncorrelated. To illustrate what this means, consider the attributes quality and price. In real life alternatives, we find quality and price to be correlated: that is, a higher quality service is generally more expensive. However, if you apply a basic plan to construct hypothetical profiles, you obtain profiles in which quality and price are not correlated. Hence, you construct the profiles in such way that you have as many profiles in which low quality is paired with a low price option as you have profiles in which a low quality is paired with a high price. Although the complete set of profiles may not be representative of all the alternatives you find in real markets, you need those orthogonal profiles to estimate models in an efficient way. If one estimates linear models (like regression models), orthogonal designs result in the most efficient models. This means that estimated parameters have the lowest standard errors possible. Thus, orthogonal designs result in the most reliable parameters, thus the lowest required n.o. respondents, if linear model are estimated. This does not hold for non-linear models such as Logit models. Although such optimizations will not be achieved with Logit models, it still provides a solid basis against the full factorial design schemes. Orthogonal design schemes have been frequently published by mathematicians and can be constructed with the software Ngene.

By making use of the software Ngene, there have been experimented with the step size within the maximum attribute level ranges from Table 6.2 to limit the number of S. A smaller size of S reduces the overall choice task demand which will limit the time duration of the SC experiment and therefore the required n.o. respondents. The step size determines the set of values an attribute can take. As an example, the range [0,12] of attribute CAR_2 in choice scenario 2R.1 can be split into 0,3,6,9,12 with step size 3 or 0,4,8,12 with step size 4. It turned out that S is minimized and ALB is preserved if ranges were only divided into a set of two and four levels, instead of also splitting them in three or more levels. The latter either tripled the size of S or failed in finding an orthogonal design. However, the maximum attribute level ranges as defined in Table 6.2 cannot all be equally split into sets of two and four levels. Therefore, slight adjustments has te be made to shape the attribute levels within the boundaries of a relative small size of S, these are given in Table 6.5.

Table 6.5. – Attributes Levels Per Choice Scenario and Corresponding Size of Choice Task S

Attribute	**# Heavy good vehicles**				**# Vehicles of car type**				**# Rows**
Choice Scenario	$HGV1_1$	HGV_2	HGV_3	HGV_4	CAR_1	CAR_2	CAR_3	CAR_4	N/A
2R.1	{0,1,2,3}	{0,1}			{2,4,6,8}	{0,4,8,12}			8
3R.1	{0,1,2,3}	{0,1}			{2,4,6,8}	{0,4,8,12}	{0,2,4,6}		12
2L.4			{0,1,2,3}	{0,1}			{2,4,6,8}	{0,4,8,12}	8
3L.4		{0,1,2,3}	{0,1}			{0,1,2,3}	{0,4,8,12}	{0,4,8,12}	12
3T.2	{0,1,2,3}	{0,1}			{2,4,6,8}	{0,4,8,12}	{0,4,8,12}		12
3T.3	{0,1,2,3}	{0,1}			{0,1,2,3}	{0,4,8,12}	{0,4,8,12}		12
4T.2	{0,1,2,3}	{0,1}			{2,4,6,8}	{0,4,8,12}	{0,4,8,12}	{0,2,4,6}	12
4T.3	{0,1,2,3}	{0,1}			{0,1,2,3}	{0,4,8,12}	{0,4,8,12}	{0,4,8,12}	12
2R.1_C	{0,1,2,3}	{0,1}			{2,4,6,8}	{0,4,8,12}			8
2L.4_C			{0,1,2,3}	{0,1}			{2,4,6,8}	{0,4,8,12}	8

6.2.2. The experimental design strategy of the SC experiment

So far only the default design approach of orthogonal designs have been proposed as a potential experimental design strategy for the SC experiment. Although this is the most common design methodology, it still is not the most desired methodology for this study due to the lack of information optimization for the incorporated Logit models. Hence, orthogonal designs are not able to optimize the parameter estimation and therefore require more respondents to reach statistical significance. A more state-of-the-art design strategy called *efficient designs* on the other hand tries to maximize the information gathered from choices by balancing the utilities of alternatives in the choice set. Then, dominant alternatives in the choice set are replaced by information-rich alternatives by design, yielding a decrease in the size of S. Dominant alternatives can be seen as alternatives which are obviously the best or worse scoring alternatives, and thus containing zero to little information about the respondent's trade-off. Dominant alternatives are at least better on one attribute and not worse on all others. For the SC experiment, this means that traffic queues of alternatives will be more or less balanced against each other with respect to their required n.o. lane changes. This would be another reason to apply efficient designs since it further illuminates unrealistic traffic environments by design, following from the reasoning that large traffic imbalances within the sorted area are unrealistic. Finally, a third reason to apply efficient designs is the ability to calculate the exact n.o. respondents that are required for each parameter to reach statistical significance, instead of relying on some rule of thumb which may be much larger than actually required.

Efficient designs require priors, which are 'best guesses' of the parameters to be estimated, and are needed to balance the utilities of the choice alternatives. Priors can be obtained by consulting previous literature or by conducting a small pilot study of about 30 respondents (E.J.E., 2022). Since the former is not available, as this is the pure objective of this study, a small pilot study must be conducted to obtain priors. Utility functions and the choice model must be specified beforehand, given that a design is only efficient for a particular model and if the priors are representative for the final estimated parameter values.

6.2.3. Data analysis strategy

Since the utility functions and underlying choice model must be defined beforehand when using efficient designs, and given that these also affect the data analysis part, it is crucial to simultaneously define one strategy that includes both. Figure 6.3 schematically displays this strategy. It includes the steps that are, from this point on, required to estimate the best performing model under the decision to incorporate efficient designs. These steps are hierarchically structured from top to bottom with some additional characteristics provided on the sides that concern the choice model and experimental design type.

As illustrated in Figure 6.3, the profiles of the pilot study will be constructed with the use of orthogonal designs after the utility functions for alternatives have been defined. Before the pilot study can be distributed, the questionnaire design needs to be completed. General tasks in this process are incorporating the remaining parts of the questionnaire, such as the addition of the introduction, videos from the 3D traffic environment, sociodemographics and other screen-out questions. All these steps will be completed within the current chapter. The next chapter includes the acquiring of priors, the redesign of the SC experiment, and the execution of the main experiment. After the priors have been estimated, profiles will be reconstructed with the use of efficient designs to balance the utilities of alternatives, and the videos of the 3D traffic environment need to be readopted according to the changed profiles.

Figure 6.3 also illustrates the data analysis strategy, which is not relevant for now. Therefore, this part will be elaborated upon greater in-depth in Chapter 7.

6.2.4. The construction of the pilot study´s profiles

Before any profiles can be constructed, the alternatives' utility functions have to be specified. These can directly be derived from Table 6.5, which specified the levels that attributes can take with respect to choice scenarios. Appendix A.1 gives an overview of the utility functions of alternatives for all choice scenarios, and Equation 6.3 only gives one example of

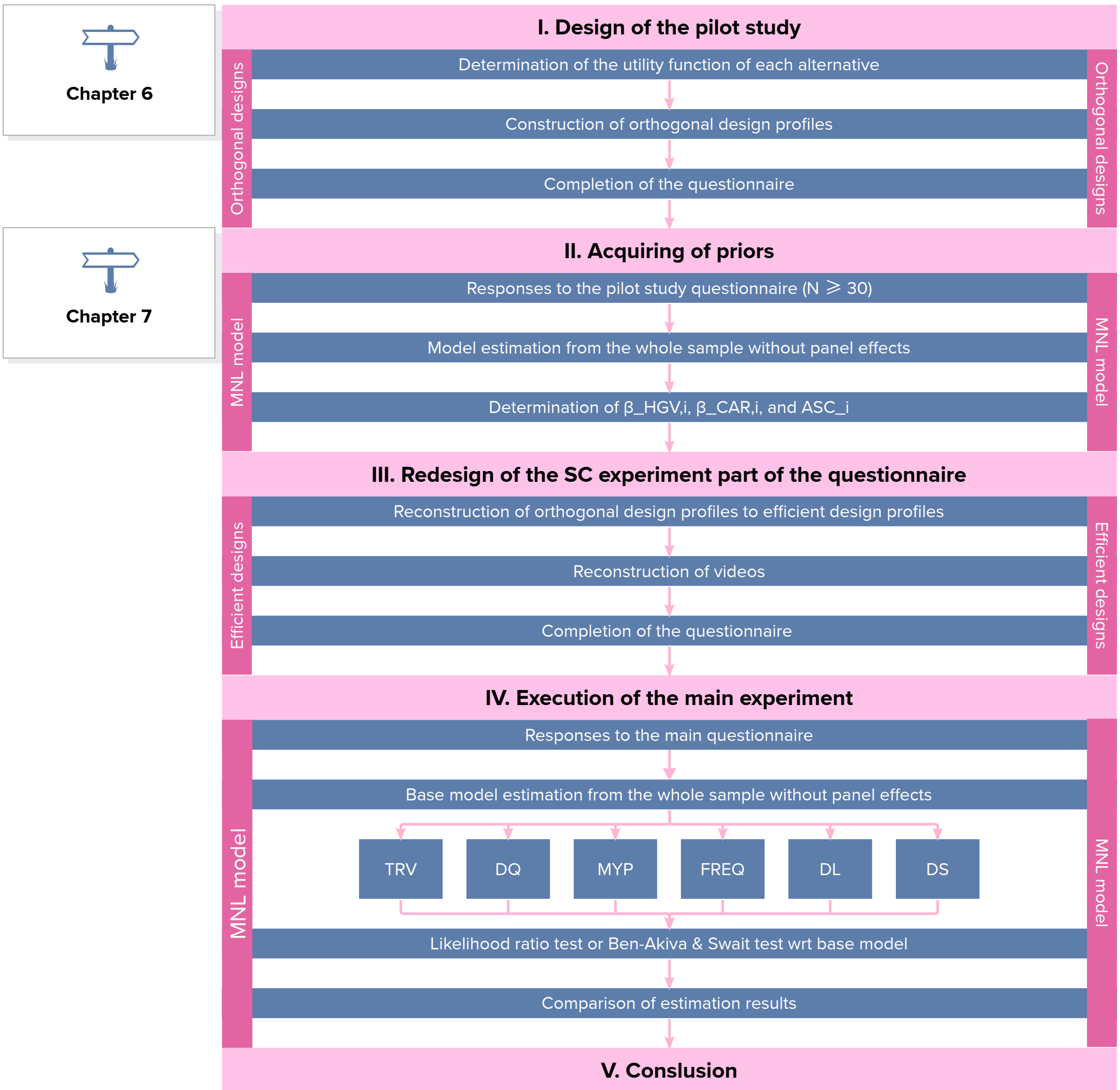


Figure 6.3. – Experimental Design and The Data analysis Strategy

the 4T.2 choice scenario. Note that the required n.o. lane changes cannot be included in the utility function as a separate attribute, because it is inherent to the alternative and therefore described by its label. However, it is possible to add an alternative specific constant (ASC) to the utility functions for alternative that require lane changes. An ASC is a parameter that estimates the average preference / utility that is associated with factors other than the observed attributes. Although this is a somewhat indirect way of measuring the effect of lane changes, it is expected that the majority of the average preference originates from the lane-changing aspect. Nevertheless, unforeseen preferences may also be reflected by the ASC parameters.

$$
\begin{aligned}
\mathrm{U}_{4T.2}(L1) &= ASC_1 + \beta_{HGV,1} \cdot HGV_1 + \beta_{CAR,1} \cdot CAR_1 + \varepsilon_{4T.2} \\
\mathrm{U}_{4T.2}(L2) &= \beta_{HGV,2} \cdot HGV_2 + \beta_{CAR,2} \cdot CAR_2 + \varepsilon_{4T.2} \\
\mathrm{U}_{4T.2}(L3) &= ASC_3 + \beta_{CAR,3} \cdot CAR_3 + \varepsilon_{4T.2} \\
\mathrm{U}_{4T.2}(L4) &= ASC_4 + \beta_{CAR,4} \cdot CAR_4 + \varepsilon_{4T.2}
\end{aligned}
\tag{6.3}
$$

Where:

$\mathrm{U}_{4T.2}(Li)$ = Systematic utility of alternative with lane number$i$in choice scenario 4T.2;

ASC_i = Alternative specific constant of alternative i;

$\beta_{HGV,i}$ = Alternative specific attribute weight of heavy good vehicles for alternative i;

HGV_i = Number of heavy good vehicles in alternative i;

$\beta_{CAR,i}$ = Alternative specific attribute weight of car vehicles for alternative i;

CAR_i = Number of car vehicles in alternative i.

The utility functions and some basic coding served as in input for Ngene to construct profiles. As an example, this resembled for choice scenario 4T.2 as:

```
design
;alts = L1, L2, L3, L4
;rows = 4
;orth = sim
;model:
U(L1) = b0 + b1 * HGV1[0,1,2,3] + b2 * CAR1[2,4,6,8]/
U(L2) = b3 * HGV2[0,1] + b4 * CAR2[0,4,8,12]/
U(L3) = b5 + b6 * CAR3[0,4,8,12]/
U(L4) = b7 + b8 * CAR4[0,2,4,6]
$
```

The first line of the syntax is the keyword for the start of the design. Next, the labels of alternatives and the target for the n.o. rows are defined. The latter is set to an arbitrary value of 4, which is by far too low for an orthogonal design, and is chosen so that Ngene constructs an orthogonal design with a minimum n.o. profiles. Then, Ngene is instructed to apply simultaneous construction for generating the choice sets, which is required for labeled alternatives. As a result, each row of the constructed orthogonal design represents a choice set, and there will be no correlations within and between alternatives. This is desired because the higher the correlations between attributes, the larger the standard error of the parameters. Finally, the model is shaped by its utility functions. After running the script, Ngene generates profiles for the 4T.2 choice scenario which are given in Table 6.6. Note that the levels of the trailing vehicle variable are manually inserted, indicated with low subscripts.

Table 6.6. – By Ngene Generated Profiles of the 4T.2 Choice Scenario with Manually Inserted TRV Levels

Design 4T.2						
Choice situation	**L1.HGV$_1$**	**L1.CAR$_1$**	**L2.HGV$_2$**	**L2.CAR$_2$**	**L3.CAR$_3$**	**L4.CAR$_4$**
1	1_1	2	1_0	4	4	2
2	2_1	4	0_0	12	4	0
3	3_1	6	0_0	8	0	2
4	1_1	8	0_1	4	8	0
5	2_0	6	1_3	0	12	0
6	0_0	4	1_1	8	8	2
7	0_0	8	0_1	0	4	6
8	3_0	4	1_3	0	0	4
9	0_0	6	1_2	12	0	4
10	2_1	2	0_2	4	8	6
11	1_1	2	0_2	8	12	4
12	3_0	8	1_3	12	12	6

A full overview of the by Ngene generated profiles per scenario are given in Appendix A.2. The adopted strategy to manually assign the levels of TRV variable is as follows. First, the generated profiles constrain parts of the levels:

- if a profile contains an alternative with no HGV, then TRV obtains a level of 0 if $HGV_i \in [0, 1]$ and [0,1,2] if $HGV_i \in [0, 1, 2, 3]$ to indicate that the trailing vehicle is not a HGV;
- if a profile contains an alternative with no vehicles of car type, then TRV obtains a level of 1 if $HGV_i \in [0, 1]$ and 3 if $HGV_i \in [0, 1, 2, 3]$ to indicate that the trailing vehicle is a HGV;
- if a profile contains al alternative with neither HGVs nor cars, then TRV obtains a level of 0 if $HGV_i \in [0, 1]$ and [0,1,2] if $HGV_i \in [0, 1, 2, 3]$ to indicate that the trailing vehicle is not a HGV.

Then, attribute level balance is preserved by equally distributing all levels across the remaining unconstrained profiles. Finally, utilities are balanced as much as possible. This provides an advantage compared to a strategy that randomly assigns the remaining levels as it increases the information-richness of choices.

6.3. Reflection on the hypothetical bias

The literature review emphasized the undoubted presence of the hypothetical bias (HB), where its main sources were reflected upon mitigation strategies. Throughout the previous two chapters, there already have been anticipated to limit the impact of the HB. These included the design of a 3D traffic environment and the decision to incorporate video based questioning. This particularly employs the strategy of referencing & pivot designs to compensate for the lack of knowledge and familiarity with pre-signals. However, there have been specified multiple sources of the HB for which no strategy have been adopted yet. For this, a distinction is made between ex-ante and ex-post mitigation strategies.

6.3.1. Ex-ante mitigation

Ex-ante mitigation strategies are characterized by their application in the design process of an experiment. Therefore, adopting such a mitigation strategy directly concerns the design of the questionnaire. The HB sources as defined in Figure 4.1 are either not relevant for this study, not possible to mitigate, or desirable to mitigate. To begin with the former, deceitful strategic answers are not expected to play any role since respondents have no reason to purposely hide true preferences in favor of themselves. Surprisingly, this is the only source of HB of which is not expected to play any role. Regarding the not mitigated sources, it is expected to find a persistent lack of dynamic learning & adaptation among respondents. This is the result of the design choice to let respondents repeatedly make a choice when the video pauses, without showing them the consequences of their choice. As a result, respondents will be actual 'dumber' than they would be in real life, and may therefore spread differently, introducing a HB. Finally, there are several sources of the HB which are desirable to mitigate: lack of consequentiality, lack of incentive compatibility, hot-cold-empathy gap, and minimizing of cognitive effort.

A lack of consequentiality is usually associated with the feeling of having no or little social or political impact, and restrains respondents from truthful behavior and a considerable cognitive effort into their responses. Therefore, a consequentiality script will be used that emphasizes the respondent's contribution to the ongoing process of improving our traffic networks. Within the questionnaire, the script will be incorporated a priori the SC experiment. To further increase the cognitive effort of respondents, a similar strategy as the time-to-think method will be applied in the questionnaire. Where the operational driving task normally forces drivers to make decisions in (split) seconds, this might not be the most appropriate time interval to allow respondents to choose their desired lane alternative. This can be strengthened with the reasoning that respondents are unfamiliar with the pre-signal concept, hence they need more time to understand the traffic environment, make a well-considered decision, and select their desired alternative. Instead of setting a time limit to each question, responses will be timed. By doing so, respondents will be unaffected by any time pressure to put as much cognitive effort as they desire. Besides that, respondents can be explicitly tracked to validate responses on both the questionnaire level as well as the individual question level, i.e. to eliminate too quick answers that are faster than the time duration of the video. It even enables the possibility to dedicate a separate variable to the response time and check if there are significant taste and preference differences between for example slow and fast respondents, which is rather ex-post. Although the time-to-think method has been proven to mitigate parts of the hot-cold-empathy gap, the relative low extension of the thinking time in this experiment is expected to reduce that impact on HB mitigation.

Given the applied Random Utility Maximization principle, the SC experiment must be incentive-compatible to mitigate the HB originating from a lack of incentive-compatibility. An instrument is called incentive-compatible if all respondents can achieve the best outcome to themselves just by acting according to their true preferences (Nisan *et al.*, 2007). A lack of it materializes itself in for example speeding, a phenomenon of fatigued respondents who rush through the question to finish the experiment or to secure their gift / reward. To prevent respondents from speeding, the time duration of the experiment must be limited to a manageable amount. Besides that, traditional encouragement for participating in the experiment such as small rewards or gift cards will not be offered to prevent respondents from being incentive-compatible towards their reward instead of the true purpose of this study: optimizing their own interest in the pre-signal environment. To the researcher's opinion, the ideal length of a questionnaire is one that balances the interest of the research with the readiness of respondents. In general, questionnaires should include about a maximum of 25-30 questions and preferably take 8-12 minutes to prevent the completion rates from falling significantly, and to limit speeding (SurveyMonkey, n.d.; Sharma, 2022). If slightly exceeded, it is expected to have limited impact on these phenomena since the use of videos will help the respondents to enjoy the questionnaire, and prevent them from endless exhausting reading. In addition, the pilot study enables the possibility to check if respondents felt exhausted due to either the time duration or the complexity level of the questionnaire. If so, slight adjustments can be considered in the design of the main experiment. Finally, real talk scripts will be used to inform respondents before the experiment about the version of hypothetical scenarios they will encounter, and to emphasize that there will be a similar version as follow-up that included non-hypothetical scenarios. This will prompt respondents to be consistent with their real preferences. Those real talk scripts are only relevant for choice scenarios 2R.1 and 2L.4 which both have a counterpart scenario.

6.3.2. Ex-post mitigation

Ex-post mitigation strategies are characterized by their application in the model estimation process. Two ex-post mitigation strategies already have been considered in the design of the SC experiment, although not mentioned explicitly. One of them includes the potential application of ML models to compensate for panel effects, i.e. to mitigate the coherent arbitrariness, which states that respondents tend to seek consistency in their choices and the first choice, even if chosen randomly, will affect consecutive choices. Unfortunately, ML models will not be estimated, therefore ignoring the panel structure in the data. The other includes some form of choice certainty scales to compensate for social desirability & self-image regarding the self-assessment of the respondents' driving style. The driving styles were extremes on the social higher and lower end of the range, arguing that no one would rather associate themselves with a somewhat negative designation. Therefore, it was chosen to provide a sort of certainty scale for each driving style, and to normalize that obtained data.

RP assisted estimations turned out to be a frequently applied method in the field of behavioral studies for transport and traffic to investigate the existence of the HB. Since revealed preference data is unavailable, RP assisted estimation cannot be incorporated.

6.4. Questionnaire development

This section translates the in Chapter 5 & 6 defined design components into a questionnaire that is ready to be distributed as pilot study. The questionnaire is split up into three main sections: introduction, SC experiment, and screen-out questions.

6.4.1. Part I introduction

The introduction provides respondents with general information about the experiment. Consequentiality scripts and real talk have been applied here to mitigate the HB. Further attention must be paid to the privacy & security regulations of the TU Delft with respect to dealing with personal data. For that, the suggested informed consent script from the TU Delft has been included in the questionnaire. This resembled as:

Consent and Data Protection Notices.

You are being invited to participate in a research study on lane change behavior at pre-signals. This is being done by R.C. van Rooijen from the TU Delft.

This research aims to investigate the spreading behavior of human drivers at a new type of traffic light, **the pre-signal**, and will take approximately **X minutes** to complete. The data will be used for **scientific reasons** only to investigate whether such an innovative traffic light can be effective in solving delays at crowded signalized intersections. For that, we need **your help**! While participating in this questionnaire, you therefore directly contribute to the ongoing process of improving our traffic networks.

Before the start of the questionnaire, you will be briefly informed about the working of the pre-signal. Then, you will be asked to watch a short video that is recorded from your perspective as a driver of the car. When the video stops, you will be asked to **select the lane in which you prefer** to queue up. This will be repeated X times. Finally, some personal questions will be asked.

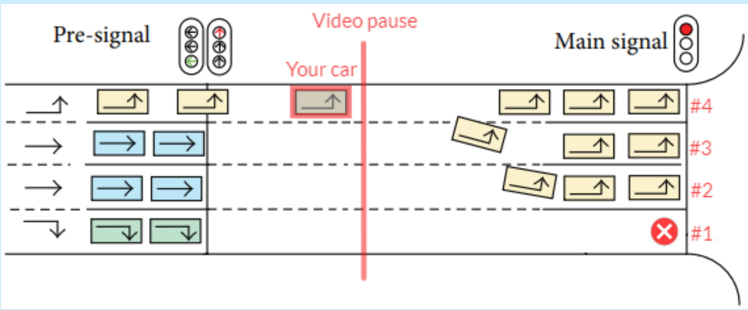
As with any online activity, the risk of a breach is always possible. To the best of our ability, your answers in this study remain confidential. We will minimize any risks by keeping the questionnaire **anonymous** and collecting data in accordance with the General Data Protection Regulation (GDPR). Your participation in this study is entirely **voluntary** and you can withdraw at any time.

	Yes	No
I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	◯	◯
Please confirm that you have a valid driving license.	◯	◯

Till this point, respondents are only informed about the general purpose and outlook of the questionnaire. This prior knowledge is not sufficient for being able to participate in the next part of the questionnaire: the SC experiment. Respondents have to understand the working of the pre-signal system before they can even select their desired alternatives. Hereby it is of interest to always keep in mind that such additional knowledge may steer the behavior of respondents. Therefore, respondents will be only taught in the core elements of a pre-signal system and the decisions drivers face while encountering such a system. Additional knowledge such as the conditions when pre-signals can be effective in solving delays at crowded signalized intersections will not be granted, since it steers behavior to the needs of this research. This section resembled as follows:

An introduction to pre-signals.

The figure below gives a schematic example of the environment you will enter while watching short videos from the driver´s seat perspective. The pre-signal is **an additional** traffic light before the one of the main intersection, and **works the same** as the traffic lights you are used to. The purpose of the pre-signal is to give green to only one traffic stream (i.e. right, straight, and left) at the same time to let them continue their route to the main intersection. As traffic streams are now **fully separated** by the pre-signal, drivers can spread themselves across **multiple lanes** of the main intersection´s cross-section instead of just only one. This **shortens the queue lengths** of the main intersection, hence you may experience shorter delays.



The videos start with your car approaching a red pre-signal. The car starts driving towards the main intersection when you get green from the pre-signal. After a distance of 50 meters, the **video pauses** and **zooms out** to provide you with a clear view of the traffic situation. Then, you will be asked to **select the lane in which you prefer** to queue up for the main intersection (#1, #2, #3, or #4). Press play to view an example of the video.

<Video example.>

The video above represents just one **random example** of left-turning traffic that can spread itself across the three most left lanes (#2, #3, and #4). You may encounter other traffic conditions.

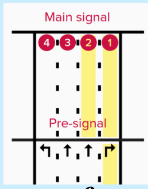
6.4.2. Part II stated-choice experiment

Most of the effort spent in this chapter has been dedicated to this part of the questionnaire. Largely all elements have already been defined yet, with the exception of the SC experiment's outlook in the questionnaire. This looks similar to:

Stated Choice Experiment.

After completing the questions relating to pre-signals, you will also be asked to execute the same process in a traffic environment as you would encounter it in real traffic, so without any pre-signals [a].

For now, **imagine**[b] that you want to turn right to the A27 at an intersection with pre-signals and the pre-signal indicates that the **two most right lanes are open**:



In the upcoming questions, please **select the lane in which you prefer** to queue up for the main intersection.

If you are using a mobile phone, please rotate your screen horizontally for a higher-quality experience.

---

[a] This section implies the real talk script and will only be shown to respondents who encounter choice scenarios 2R.1 and 2L.4, which both have a counterpart scenario.

[b] The provided context to respondents depends on the choice scenario(s) they will encounter, see Table 6.1.

6.4.3. Part III screen-out questions

After the completion of the SC experiments, respondents will be asked to fill in some personal information. Retrieved data from this section will serve as the data input for the estimation of the parameters that relate to sociodemographics. These questions are the main reason why a data protection protocol has been drawn up. This section is designed as follows:

Screen-Out Questions.

To what driving direction are you familiar?

Drop down menu. ⌄

How long have you been in possession of a valid driving license?

Drop down menu. ⌄

How frequently do you drive a motorized vehicle?

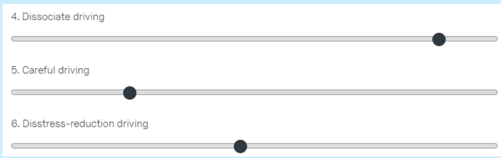
Drop down menu. ⌄

While making a desired lane choice, did you plan ahead to potentially avoid any lane changes downstream your route?

Drop down menu. ⌄

Six driving styles are described below by their general characteristics. Please read them carefully and rate them according to how much they suit your driving style.

<Description of driving styles.>



You are invited to leave any comments about the questionnaire and your experience. Note that this is optional.

<Put your comments here. >

We thank you for you time spent taking this survey.
Your response has been recorded.

6.4.4. Questionnaire distribution setup

Depending on the scenario, the questionnaire includes 9 or 13 videos of 23 seconds each with a total duration of approximately 3.5 and 4.5 minutes respectively. There remains enough time for respondents to finish the questionnaire within the maximum of 12 minutes. The Qualtrics environment is designed such that respondents will be randomly assigned to one choice scenario, while assuring that all will be evenly distributed among N respondents. This approach may not be the most desired for the two choice scenarios that also have a counterpart scenario, i.e. 2R.1 & 2L.4. It might be of value to let respondents who filled in the the 2R.1 or 2L.4 choice scenario, also present them with the corresponding counterpart choice scenario. This assures that the samples of respondents for these choice scenarios will be equal, therefore allowing to research the differences in driving behavior between traffic situations with and without a pre-signal more directly within the same sample.

An implication of this strategy concerns a double of video duration in the questionnaire for these particular scenarios. However, respondents are still provided with enough time to finish under 12 minutes with a total video duration of 7 minutes. By adopting this strategy, a 20% reduction of the required respondents will be achieved, because now Qualtrics will randomly vary 8 versions instead of 10. Considering all this, the decision has been made to combine the counterpart choice scenarios with their corresponding pre-signal choice scenarios. The pilot study offers an excellent opportunity to test the duration of the questionnaire. If too long, this decision still can be reversed for the main experiment.

6.5. Conclusion

This chapter implemented the design choices from Chapter 5 into the design of the SC experiment. The objective of this chapter was not to answer any research questions, but to develop a questionnaire that is able to extract the respondents' decision-making process of their preferred lane choice. The deliverables of this chapter therefore serve as a tool for answering the remaining research questions.

The questionnaire is split into three main parts: introduction, SC-experiment, and sociodemographics. The first part informs respondent about the research goals and the outlook of the experiment they are participating in. Hereby, it tries to explain as briefly as possible the pre-signal concept and its main working. The third part is more focused on extracting personal information from respondents, also known as the sociodemographics. Variables for driving direction, myopic level, driving style and frequency of driving have been incorporated here. Such personal data raised the the need for a data protection protocol. There have been accounted for the privacy & security regulations of the TU Delft, which is explicitly adjusted to the use of Qualtrics software.

The SC experiment in the questionnaire is the core component of the questionnaire. The design of this part concerned the specification of alternatives, attributes, attribute levels and their coding schemes, the n.o. choice tasks, and the experimental design strategy. Each lane of the sorted area is defined as a labeled alternative, which are characterized by three core attributes: n.o. heavy good vehicles, n.o. cars, and n.o. lane changes. Variables that might be extended to this base model concerned the distance to the end of each queue, and a heavy good vehicle being the trailing vehicle or not. The n.o. choice tasks and its underlying profiles are defined by Ngene. In this process, concessions had to be made to prevent the choice task size from being unacceptable large. These included the introduction of choice scenarios, managing the n.o. attributes, and the alignment of attribute level ranges. Regarding the experimental design strategy, efficient designs with priors turned out to be of high value for the reliability and validity of the experiment. This strategy increases the information-richness of choices by balancing the alternatives' in the choice sets, yielding to less required respondents and the ability to calculate its magnitude for statistical significance. Balanced utilities are found to secure balanced traffic queues with respect to their required n.o. lane changes, therefore representing real traffic conditions more closely, hence increasing the validity of the main experiment. To achieve this, priors have to be estimated in an additional pilot study of approximately 30 respondents per choice scenario.

Throughout the design of the questionnaire, attention have been paid to the presence and mitigation of the HB. Besides previous adopted measures, additional measures are applied to compensate for social desirability, the lack of consequentiality, the lack of incentive-compatibility, the hot-cold-empathy gap, and to increase the cognitive effort and consistency of respondents.

Part III. Data Generation & Model Estimation

7. Data generation & model estimation

This chapter represents the first and last chapter of the data generation & model estimation part. The pilot study questionnaire has been distributed for data collection. This chapter provides the route from processing this data into a new efficient design for the main experiment questionnaire. It also concerns the final model estimations to acquire results obtained from the main experiment, which allow to answer the the following three research questions:

- What trade-offs between the relevant lane-changing factors make human drivers in their desired lane choice downstream the pre-signal?
- How are these trade-offs affected by the driver's intended turning direction and the number of lanes in the sorted area?
- To what extent does the drivers' preferred lane choice downstream the pre-signal differ from one of a conventional signalized intersection without a pre-signal, and what are the implications of these differences for the applicability and efficiency of pre-signals in general?

The chapter starts with a brief review of the executed pilot study in Section 7.1. Then, the prior estimation for efficient designs in Section 7.2. These priors form the basis of the main experiment's efficient designs, which will be elaborated upon in the same section. Before the the main experiment can be executed, some anticipated changes from the pilot study will be adopted in the main experiment, which is elaborated upon in Section 7.3. After the execution of the main experiment, Section 7.4 provides a brief review of the main experiment's execution, and a more elaborated view on the gathered data set. Finally, the acquired model estimation strategy that is elaborated upon Section 7.5 lead to results, which are presented in the second part of this chapter. These results answer the sub-research questions of this chapter.

7.1. Pilot Study review

The distribution of the pilot study questionnaire faced some difficulties which were beyond exception. First, the videos in the questionnaire had troubles with loading properly for the majority of Apple phone users, and somewhat more irregular for respondents behind a secured connection. Furthermore, the respondents' feedback mostly concerned a discomfort regarding the video based questions. Although these videos were expected to be enjoying, some respondents felt annoyed by repeatedly watching 'the same' video and the need to wait until the end of each video. The latter originated from respondents who chose their preferred lane before the video end. This resulted in the belief of the questionnaire being too long. Nonetheless, there were also a lot of positive comments about the concept of a pre-signal and the questionnaire for not being as standard as expected.

All together, this led to a total of 243 respondents with a finishing rate of less than 50%. Such a low finishing rate is not desired for the main experiment, thus adjustments have to be made to reduce the impact of these unforeseen problems, and to maintain its feasibility. This will be elaborated upon in Section 7.3.

7.2. Prior estimation for efficient designs

The pilot study data set has been sorted per choice scenario and rearranged per individual, such that it can be run by an MNL choice model. An example of such a model is given in Appendix B.1 for the 4T.2 choice scenario. Each choice scenario has its own model, but all rely on the same type of inputs. These inputs include their corresponding utility functions and the alternatives that are part of its choice set. Priors are then estimated by running the models. An example of the 4T.2 choice scenario output as a result of running that model is given in Appendix B.2. Besides the prior estimates, the model also generates the statistics of the estimates in terms of its (robust) standard error and (robust) t-ratio. These allow to calculate the priors' significance level from zero, and the required n.o. respondents for the main experiment, i.e. the S estimate. For any significance level calculation, the robust standard error has been preferred over the standard error. Although there is no correlation modeling across the same individuals in MNL models, the script recognizes panel data, and processes this into the robust standard errors. Table 7.1 gives an example of such a calculation for the 4T.2 choice scenario. The full set of results can be found in Appendix B.3.

Table 7.1. – Example of Parameter Significance From Zero for the 4T.2 Choice Scenario

Choice Scenario							
4T.2	**Estimate**	**s.e.**	**t.rat.(0)**	**Rob.s.e.**	**Rob. t.rat.(0)**	**Confidence level**	**S estimate D / S error**
BETA_HGV1	-1.0722	0.2669	-4.0172	0.31315	-3.4238	99.9%	3.13 / 7.68
BETA_HGV2	-0.9656	0.41036	-2.353	0.36295	-2.6603	99.0%	15.73 / 33.49
BETA_CAR1	-0.146	0.10259	-1.4227	0.11876	-1.229	70.0%	28.32 / 35.37
BETA_CAR2	-0.3249	0.05752	-5.6495	0.06413	-5.0672	99.9%	2.19 / 4.11
BETA_CAR3	-0.3271	0.04792	-6.8273	0.05726	-5.713	99.9%	2.05 / 2.15
BETA_CAR4	-0.1495	0.08897	-1.6803	0.08322	-1.7962	90.0%	28.32 / 33.15
ASC1	-0.7127	0.67515	-1.0556	0.65494	-1.0882	70.0%	66.97 / 35.6
ASC3	0.1964	0.42509	0.4621	0.31901	0.6157	0.0%	Nan
ASC4	-1.9343	0.4236	-4.5664	0.58956	-3.281	99.8%	5.72 / 5.26

7.2.1. From priors to efficient designs

From Table 7.1, it can be noticed that the required n.o. respondents for the main experiment increases for priors with a lower confidence level, and that it decreases if the S error has been used instead of the D error. Ngene makes a difference between D-efficient and S-efficient designs. With such efficient designs, the orthogonality usually deteriorates, yielding parameter estimates to be correlated. D-efficient designs are optimized such that the variances of all parameters in a specific model are minimized. S-efficient designs on the other hand are optimized such that the variance is minimized for only one parameter, i.e. the parameter for which it is hardest to reach statistical significance. As a result, S-efficient designs decrease the required n.o. respondents for the least reliable parameter, hence decreasing the minimum required n.o. respondents for the whole model. Although a lower minimum for the model will be achieved, the required n.o. respondents increase for the other parameters of the model. The latter is exactly the reason why D-efficient designs are generally preferred above S-efficient designs: it takes into account the reliability of all parameters instead of being focused on the least reliable one. All choice scenarios except from 3T.2 & 4T.2 were estimated by using D-efficient designs. S-efficient designs have been applied on the 3T.2 & 4T.2 choice scenarios since they both produced one outlier of the required n.o. respondents. As an example, Table 7.1 shows the initial need of 67 respondents for the ASC1 parameter under a D-efficient design, while this decreased to 36 respondents under an S-efficient design. As as result, standard errors of the other parameters increase, yielding a higher required n.o. respondents for those ones, but without exceeding the 36 required respondents for the ASC1 parameter. Hence, the minimum required n.o. respondents for the 4T.2 choice scenario has been decreased from 67 to 36 through the S-efficient design.

The input for Ngene to generate the S-efficient design profiles is similar to the one in Section 6.2.4 for generating the pilot study profiles. However, this time Ngene is provided with additional prior estimates in brackets after the corresponding parameter. This allows Ngene to balance utilities in the constructed profiles. The Ngene's input resembled for choice scenario 4T.2 as:

```
design
;alts = L1, L2, L3, L4
;rows = 8
;eff = (mnl,s)
;con
;model:
U(L1) = b0[-0.7127] + b1[-1.0722] * HGV1[0,1,2,3] + b2[-0.146] * CAR1[2,4,6,8]/
U(L2) = b3[-0.9656] * HGV2[0,1] + b4[-0.3249] * CAR2[0,4,8,12]/
U(L3) = b5 + b6[-0.3271] * CAR3[0,4,8,12]/
U(L4) = b7[-1.9343] + b8[-0.1495] * CAR4[0,2,4,6]
$
```

Ngene's output again is a set of profiles for the 4T.2 choice scenario, which are given in Table 7.2. A full overview of the by Ngene generated profiles per scenario is given in Appendix A.3. Based on prior estimates and the generated profiles, Ngene also calculates the expected probability of an alternative being chosen in the choice set. If such a probability exceeds P=0.90, it is designated as a dominant alternative. Then, the whole profile must be removed from the choice task, since the respondents' choices are expected to provide too little information about their trade-offs. This phenomenon appeared in 2R.1, 2R.1_C, 2L.4 & 2L.4_C choice scenarios with a result of the attribute level balance characteristic being canceled.

Table 7.2. – By Ngene Generated Profiles of the 4T.2 Choice Scenario with Manually Inserted TRV_{HG} Levels and Corresponding Probability Distribution among Alternatives

Design 4T.2						
Choice situation	**L1.HGV$_1$**	**L1.CAR$_1$**	**L2.HGV$_2$**	**L2.CAR$_2$**	**L3.CAR$_3$**	**L4.CAR$_4$**
1	2_0	8	1_0	8	12	0
2	0_0	4	0_0	0	4	2
3	1_1	8	1_3	12	12	6
4	3_1	6	0_1	0	0	0
5	1_0	2	1_3	4	8	4
6	3_0	6	0_1	8	0	2
7	2_1	4	1_2	12	8	4
8	0_0	2	0_2	4	4	6
Probability distribution	**P(L1)**		**P(L2)**		**P(L3)**	**P(L4)**
1	0.08		0.13		0.09	0.69
2	0.17		0.61		0.16	0.06
3	0.38		0.06		0.14	0.43
4	0.00		0.46		0.46	0.07
5	0.33		0.27		0.19	0.21
6	0.01		0.06		0.84	0.09
7	0.17		0.04		0.38	0.41
8	0.38		0.28		0.28	0.06

7.2.2. Visual guidance to understand the process of efficient designs

This section is dedicated to novice readers in the field of choice modeling, who might not fully understood how priors led to a more efficient design. Remember that the main objective of the pilot study was to estimate priors, which are the 'best guesses' of the base models' parameters. With this additional prior knowledge, the researcher was able to balance the utility of alternatives in choice sets, therefore preventing dominant alternatives which do provide limited information about the respondent's choice. Hence, the information-richness of the respondents' choices becomes more efficient. Within Figure 7.1, this can be visually retraced for choice scenario 3R.1 by just comparing the vertical space between the profiles' probability. Where probabilities in the pilot study are positioned more on the higher and lower limits, they are significantly more balanced in the main experiment. As a result, the required n.o. respondents decrease as well as the choice task size for each respondent, i.e. from 12 to 8 preferred lane choices per respondent. Besides that, the balanced utilities secured more realistic traffic conditions, because it prevents large traffic imbalances within the sorted area. Hence, efficient designs increased the efficiency, reliability and validity of the acquired data.

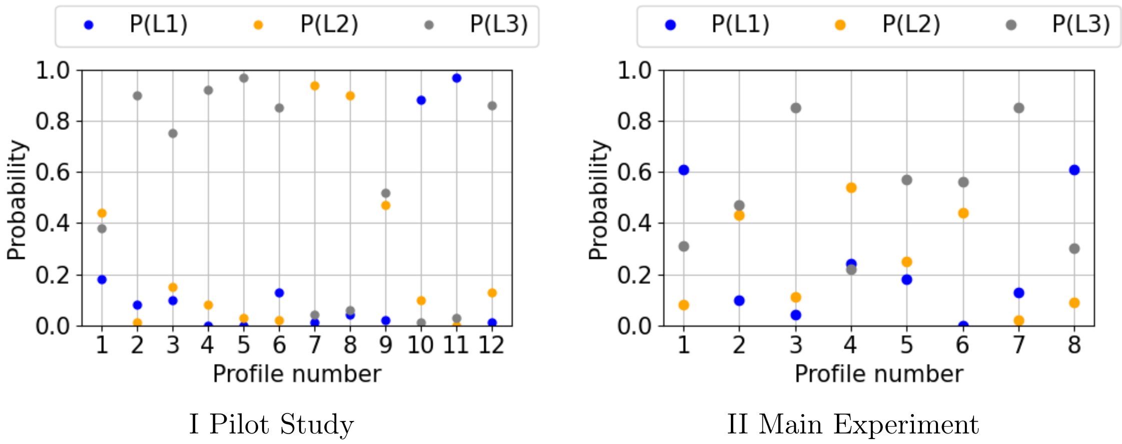


Figure 7.1. – Probability Distribution of the 3R.1 Choice Scenario for Both Pilot Study and Main Experiment

7.3. Anticipated changes from pilot study to the main experiment

Before any changes to the main experiment can be considered, it is valuable to get insight in the size of the main experiment in terms of the required n.o. respondents per choice scenario. This is summarized in Figure 7.2. It seems to hold that the minimum required respondents increase with the size and complexity of the choice scenario. This could be the result of driving behavior among respondents being less consistent when the alternatives in the choice set increase, and when traffic situations occur where the driver has room to both change lanes to the left and right. When considering the response rate and the same questionnaire distribution setup of the pilot study, a total of $8*38/0.46 = 661$ full responses would just comply with the minimum. To reduce this amount, the Qualtrics environment can be adapted such that it randomly assigns respondents to choice scenarios according to a given weight, instead of just equally random. This will balance respondents according to the anticipated need of choice scenarios.

As mentioned before, there also have to be anticipated on the questionnaire length and the discomfort of the video questions, as discussed in Section 7.1. A drastic decision has been made to discard the video based questions, and replace them with static images. To compensate for the loss of the respondent's ability to imagine the hypothetical traffic environment of pre-signals, respondents get a choice scenario specific video explanation of the pre-signal concept they will encounter in their questionnaire. Thus, respondents still get along with the dynamics of the 3D traffic environment, while discomfort and questionnaire length has been significantly reduced. Furthermore, the questionnaire length has been reduced such that now two choice scenarios can be assigned to a single respondent instead of just one,

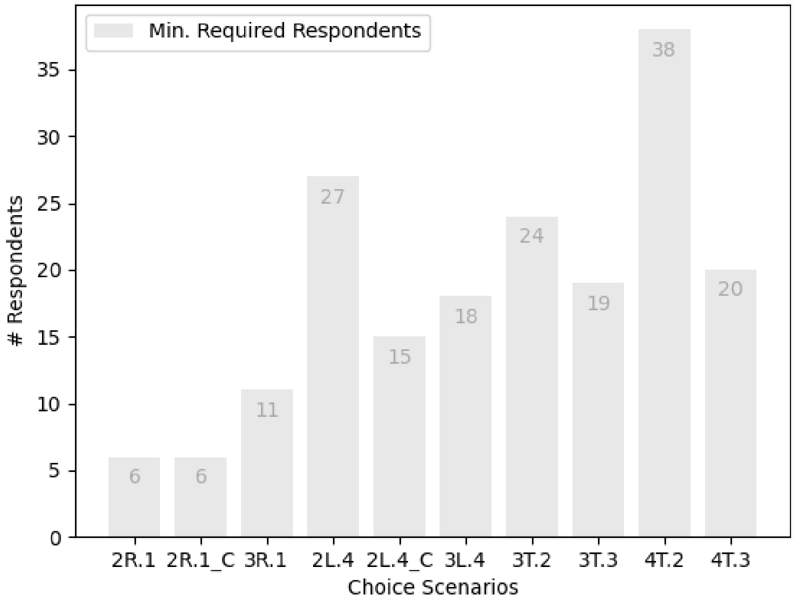


Figure 7.2. – Minimal Required Respondents from Pilot Study Estimation

hence cutting the required n.o. respondents in half. Considering all this, the loss of the respondents' imaginary ability is not proportionate to the feasibility gain and potential data set size increase of the main experiment. Thereby, the minimum required n.o. respondents serves a guideline, but definitely not guaranteed the researcher of finding proper significant estimates as priors may be less accurate due to the relatively small sized pilot study.

An example of a static image question in the main experiment questionnaire is given for choice scenario 4T.2 in Figure 7.3. The static image consist of four elements: an in-car view of the driver, a top-view of the 3D traffic environment, a schematic representation of the choice scenario, and the question itself. The black framework has been designed such that respondents be inclined to look at all four elements. The reasoning behind the in-car view and top-view are similar to the one behind the video pause and bird-eye view of the video questions.

Finally, the question '*To what driving direction are you familiar?*' was misunderstood frequently. The purpose of this question was to filter respondents from e.g. England, because they are used to drive on the left side of the road. However, respondents confused it with their preferred driving side of the road. Therefore, this question has been reshaped to '*In your country, do you have to drive on the right or left side of the road?*'.

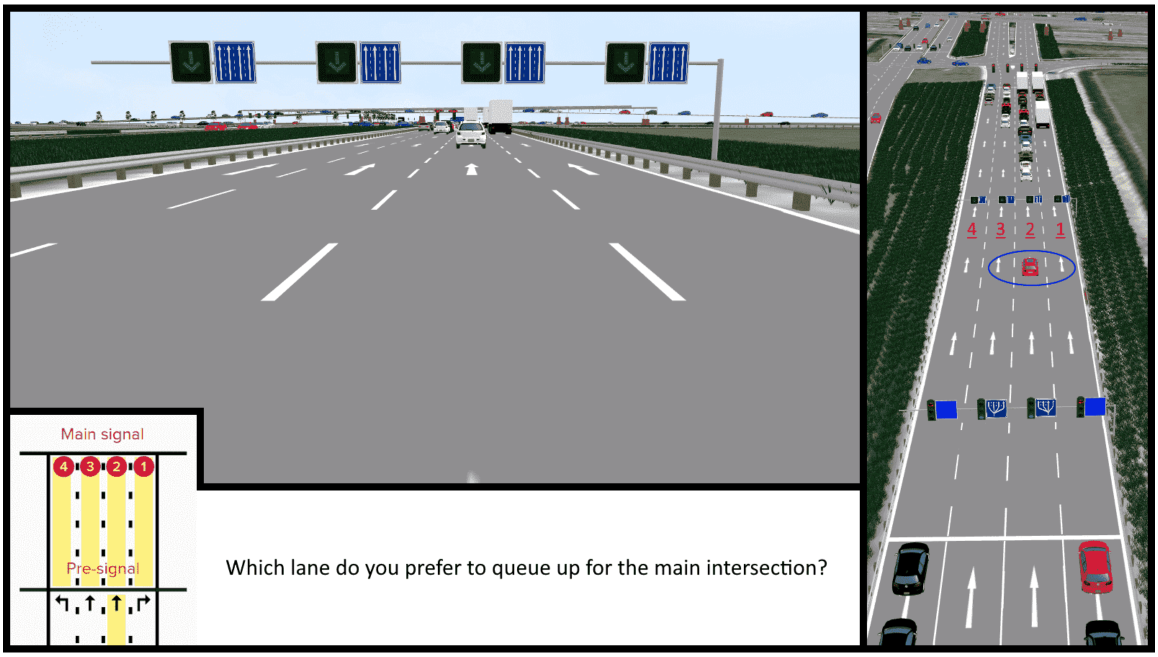


Figure 7.3. – Example of a 4T.2 Choice Scenario Static Image Question of the Main Experiment Questionnaire

7.4. Data generation main experiment

Till this point, the main experiment questionnaire has been executed. Well over a 1000 respondents have participated in the main experiment with a completion rate of over 60%. Compared to the pilot study, this is a significant improvement of the completion rate, and the respondents target is met easily as illustrated in Figure 7.4. So, the anticipated changes from the pilot study were effective in their goal. Figure 7.4 also reflects the outcomes of the readopted questionnaire distribution setup, since the gathered respondents are well aligned on a relative basis with the minimum required respondents. Misalignment in this case reflects the case that a specific choice scenario has been (un)finished significantly more than others. Nevertheless, data scarcity is not a problem at all. Therefore, obtained results will truly reflect the respondents' behavior as a result of this research and will not be misleading due to data scarcity.

7.4.1. Data set description

The main experiment questionnaire has been filled in by a variety of respondents' types, which were reflected by the screen-out questions, i.e. the third part of the questionnaire. A distinction was made between driving direction, the experience of the driver in terms of driving license and the frequency of driving, myopic and non-myopic drivers, and driving styles. Note in the upcoming figures that the representation of these respondents characteristics are well balanced between the choice scenarios. Within choice scenario balance is more skewed due to the presence of both common and scarce respondents' characteristics.

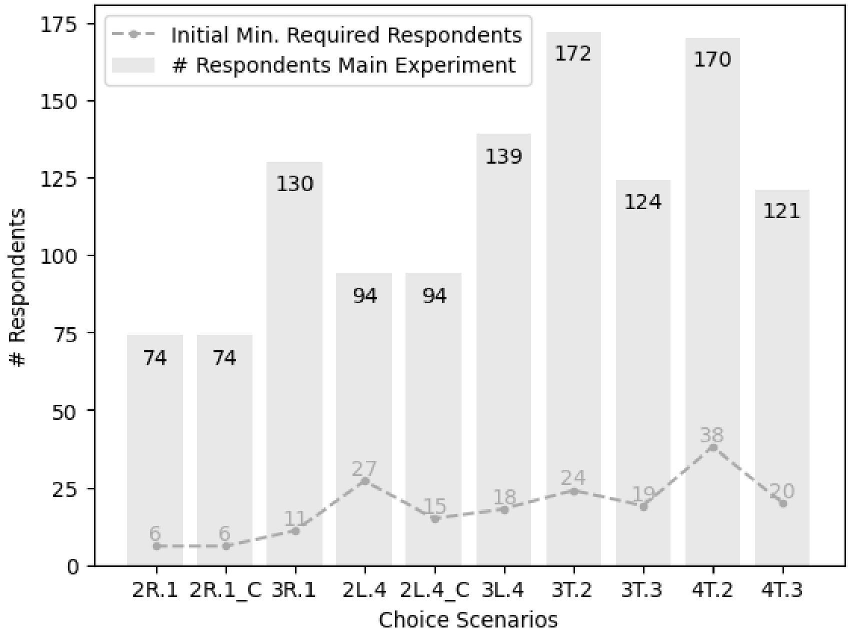


Figure 7.4. – Required Respondents from Pilot Study vs. Gathered Respondents Main Experiment

Driving experience

Driving experience of respondents is measured by the possession of their driving license and their frequency of driving. A respondent is called an experienced driver if they are in a possession of a valid driving license for a period of 5 years or more. Respondents are assigned as frequent drivers if they opted for daily, weekdays or 1-3 times a week. Figure 7.5 & 7.6 give the distribution of driving experience per choice scenario in the data set.

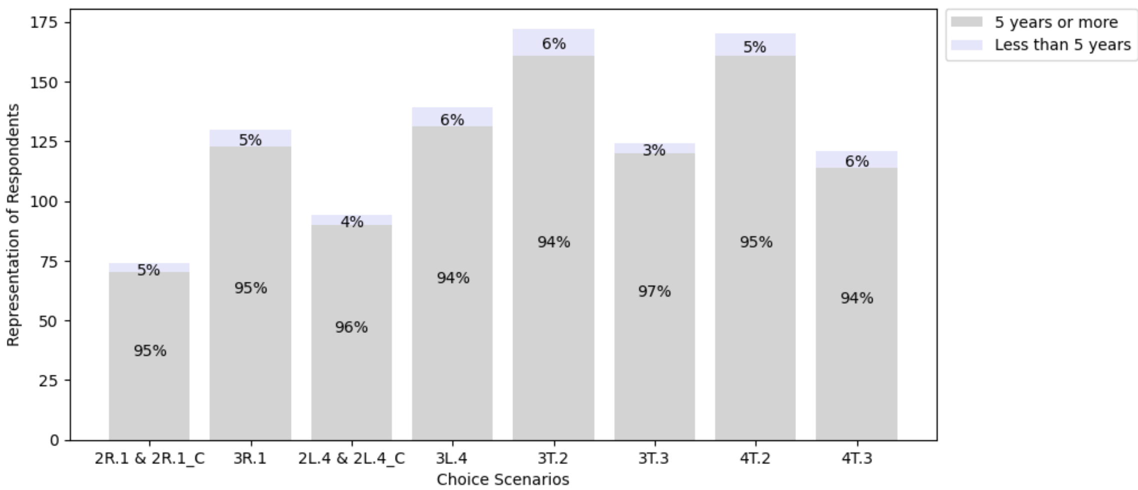


Figure 7.5. – Distribution of Experienced Drivers among Choice Scenarios in the Data Set

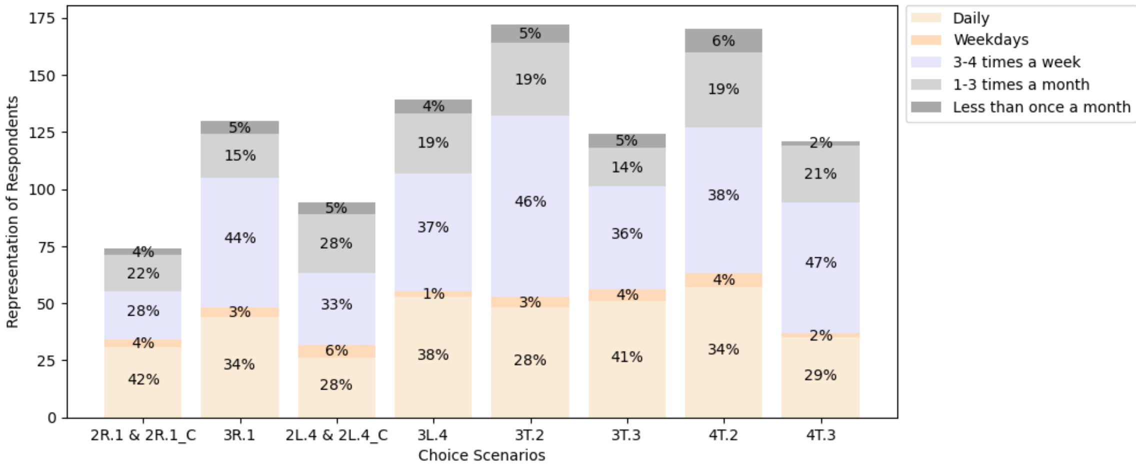


Figure 7.6. – Distribution of Driving Frequency among Choice Scenarios in the Data Set

Myopic vs. non-myopic

After respondents had finished the stated-choice experiment of the questionnaire, they could indicate whether or not they anticipated to avoid potential lane changes downstream their route. If yes, respondents are assigned as non-myopic drivers. Figure 7.7 gives the distribution of (non-)myopic drivers per choice scenario in the data set.

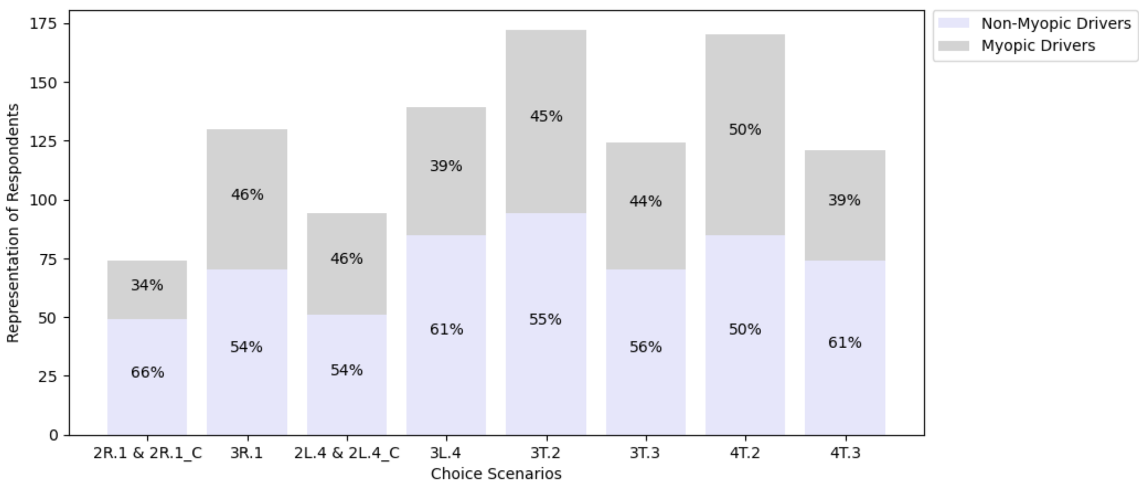


Figure 7.7. – Distribution of (Non-)Myopic Drivers among Choice Scenarios in the Data Set

Driving styles

Respondents self-assessed their driving style by rating it against common characteristics of six pre-defined driving styles. It was assumed that a driving style can be both one- and two-dimensional, as explained in Section 6.1.6. Figure 7.8 gives the distribution of driving styles per choice scenario in the data set. The category 'Other' represents any two-dimensional driving styles, which are a combination of the six pre-defined driving styles.

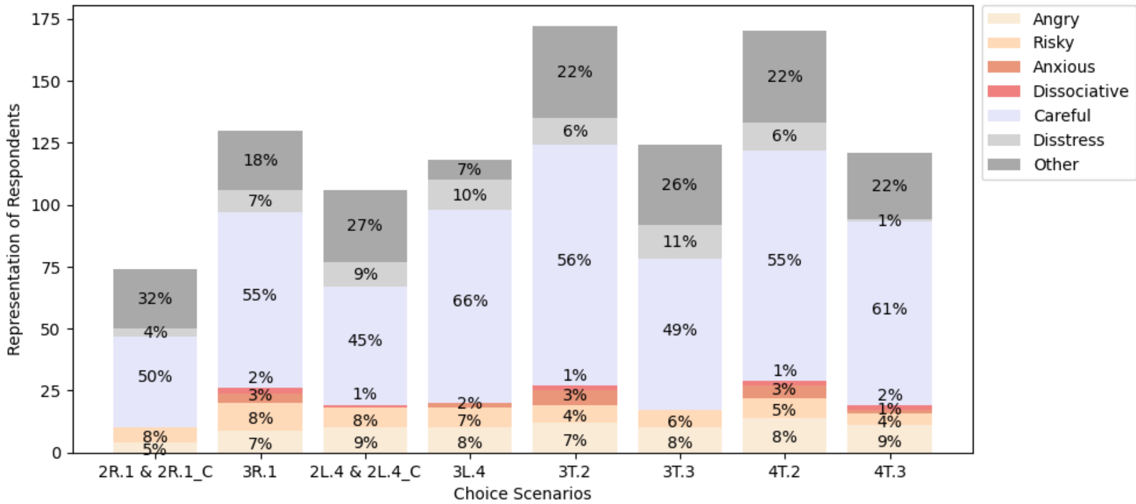


Figure 7.8. – Distribution of Driving Styles among Choice Scenarios in the Data Set

Driving direction
Only 10 respondents who completed the questionnaire indicated that they have to drive on the left side of the road in their country. This relative low representation is not enough for any incorporating in the parameter estimation process. Therefore, these respondents are discarded from the data set.

7.5. Model estimation strategy

This section is predominately dedicated to the model estimation process. Although this process has shortly been illustrated in Figure 6.3 in Section 6.2.3, it still requires some additional explanation. The base model represents the same model as the one that has been estimated for the pilot study, but this time applied on the main experiment's data. Thus, this model only includes the CAR_i, HGV_i, and ASC_i variable in its utility function, therefore it does not allow to test the contribution of the other assumed relevant variables in Table 6.4. For that, the base model has to be expanded with those variables, and re-estimated for a model comparison. 11 Models are defined which all include one additional variable with respect to the base model. By doing so, independent variable contribution can be examined without the dependency of other variables effecting the model output. These defined models include the following.

- **Base Model:** $ASC_i + BETA_{HGV,i} * HGV_i + BETA_{CAR,i} * CAR_i$;
- **M1:**[1] Base Model $+ BETA_{TRV} * TRV_i$;

[1] Additional variables for alternatives with heavy good vehicles.

- **M1a:**[2] Base Model + $BETA_{TRV,i}$ * TRV_i;
- **M2:**[3] Base Model + $BETA_{DQ}$ * DQ_i;
- **M2a:**[3] Base Model + $BETA_{DQ,i}$ * DQ_i;
- **M3:**[4] Base Model + $BETA_{MYP}$ * MYP;
- **M3a:**[4] Base Model + $BETA_{MYP,i}$ * MYP;
- **M4:**[5] Base Model + $BETA_{FREQ}$ * $FREQ$;
- **M4a:**[5] Base Model + $BETA_{FREQ,i}$ * $FREQ$;
- **M5:**[5] Base Model + $BETA_{DL}$ * DL;
- **M5a:**[5] Base Model + $BETA_{DL,i}$ * DL;
- **M6:** Base Model + $BETA_{Angry}$ * $ANGRY$ + $BETA_{Risky}$ * $RISKY$ + $BETA_{Anxious}$ * $ANXIOUS$ + $BETA_{Dissociative}$ * $DISSOCIATIVE$ + $BETA_{Careful}$ * $CAREFUL$ + $BETA_{Disstress}$ * $DISSTRESS$.

Except from drivings styles, two models are defined per additional variable, one for the generic taste parameter case, and the other for the alternative specific case. This is done to highlight potential between alternative differences within the same model, e.g. to highlight in for example the 4T.2 choice scenario if non-myopic drivers are significantly more interested in the most right line compared to the group of the two most right lanes. Such insights are crucial to understand the driving behavior at pre-signals across the choice scenarios. However, this approach resembled in a total of 10 (choice scenarios) * 12 (models) = 120 models to be estimated. Therefore, a proper data processing strategy is required to assess the data in a structured and efficient manner. To establish this goal, hypothesis testing against the base model has been argued for all models. This will be elaborated upon in the next section.

7.5.1. Hypothesis testing

There are a few requirements for a model before it can be stated as the better model. First, an improvement must be achieved in ρ^2 compared to the base model. This measure represents the proportion of the variance from dependent variables that is explained by the explanatory variables of the model. In this case, it is an indicator of model performance in terms of how well it can describe driving behavior with the explanatory variables of a certain model. Second, if the ρ^2 has been approved, it also must be a significant improvement against the base model. The likelihood ratio test is used for this analysis. The outcome of the test is the conclusion that model x is better than the base model at

[2] Additional variables for alternatives with heavy good vehicles.
[3] Additional variables for alternatives with an associated lane change.
[4] Additional variable for the most right lane alternative when the choice set size equals 2, and if larger, additional variables for the two most right lane alternatives.
[5] Additional variable for the most left lane alternative when the choice set size equals 2, and if larger, additional variables for the two most left lane alternatives.

a particular significance level. It takes into account the final likelihood differences multiplied by two, and the degrees of freedom (df) between the models. This threshold determines the significance level according to the χ^2 table. If df=0, the Ben-Akiva & Swait test is used to still be able to test the model improvement. This is done according to $P = NormSDistr(-\sqrt{-2 * N * ln(J) * (LL_{BaseModel} - LL_{Mx})/LL(0)})$, with N being the number of observations, J being the number of alternatives in the choice set, LL being the likelihood of the models, and LL(0) being the null-likelihood. Third, variables additional to the base model have to be different from zero in order to be different from the base model. All of the above mentioned tests against the base model are set to be passed at a significance level of at least 95%. The alternative hypothesis of model Mx against the base model's null hypothesis is defined as follows.

- **M1:** Besides the presence and amount of heavy good vehicles, drivers are also affected in their desired lane choice by it being the trailing vehicle of the queue.
  - H_0: $\rho^2_{BaseModel} > \rho^2_{M1}$;
  - H_1: $\rho^2_{BaseModel} < \rho^2_{M1} \wedge BETA_{TRV} \neq 0$.
- **M1a:** Besides the presence and amount of heavy good vehicles, drivers are also affected in their desired lane choice by it being the trailing vehicle of queue, and the lateral position of the trailing vehicle in the sorted area.
  - H_0: $\rho^2_{BaseModel} > \rho^2_{M1a}$;
  - H_1: $\rho^2_{BaseModel} < \rho^2_{M1a} \wedge BETA_{TRV,i} \neq 0 \wedge BETA_{TRV,i} \neq BETA_{TRV}$.
- **M2:** Drivers are more tend to change lanes when the distance to the target lane is lager.
  - H_0: $\rho^2_{BaseModel} > \rho^2_{M2}$;
  - H_1: $\rho^2_{BaseModel} < \rho^2_{M2} \wedge BETA_{DQ} \neq 0$.
- **M2a:** Drivers are more tend to change lanes when the distance to the target lane is lager, and their taste differ across lane change options.
  - H_0: $\rho^2_{BaseModel} > \rho^2_{M2a}$;
  - H_1: $\rho^2_{BaseModel} < \rho^2_{M2a} \wedge BETA_{DQ,i} \neq 0 \wedge BETA_{DQ,i} \neq BETA_{DQ}$.
- **M3:** Non-Myopic drivers tend te keep more right to avoid potential lane changes downstream their route.
  - H_0: $\rho^2_{BaseModel} > \rho^2_{M3}$;
  - H_1: $\rho^2_{BaseModel} < \rho^2_{M3} \wedge BETA_{MYP} \neq 0$.
- **M3a:** Non-Myopic drivers tend te keep more right to avoid potential lane changes downstream their route, and their taste differ within the group of right lane alternatives.
  - H_0: $\rho^2_{BaseModel} > \rho^2_{M3a}$;
  - H_1: $\rho^2_{BaseModel} < \rho^2_{M3a} \wedge BETA_{MYP,i} \neq 0 \wedge BETA_{MYP,i} \neq BETA_{MYP}$.

- **M4:** Frequent drivers tend to keep more left.
  - H_0: $\rho^2_{BaseModel} > \rho^2_{M4}$;
  - H_1: $\rho^2_{BaseModel} < \rho^2_{M4} \wedge BETA_{FREQ} \neq 0$.
- **M4a:** Frequent drivers tend to keep more left, and their taste differ within the group of left lane alternatives.
  - H_0: $\rho^2_{BaseModel} > \rho^2_{M4a}$;
  - H_1: $\rho^2_{BaseModel} < \rho^2_{M4a} \wedge BETA_{FREQ,i} \neq 0 \wedge BETA_{FREQ,i} \neq BETA_{FREQ}$.
- **M5:** Experienced drivers tend to keep more left.
  - H_0: $\rho^2_{BaseModel} > \rho^2_{M5}$;
  - H_1: $\rho^2_{BaseModel} < \rho^2_{M5} \wedge BETA_{DL} \neq 0$.
- **M5a:** Experienced drivers tend to keep more left, and their taste differ within the group of left lane alternatives.
  - H_0: $\rho^2_{BaseModel} > \rho^2_{M5a}$;
  - H_1: $\rho^2_{BaseModel} < \rho^2_{M5a} \wedge BETA_{DL,i} \neq 0 \wedge BETA_{DL,i} \neq BETA_{DL}$.
- **M6:** The driving style of a driver determines the willingness to change lanes.
  - H_0: $\rho^2_{BaseModel} > \rho^2_{M6}$;
  - H_1: $\rho^2_{BaseModel} < \rho^2_{M6} \wedge BETA_{DL,i} \neq 0$.

Results

Results of the model estimation will be presented from the perspective of the model-, alternative-, and parameter level in Section 7.6, 7.7, and 7.8 respectively. This top-down structure will help to increase the understandability of the acquired results.

7.6. Results acquired at model level

Results obtained from the hypothesis testing reflect the performance of model Mx against its corresponding base model across choice scenarios. These are presented in Table 7.3 & 7.4, which show the significance levels and ρ^2 values for all models. Color coding is applied to separate models that failed on all conditions of the alternative hypothesis for being the better model, from models that achieved a significant increase in the ρ^2 but failed in the requirement of the additional parameters being significantly different form zero. The latter is represented by an orange cell fill, while no fill is applied to the former. Green fills represent the significantly better models which met all requirements of the alternative hypothesis. Grey fills represent missing data, either from produced Nans or from choice scenarios with a choice set size of two, which are not able to differentiate between generic and alternative specific parameters. Then, the generic parameter in fact equals the alternative specific model. This color coding will be maintained throughout the whole chapter.

Legend color coding:

X	Y	Z	
Significantly better model	ρ^2 increase, but additional parameter insignificant	Not significant	No data

Table 7.3. – Significance of Model Performance against Base Model per Choice Scenario

Choice scenario	M1	M1a	M2	M2a	M3	M3a	M4	M4a	M5	M5a	M6
2R.1	NS	99.0%	NS		NS		NS		NS		NS
2R.1_C	99.9%	Nan	NS		95.1%		99.0%		NS		99.0%
3R.1	NS	NS	NS	99.0%	99.0%	99.0%	99.4%	99.9%	NS	NS	99.9%
2L.4	99.0%	98.7%	NS		NS		NS		NS		NS
2L.4_C	99.0%	Nan	99.0%		96.0%		NS		NS		99.0%
3L.4	NS	96.0%	NS	NS	NS	NS	NS	NS	NS	NS	NS
3T.2	99.0%	99.0%	99.8%	99.0%	98.3%	98.3%	NS	99.3%	NS	NS	99.0%
3T.3	NS	99.2%	99.0%	99.0%	NS	98.8%	NS	99.3%	98.3%	100.0%	99.0%
4T.2	99.0%	99.0%	NS	NS	99.0%	99.9%	NS	99.0%	NS	NS	99.0%
4T.3	99.0%	99.0%	NS	NS	NS	99.7%	NS	99.0%	NS	NS	NS

7.6.1. Interpretation of the results

Table 7.3 shows at first sight some interesting trends in model performance. First, the models M1 & M1a, which incorporated the TRV variable, are clearly the better performing models across all choice scenarios. The alternative specific M1a models are thereby the more consistent better performers. These results support the alternative hypotheses of the M1 and M1a models, indicating that drivers are affected in their desired lane choice by the trailing

Table 7.4. – ρ^2 Model Performance with Significant Green Color Coding

Choice scenario	Base Model	M1	M1a	M2	M2a	M3	M3a	M4	M4a	M5	M5a	M6
2R.1	0.313	0.315	0.368	0.312		0.313		0.313		0.310		0.316
2R.1_C	0.345	0.379	Nan	0.347		0.354		0.365		0.347		0.369
3R.1	0.252	0.253	0.253	0.252	0.264	0.279	0.280	0.257	0.261	0.253	0.253	0.261
2L.4	0.253	0.262	0.262	0.253		0.252		0.252		0.256		0.256
2L.4_C	0.324	0.349	Nan	0.349		0.330		0.324		0.324		0.341
3L.4	0.396	0.396	0.399	0.396	0.396	0.396	0.396	0.396	0.397	0.397	0.397	0.397
3T.2	0.287	0.302	0.302	0.293	0.301	0.290	0.290	0.288	0.291	0.287	0.288	0.293
3T.3	0.324	0.327	0.330	0.329	0.330	0.324	0.329	0.325	0.330	0.329	0.335	0.334
4T.2	0.384	0.393	0.401	0.384	0.386	0.387	0.389	0.385	0.393	0.385	0.385	0.386
4T.3	0.277	0.287	0.288	0.277	0.278	0.277	0.283	0.279	0.280	0.277	0.278	0.283

heavy good vehicle and its lateral position in the sorted area.

Second, driving styles seem to contribute to a better model performance, however their parameters are not significantly different from zero. Although driving styles will undoubtedly matter in real traffic, the models were not able to find a persistent behavioral difference for the self-assessed driving styles. This may be the result of the simplified self-assessment process that was implemented in the questionnaire, or an incorrect formulation of the M6 alternative hypothesis.

Third, the performance of M3 & M3a models suggest the importance of the non-myopic character of the respondent. Although the MYP parameter did not manage to persistently differ significantly from zero at a significance level of 95%, it did under a significance level of 70%-90% for the better models. Furthermore, the choice set size of the choice scenario was dependent for this significance level of the MYP parameter, since higher significance levels were achieved for choice scenarios with 3 or 4 lanes in the sorted area compared to the 2 lanes ones. This suggest that non-myopic drivers maintain a more significant higher keep-right desire as the size of the sorted area increases. However, this statement seems not to hold for choice scenarios in which drivers are positioned in the most left lane, e.g. 2L.4 & 3L.4, because their corresponding models and MYP parameters are insignificant. Thus, non-myopic drivers do not maintain a higher keep right desire compared to myopic drivers in situations where they are positioned in the most left lane of the sorted area.

Fourth, the same line of reasoning can be applied to the M4 & M4a models, which incorporate the FREQ variables. However, in this case it is argued that frequent drivers are tend to keep more left. The results suggest that frequent drivers are indeed tended to keep more left compared to non-frequent drivers, and that this decades when drivers are positioned in the most left lane of the sorted area. In other words, frequent drivers are more intended to make lane changes to the left compared to non-frequent drivers.

Finally, the results in Table 7.4 do not show a clear direction for model fit performances in terms of the between choice scenario ρ^2 indicator. Relatively spoken, both low and high ρ^2 values occur in left- and right turning choice scenarios, and across all choice set sizes. Although the within choice scenario ρ^2-differences are minimal considering the maximum of 3%, the M1a models consistently outperform the others within-and between choice scenarios. This is visualized in a heat map in Table 7.5. Note that there are some exceptions, e.g. M5a in the 3T.3 choice scenario, which are the result of randomness. Such a single former is not credible for drawing conclusions about a model nor choice scenario in its entirety. Therefore, it can be assumed that the M1a model is the best performing model that is able to extract the largest proportion of driving behavior variance from the data set with its explanatory variables.

Table 7.5. – ρ^2 Heat Map for Within- and Between Choice Scenario ρ^2 Model Performance

Choice scenario	**Base Model**	**M1**	**M1a**	**M2**	**M2a**	**M3**	**M3a**	**M4**	**M4a**	**M5**	**M5a**	**M6**
2R.1												
2R.1_C												
3R.1												
2L.4												
2L.4_C												
3L.4												
3T.2												
3T.3												
4T.2												
4T.3												

7.6.2. The reliability of the obtained ρ^2 model performances

A question arises about the reliability of the results in terms of whether the ρ^2 is acceptable for drawing conclusions from it. One could argue that the achieved ρ^2 model fit in the range [0.25, 0.40] is too low for being acceptable when comparing it against e.g. close to 1 ρ^2 in pure science. Ozili (2022) did research on the acceptable ρ^2 in empirical social science research. He particularly highlights that a low ρ^2 is not necessarily bad, because the goal of most social science research is not to predict human behavior, but rather to assess the significance of explanatory variables on the dependent variables. Furthermore, he addresses the fact that social science deals with human behavior, which is subject to change from time to time and vary from individual to individual, therefore hard to accurately predict. This will cause weak or non-linear relationships between the dependent and explanatory variable, therefore weakening the ρ^2 model fit. A ρ^2 between 0.10 and 0.50 has been found acceptable in social science research under the condition that explanatory variables are statistically significant. This aligns very well with the presented results, therefore confirming the models to be reliable for investigating driving behavior at pre-signals.

7.6.3. Key takeaways

The objective of this section is to summarize the key takeaways of the model level results, and to help the reader understanding the quantitative results from Table 7.3, 7.4, and 7.5. The key takeaways from this analysis concerned:

- The M1 and M1a models are the best performing models, because they were the most consistent in outperforming the base model across choice scenarios, while achieving a relative high average ρ^2 model fit within choice scenarios.

- Although the MYP parameter in the M3 & M3a models did not manage to persistently differ significantly from zero at a 95% significance level, it did under an 80% significance level, therefore suggesting that non-myopic drivers do maintain a higher keep-right desire compared to myopic drivers.

  - This statement does hold in case when the driver is positioned in the most left lane of the sorted area, then non-myopic drivers do not maintain a higher keep-right desire compared to myopic drivers.

- Models except from the M1, M1a, M3, M3a did not manage to consistently outperform the base model, therefore debunking their credibility of describing true driving behavior.

- Frequent drivers are tended to keep more left compared to non-frequent drivers, with the exception of situations when drivers are positioned in the most left lane of the sorted area.

Figure 7.9 & 7.10 provide some additional visual guidance for understanding the quality of each model. Within these figures, four quadrants have been defined to judge models on their better performance consistency and its corresponding average significance level. Since the minimum significance level has been set on 95%, hence significant already, the consistency aspect becomes the predominant factor to judge model performance. Thus, the blue and green quadrants represent the best performing models. Figure 7.10 has been exclusively presented to underpin the importance of the M3 & M3a model when the additional parameters of these models are 80% significantly different from zero instead of the initial 95% significance level.

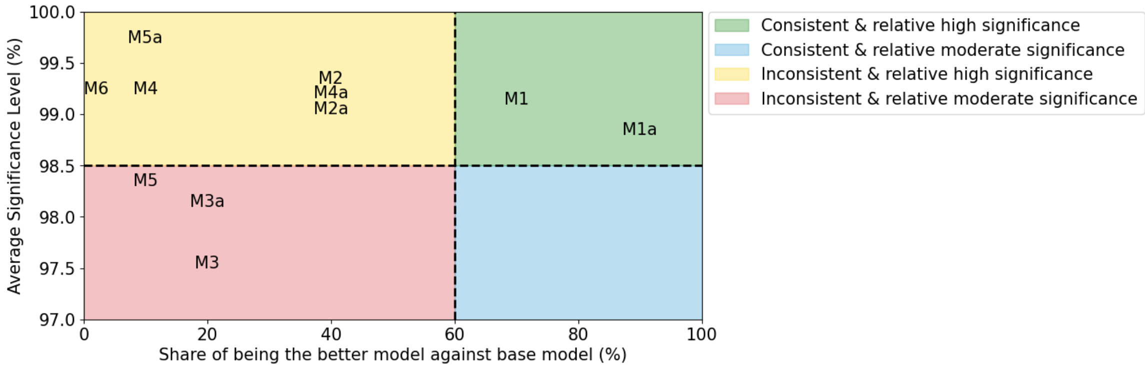


Figure 7.9. – Visual Guidance for the ρ^2 Model Performances Against Base Model as a Result of the Hypothesis Testing Strategy

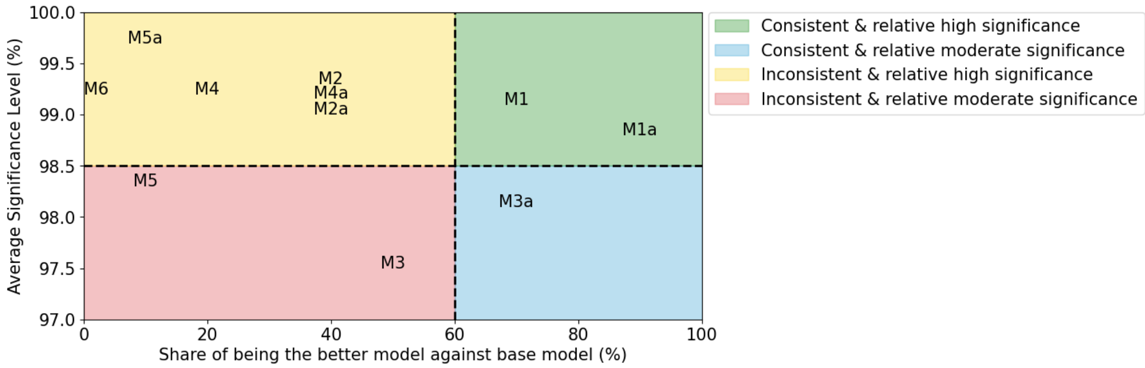


Figure 7.10. – Adapted Form of Figure 7.9: Relaxation of the Significance Level From 95% to 80% for the Additional Parameter(s) Being Different From Zero

7.7. Results acquired at alternative level

Results at the alternative level are analyzed from a different angle compared to the above discussed model results. Instead of the models being the comparing factors, it will be the alternative of a specific choice set derived from a certain choice scenario.

The distribution of the respondents' chosen alternatives in a specific choice scenario is the most direct way to present the questionnaire results. It is therefore a direct indicator for the spreading behavior in the sorted area of pre-signals. However, it is important to be aware of the fact that such results originated from a set of 8 fixed traffic situations, which were designed mathematically to secure large varieties among the alternatives' utility, and not to exactly mimic real traffic conditions. The obtained distributions of chosen alternatives are thus highly dependent on the by Ngene generated profiles, therefore not suitable to directly extract results from the parameter level perspective. In other words, the distribution of the respondents' chosen alternatives provides a valid representation for the spreading behavior obtained in the questionnaire, and for their specific mathematical designs only. Quite interesting that the most direct way of measuring the results is in fact the least reliable contributor to the research questions. Nevertheless, these results are presented since they provide the basis for understanding the more detailed results at the parameter level. An example of the alternative results is given in Figure 7.11 for the 4T.2 choice scenario. Results for all choice scenarios can be found Appendix C.1. Note that the respondents' demographics are visualized along with their chosen alternative. To illustrate, 93% of the respondents who opted for lane 2 in the 4T.2 choice scenario were experienced drivers, while this percentage concerned 95% for lane 1 & 3 and 96% for lane 4, therefore suggesting that experienced drivers are more likely to switch lanes. Such information provides a more profound insight in the type of respondents who opted for a particular alternative. Besides that, it could be helpful to visually retrace some results obtained from the parameter level, which will be presented in the next section.

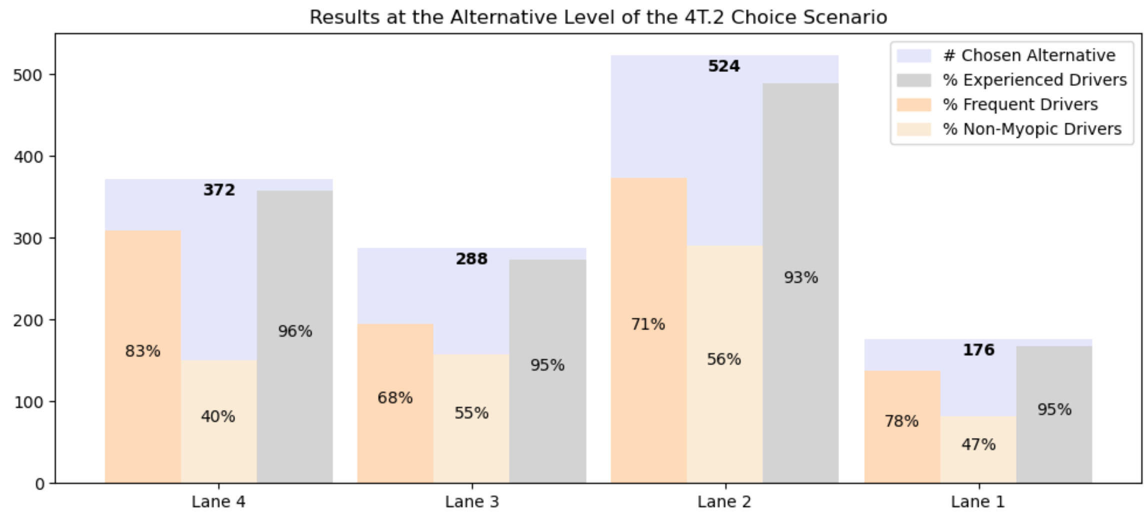


Figure 7.11. – Distribution of Chosen Alternatives in the 4T.2 Choice Scenario

7.7.1. Interpretation of the results

Regarding the spread distributions within choice scenarios, there does not seem to appear any consistency in behavioral trends. Of course, some similarities can be found within several subsets of grouped choice alternatives, but on first sight it seems to be that the choice scenario plays a dominant role in the driving behavior at pre-signals. The trend that is traceable in most of the choice scenarios is a discomfort of lane changing, which is reflected by the majority opting for the alternative without a required lane change. This trend does not hold for the 2R.1_C & 3R.1 choice scenarios. Again, this does not say anything about the discomfort not being valid for these choice scenarios, because alternatives with a required lane change could be presented slightly more attractive on a relative basis in the 2R.1_C & 3R.1 choice scenarios. If this is the case, results at the parameter level will compensate for this by taking into account the utilities of all alternatives in the choice set instead of just taking the raw number of chosen alternatives. There also seems to appear a general discomfort for the most right lane in choice scenarios with a choice set size of 3 or 4 alternatives, which reflect a discomfort of HGVs that exceeds the general keep-right desire of drivers.

7.8. Results acquired at parameter level

Previous results led to the formulation of a hand full of trends. The lack of statistical support on the alternative level made these results hard to interpret. Results at the parameter level are, just as the results at model level, supported with statistics to filter the reliable and valid parts of the data set. The results presented in this section provide the most profound insights in the trade-offs of human drivers across the different choice scenarios. Assessing such trade-off differences will eventually form a general view point of the driving behavior at pre-signals, and behavioral differences with conventional signalized intersections. Results at parameter level are obtained from the model estimation strategy as defined in Section 7.5, and are therefore similar to the results at the model level. However, instead of comparing model characteristics, this section takes a closer look into the core components of each model, i.e. the parameters of the explanatory variables within each model. Parameter estimates are the result of the MNL choice while making the data set the most likely. Since the MNL choice model accounts for utility differences among alternatives in the choice set, it takes the results at alternative level out of context, and extracts the core trade-offs that the respondents made from the chosen alternatives. This allows to reflect such behavioral results beyond the in the questionnaire pre-defined traffic situations. Parameter estimates on its own do not matter when multiple choice scenarios are being compared. This is due to scaling differences between utility functions. Therefore, parameter estimates will be measured relatively by making use of ratio estimates. A ratio estimate of a specific parameter is nothing more than the parameter estimate divided by the sum of all significant parameter estimates within the same utility function. The upcoming paragraphs each focus on the performance of one specific explanatory variable across the choice scenarios.

7.8.1. The utility contribution of the right & left lane HGV variable

Each choice scenario concerned two alternatives with heavy good vehicles. The right lane HGV variable corresponds with the most right alternative present in the choice set (e.g. for 3R.1 it corresponds with the HGV_1 variable in the utility function, while for 3L.4 this corresponds with HGV_2). Vice versa for the left HGV variable. By doing so, the same type of explanatory variables will be compared with each other. Ratio estimates of the right & left lane HGV variable are presented in Table 7.6 & 7.7 for all choice scenarios. The same color coding has been extended with a red colored text, representing a specific parameter estimate not being significantly different from zero with a 95% confidence level.

Legend color coding:

X	Y	Z	
Significantly better model	ρ^2 increase, but parameter insignificant	Estimate not significantly different from zero	No data

Table 7.6. – Parameter Ratio Estimate of the Right HGV Variable for All Choice Scenarios

Choice scenario	Base Model	M1	M1a	M2	M2a	M3	M3a	M4	M4a	M5	M5a	M6
2R.1	-0.77	-0.81	-0.12	-0.78		-0.79		-0.78		-0.79		-0.81
2R.1_C	-0.39	-0.43		-0.45		-0.39		-0.36		-0.38		-0.32
3R.1	-0.12	-0.11	-0.11	-0.26	-0.01	-0.11	-0.11	-0.10	-0.10	-0.15	-0.15	-0.12
2L.4	-0.47	-0.13	-0.16	-0.47		-0.48		-0.47		-0.46		-0.38
2L.4_C	-0.31	0.08		-0.09		-0.29		-0.30		-0.38		-0.26
3L.4	-0.13	-0.13	-0.17	-0.12	-0.20	-0.13	-0.13	-0.14	-0.13	-0.11	-0.11	-0.14
3T.2	-0.19	-0.15	-0.13	0.01	-0.06	-0.20	-0.20	-0.19	-0.17	-0.19	-0.17	-0.16
3T.3	-0.15	-0.14	-0.12	0.01	0.03	-0.15	-0.16	-0.15	-0.14	-0.15	-0.11	-0.12
4T.2	-0.22	-0.20	-0.25	-0.22	-0.13	-0.22	-0.23	-0.21	-0.20	-0.20	-0.20	-0.20
4T.3	-0.13	-0.12	-0.10	-0.13	-0.01	-0.13	-0.13	-0.13	-0.11	-0.13	-0.16	-0.10

Table 7.7. – Parameter Ratio Estimate of the Left HGV Variable for All Choice Scenarios

Choice scenario	Base Model	M1	M1a	M2	M2a	M3	M3a	M4	M4a	M5	M5a	M6
2R.1	0.14											
2R.1_C	-0.44	-0.09		-0.42		-0.44	-0.40			-0.44		-0.35
3R.1	-0.18	-0.18	-0.18	-0.46	-0.08	-0.17	-0.15	-0.15	-0.16	-0.23	-0.23	-0.18
2L.4	-0.30	-0.09	-0.13	-0.29		-0.28	-0.29			-0.32		-0.23
2L.4_C	-0.33	0.45		-0.21		-0.31	-0.33			-0.41		-0.28
3L.4	-0.38	-0.38	-0.14	-0.37	-0.80	-0.37	-0.37	-0.39	-0.39	-0.32	-0.33	-0.37
3T.2	-0.17	-0.14	-0.12	-0.02	-0.04	-0.18	-0.18	-0.17	-0.15	-0.17	-0.15	-0.14
3T.3	-0.36	-0.32	-0.33	-0.07	-0.07	-0.36	-0.38	-0.37	-0.34	-0.36	-0.26	-0.30
4T.2	-0.18	-0.09	-0.08	-0.20	-0.16	-0.18	-0.18	-0.17	-0.16	-0.16	-0.16	-0.17
4T.3	-0.31	-0.26	-0.25	-0.32	-0.20	-0.31	-0.34	-0.31	-0.27	-0.31	-0.39	-0.25

Interpretation of the results
Examining the ratio estimates of the HGV parameters, it can be stated that the amount of heavy good vehicles is a large contributing factor in the preferred lane choice. However, quite some differences between the left-and right HGV variable occur within choice scenarios. Heavy good vehicles contribute to a larger discomfort of a certain alternative, but this discomfort increases when the those heavy good vehicles are positioned in lanes closer to the driver. In the base model, take as an example the 3T.3 ratio estimate of the right HGV parameter of -0.15 versus the left HGV ratio estimate of -0.36. The driver in the third lane is more than twice as heavily affected in his desired lane choice by heavy good vehicles in the lane next to him compared to two lanes next to him. The same line of reasoning holds for between choice scenario comparisons of the individual right- and left HGV parameters. Figure 7.12 shows these within choice scenario interactions for all choice scenarios. Another interesting finding concerns a general decrease in discomfort for heavy good vehicles in the M1 & M1a models. This completely makes sense since the HGV parameter also accounted in

some profiles for the discomfort regarding the heavy good vehicle being the trailing vehicle. This is probably also the reason why the M1 & M1a models outperformed the base models. Regarding the remaining models, these do not affect the right and left HGV parameter considerably.

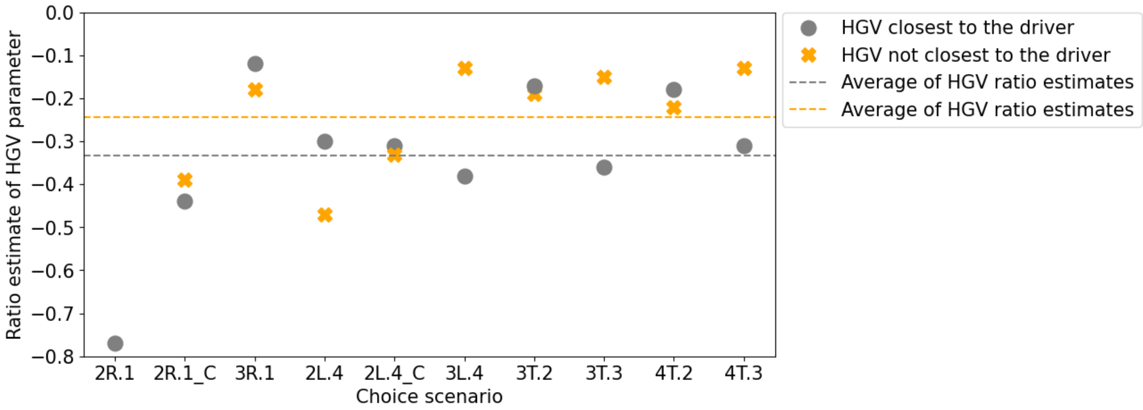


Figure 7.12. – Discomfort for HGVs With Respect To Their Position from the Driver (Base Model)

7.8.2. The utility contribution of the four CAR variables

Similar to the HGV variables, four CAR variables have been defined which are denoted as the most right, the second most right, the third most right, and the fourth most right CAR variables. Their ratio estimates are given in Table 7.8 to 7.11.

Legend color coding:

X	Y	Z	
Significantly better model	ρ^2 increase, but parameter insignificant	Estimate not significantly different from zero	No data

Table 7.8. – Parameter Ratio Estimate of the Most Right CAR Variable for All Choice Scenarios

Choice scenario	Base Model	M1	M1a	M2	M2a	M3	M3a	M4	M4a	M5	M5a	M6
2R.1	0.06	0.02	0.09	0.04		0.04		0.04		0.03		0.02
2R.1_C	-0.08	-0.05		-0.03		-0.07		-0.06		-0.09		-0.06
3R.1	-0.05	-0.05	-0.05	-0.12	-0.01	-0.05	-0.05	-0.05	-0.05	-0.07	-0.07	-0.05
2L.4	-0.10	-0.14	-0.14	-0.10		-0.11		-0.11		-0.09		-0.09
2L.4_C	-0.09	-0.01		-0.02		-0.09		-0.09		-0.11		-0.08
3L.4	-0.04	-0.04	-0.04	-0.04	-0.06	-0.04	-0.04	-0.04	-0.04	-0.03	-0.03	-0.04
3T.2	-0.04	-0.04	-0.04	0.02	-0.01	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.03
3T.3	-0.03	-0.02	0.00	0.01	0.02	-0.03	-0.03	-0.03	-0.03	-0.03	-0.02	-0.02
4T.2	-0.03	-0.01	-0.05	-0.01	-0.02	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03
4T.3	-0.04	-0.04	-0.04	-0.04	0.00	-0.04	-0.05	-0.04	-0.04	-0.04	-0.05	-0.03

Table 7.9. – Parameter Ratio Estimate of the Second Right CAR Variable for All Choice Scenarios

Choice scenario	Base Model	M1	M1a	M2	M2a	M3	M3a	M4	M4a	M5	M5a	M6
2R.1	-0.17	-0.19	-0.03	-0.17		-0.18		-0.18		-0.18		-0.19
2R.1_C	-0.09	-0.13		-0.09		-0.09		-0.09		-0.09		-0.08
3R.1	-0.07	-0.05	-0.05	-0.16	-0.04	-0.06	-0.06	-0.06	-0.06	-0.08	-0.08	-0.06
2L.4	-0.13	-0.11	-0.12	-0.13		-0.13		-0.13		-0.14		-0.11
2L.4_C	-0.07	-0.01		-0.05		-0.07		-0.07		-0.09		-0.06
3L.4	-0.05	-0.04	-0.05	-0.05	-0.10	-0.05	-0.05	-0.05	-0.05	-0.04	-0.04	-0.04
3T.2	-0.06	-0.06	-0.05	-0.01	-0.02	-0.06	-0.06	-0.06	-0.05	-0.06	-0.06	-0.05
3T.3	-0.06	-0.06	-0.05	0.01	0.00	-0.06	-0.07	-0.06	-0.06	-0.06	-0.04	-0.05
4T.2	-0.03	-0.03	-0.03	-0.03	-0.02	-0.03	-0.03	-0.03	-0.02	-0.03	-0.03	-0.03
4T.3	-0.04	-0.04	-0.04	-0.05	-0.03	-0.05	-0.05	-0.05	-0.04	-0.05	-0.06	-0.04

Table 7.10. – Parameter Ratio Estimate of the Third Right CAR Variable for All Choice Scenarios

Choice scenario	Base Model	M1	M1a	M2	M2a	M3	M3a	M4	M4a	M5	M5a	M6
3R.1	0.02	0.02	0.02	0.01	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02
3L.4	-0.05	-0.05	-0.06	-0.05	-0.11	-0.05	-0.05	-0.05	-0.05	-0.04	-0.04	-0.06
3T.2	-0.03	-0.03	-0.03	0.02	0.03	-0.03	-0.03	-0.03	-0.02	-0.03	-0.02	-0.02
3T.3	-0.04	-0.04	-0.04	-0.01	-0.01	-0.04	-0.04	-0.04	-0.04	-0.04	-0.03	-0.03
4T.2	-0.02	-0.02	-0.02	-0.01	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
4T.3	-0.04	-0.04	-0.04	-0.04	-0.03	-0.04	-0.04	-0.04	-0.03	-0.04	-0.05	-0.03

Table 7.11. – Parameter Ratio Estimate of the Fourth Right CAR Variable for All Choice Scenarios

Choice scenario	Base Model	M1	M1a	M2	M2a	M3	M3a	M4	M4a	M5	M5a	M6
4T.2	0.00	-0.01	-0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4T.3	-0.04	-0.04	-0.04	-0.05	-0.02	-0.04	-0.05	-0.05	-0.04	-0.04	-0.06	-0.04

Interpretation of the results

Examining the ratio estimates of the CAR parameters, it can be stated that the desired lane choice is much less affected by the presence of cars with respect to heavy good vehicles. There still persist a general discomfort for cars, which decreases along with an increasing choice set size. This is visualized in Figure 7.13. Such a relationship can be found in the most right and second most right CAR variable. Since heavy good vehicles also interact with these CAR variables, it makes sense that drivers anticipate less on the presence of cars if other alternatives without heavy good vehicles are available. If not, then drivers anticipate heavier on the presence of cars as well, yielding a larger discomfort for choice scenarios with only 2 alternatives. Besides this relationship, the discomfort of cars is quite stable throughout all choice scenarios and models, therefore less interesting to influence implications for pre-signals in general.

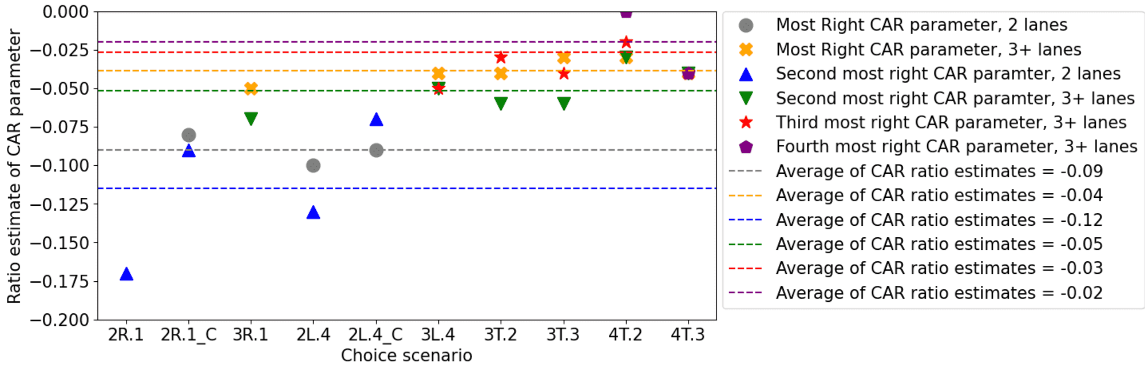


Figure 7.13. – Parameter Ratio Estimates and Average of the Four CAR Parameters Distinguished by the Number of Lanes in the Sorted Area (Base Model)

7.8.3. The utility contribution of the four ASC variables

Remember that the Alternative Specific Constant (ASC) captured the average preference of an alternative that is associated with factors other than the explanatory variables. Those were integrated in utility functions such that they reflect the discomfort of lane changing, although this was not guaranteed to have a full one-to-one relationship due to the presence of other potential unforeseen preferences. Nevertheless, dominance was expected from the lane changing aspect. Similar to the CAR variables, four ASC variables have been defined which reflect 1 or 2 required lane changes to the right or left. Their ratio estimates are presented in Table 7.12 to 7.15 for all choice scenarios.

Legend color coding:

X	Y	Z	
Significantly better model	ρ^2 increase, but parameter insignificant	Estimate not significantly different from zero	No data

Table 7.12. – Parameter Ratio Estimate of the 1 Right Lane Change ASC for All Choice Scenarios

Choice scenario	Base Model	M1	M1a	M2	M2a	M3	M3a	M4	M4a	M5	M5a	M6
2R.1_C	0.22											
2L.4	-0.11											
3L.4	0.03											
3T.2	-0.19	-0.16	-0.14	-0.44	-0.04	-0.19	-0.19	-0.20	-0.22	-0.19	-0.20	-0.15
3T.3	0.16	0.16	0.14	-0.37	-0.21	0.16	0.14	0.16	0.24	0.16	0.32	0.18
4T.2	-0.03	-0.09	0.01	-0.15	-0.02	-0.03	-0.02	-0.03	-0.03	-0.03	-0.03	-0.04
4T.3	-0.01											

Table 7.13. – Parameter Ratio Estimate of the 1 Left Lane Change ASC for All Choice Scenarios

Choice scenario	Base Model	M1	M1a	M2	M2a	M3	M3a	M4	M4a	M5	M5a	M6
2R.1	-0.15											
3R.1	-0.12	-0.12	-0.12	0.11	0.44	-0.11	-0.07	-0.18	-0.10	-0.04	-0.02	-0.13
2L.4_C	-0.21	-0.19		0.55		-0.24		-0.21		-0.17		-0.15
3T.2	-0.32	-0.28	-0.25	-0.44	-0.71	-0.29	-0.29	-0.31	-0.35	-0.32	-0.35	-0.26
4T.2	-0.16	-0.17	-0.16	-0.22	-0.05	-0.14	-0.14	-0.17	-0.13	-0.19	-0.18	-0.16
4T.3	-0.19	-0.19	-0.17	-0.18	-0.17	-0.19	-0.20	-0.20	-0.22	-0.19	-0.11	-0.14

Table 7.14. – Parameter Ratio Estimate of the 2 Right Lane Change ASC for All Choice Scenarios

Choice scenario	Base Model	M1	M1a	M2	M2a	M3	M3a	M4	M4a	M5	M5a	M6
3L.4	-0.35	-0.36	-0.41	-0.37	-0.10	-0.36	-0.36	-0.34	-0.34	-0.45	-0.45	-0.35
3T.3	-0.20	-0.21	-0.20	-0.48	-0.56	-0.20	-0.18	-0.19	-0.15	-0.02	0.06	-0.13
4T.3	-0.20	-0.17	-0.15	-0.19	-0.66	-0.19	-0.15	-0.18	-0.16	-0.19	-0.24	-0.15

Table 7.15. – Parameter Ratio Estimate of the 2 Left Lane Change ASC for All Choice Scenarios

Choice scenario	Base Model	M1	M1a	M2	M2a	M3	M3a	M4	M4a	M5	M5a	M6
3R.1	-0.44	-0.40	-0.40	-0.27	-0.31	-0.31	-0.28	-0.45	-0.49	-0.44	-0.44	-0.44
4T.2	-0.33	-0.28	-0.27	-0.55	-0.80	-0.31	-0.31	-0.33	-0.34	-0.34	-0.35	-0.31

Interpretation of the results

Examining the ratio estimates of the ASC parameters, it can be stated that the required lane changes are a large contributing factor in the preferred lane choice. However, there also persist a lot of inconsistencies in the discomfort within and between choice scenarios, which eventually have a large contribution to the determination when a pre-signal might be effective to implement. Several statements can be made about the discomfort of lane changing:

- Table 7.12 shows that more than half of the one 1 right lane change ASCs are insignificant. This holds for choice scenarios 2R.1_C, 2L.4, 3L.4 & 4T.3, suggesting that drivers feel no significant discomfort for changing one lane to the right. Sum this up to the positive ASC in the 3T.3 choice scenario, and it underpins a strong keep-right desire when drivers are positioned in the most left lane of the sorted area.
- The keep-right desire as mentioned above is less persistent in situations where drivers are not positioned in the most left lane of the sorted area, but more towards the middle. Then, a moderate discomfort is felt for changing one lane to the right. In Table 7.12, this is reflected by the parameter ratio estimates in the 3T.2 and 4T.3 choice scenarios.

- The keep-right desire is further supported with the fact that drivers within the same choice scenario account a much higher discomfort for a left lane change than for a right lane change. This is visualized in Figure 7.14.

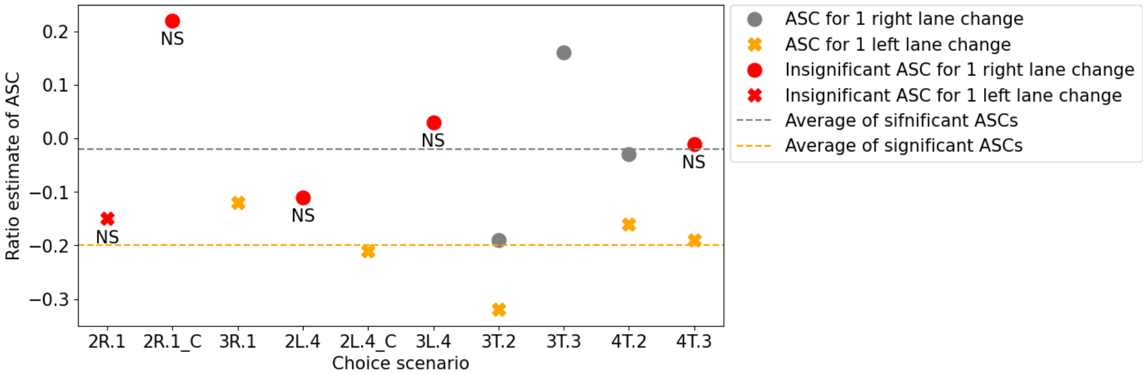


Figure 7.14. – I. The General Keep Right Desire of Drivers Originating from the Differences in ASCs Estimates and Significance (Base Model).

- A similar line of reasoning can be applied to two right lane changes. Although the discomfort of changing two lanes to the right is much higher than to just one, the keep-right desire can be further supported with the discomfort of two left lane changes being much higher than two right lane changes. This is visualized in Figure 7.15. One could even argue that two right lane changes equal one left lane change, given the similarities in discomfort.

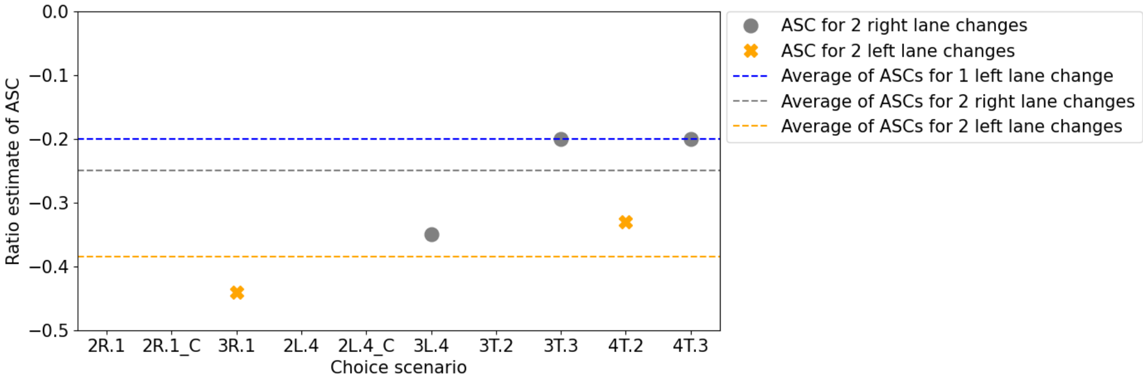


Figure 7.15. – II. The General Keep Right Desire of Drivers Originating from the Differences in ASCs Estimates and Significance (Base Model).

- Regarding left lane changes, the insignificant estimate in Table 7.13 suggests that drivers feel no significant discomfort for changing one lane to the left in the 2R.1 choice scenario. Sum this up to the relatively low discomfort associated with one left lane change in the 3R.1 choice scenario and it underpins a key difference in the spread behavior of human drivers in the sorted area. Drivers tend more to spread itself left-wise if they are positioned in the most right lane of the sorted area. This is visualized in Figure 7.16.

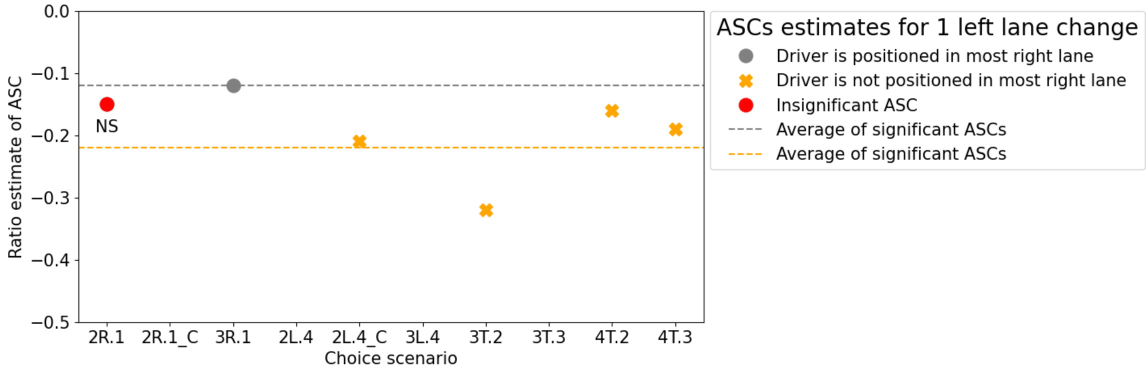


Figure 7.16. – The Willingness of Drivers to Spread When They are Positioned in the Most Right Lane of the Sorted Area (Base Model).

- Drivers also feel a much higher discomfort for changing lanes to the most left lane of the sorted area. Within Table 7.13, this can be supported with the parameter ratio differences between the 2R.1(-0.15) & 2L.4_C(-0.21), 4T.2(-0.16) & 3T.2(-0.32), and 4T.2(-0.16) & 4T.3(-0.19). In all these cases, the parameter ratio estimate for one left lane change is more negative when the target lane is the most left lane of the sorted area. This is visualized in Figure 7.17.

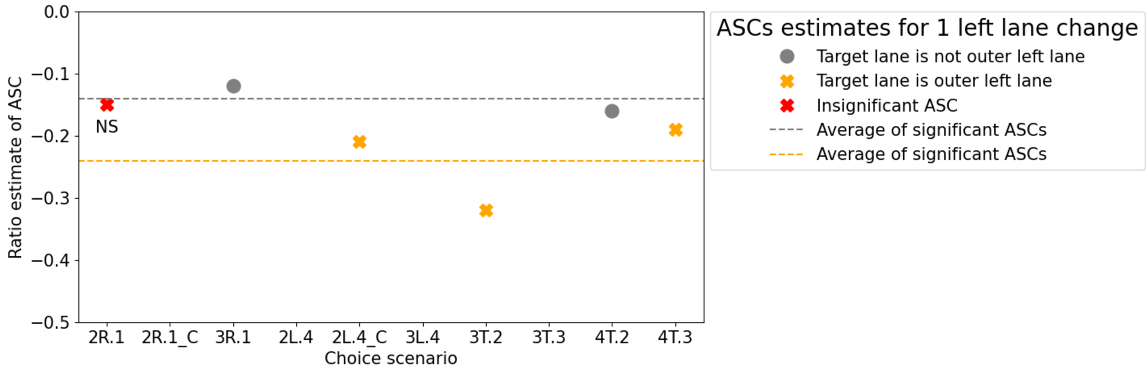


Figure 7.17. – The General Resistance of Drivers to Spread Towards the Outer Left Lane of the Sorted Area (Base Model).

7.8.4. The utility contribution of the additional explanatory variables

The parameter ratio estimates of the explanatory variables additional to the base model can be found in Appendix C.2. These results are not discussed further due to their insignificance and irrelevance to better model performances.

7.9. Pre-signals vs. conventional signalized intersections

When comparing pre-signal choice scenarios with their corresponding counterpart choice scenarios, some interesting statements can be made. Figure 7.12 & 7.13 highlighted that when it comes to the discomfort of traffic crowdedness, drivers in general are more inclined to avoid HGVs rather than cars, irrespective of the pre-signal. However, on average drivers accounted for cars more than twice as heavy in choice scenarios that only included 2 alternatives. This is not the result of the absence of a pre-signal in the 2R.1_C & 2L.4_C choice scenarios, but rather the result of drivers who anticipate heavier on the presence of cars when HGVs cannot be avoided. When it comes to the appreciation of traffic crowdedness, there are no clear signs that the pre-signal affects the driver in their associated discomfort with HGVs and cars. The contrary holds when it comes to the appreciation of lane changing, for which the pre-signal is a large contributing factor to the lane-change behavior of drivers. Hence, having a profound impact on the efficacy of pre-signals for regular traffic. This is elaborated upon below.

7.9.1. Left-turning traffic

Regarding the 2L.4 choice scenario, drivers feel no significant discomfort for changing right, because they are pushed into the most left lane of the sorted area, as visualized in Figure 7.15. This favors spreading in the sorted area with pre-signals. On top of that, drivers do feel a discomfort for spreading left-wise in the 2L.4_C choice scenario. This disfavors spreading in situations with a conventional signalized intersection. Combine this increased willingness to spread for the pre-signal choice scenario with the previous finding that pre-signals did not affect the driver in their appreciation of traffic crowdedness, and it can be concluded that pre-signals are in favor against conventional signalized intersections for this left turning traffic scenario.

What about a pre-signal with 3 left-turning lanes instead of only 2? A strong keep-right desire was found for drivers who are positioned in the most left lane of the sorted area. This definitely incline drivers to spread to the right side of the sorted area. On the other hand, drivers also account a high discomfort for executing multiple lane changes and the presence of HGVs. This also will incline drivers to use the left side of the sorted area. A closer look to the estimated utility function of the 3L.4 choice scenario in Equation 7.1 will give some clarity about these particular interactions.

$$\begin{aligned}
&\mathrm{U}_{3L.4}(L2) = -2.46 - 0.90 \cdot HGV_2 - 0.26 \cdot CAR_2 + \varepsilon_{3L.4} \\
&\mathrm{U}_{3L.4}(L3) = 0 - 2.67 \cdot HGV_3 - 0.33 \cdot CAR_3 + \varepsilon_{3L.4} \\
&\mathrm{U}_{3L.4}(L4) = -0.33 \cdot CAR_4 + \varepsilon_{3L.4}
\end{aligned} \tag{7.1}$$

From these utility functions it can be derived that a third additional lane for left-turning traffic, i.e. L2, might not be as efficient as initially expected. The ASC of -2.46 clearly indicates a strong discomfort for the two lane changes that are required for lane 2, while this can only be compensated with either HGVs present in lane 3 or a large queue of vehicles in lane 3 and 4. Therefore, the attractiveness of lane 2 is highly dependent on the traffic crowdedness of the other lanes. Hence, not supporting an equal spread in the sorted area.

This is visualized in Figure 7.18 & 7.19. These figures show the expected distribution of drivers' choices as a reflection of the systematic utility derived from the traffic situation, and the probability density function of utility U. These figures clearly highlight the lack of utility for a driver to change to the third additional lane whenever traffic crowdedness in the other lanes is proportional to lane 2.

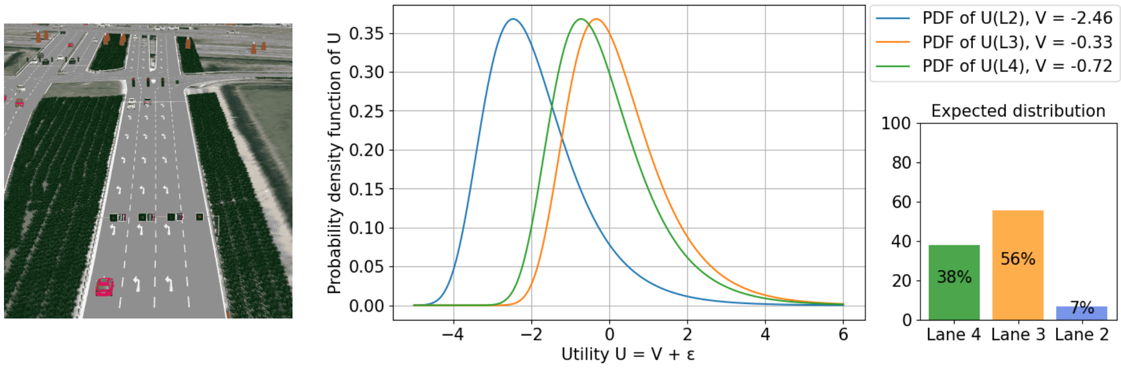


Figure 7.18. – I. Expected Distribution of Drivers in the Sorted Area Derived from a Specific Traffic Situation in the 3L.4 Choice Scenario

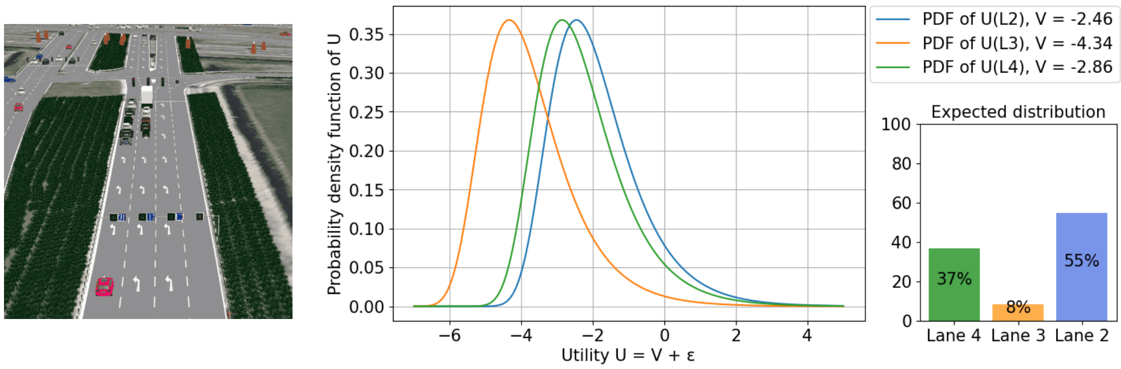


Figure 7.19. – II. Expected Distribution of Drivers in the Sorted Area Derived from a Specific Traffic Situation in the 3L.4 Choice Scenario

7.9.2. Right-turning traffic

In both the 2R.1 & 2R.1_C choice scenarios, drivers feel no significant discomfort for changing lanes to either direction. Considering the finding that pre-signals did not affect the driver in their appreciation of traffic crowdedness, it can be concluded that both pre-signals and conventional signalized intersection yield a similar willingness to spread. Therefore not disfavoring pre-signals.

What about a pre-signal with 3 right-turning lanes instead of only 2? Drivers account a high discomfort for executing multiple lane changes, which increases when the target lane is the outer left lane of the sorted area. This definitely prevents drivers from spreading towards the additional third lane, i.e. lane 3. This can also be confirmed by the estimated utility function of the 3R.1 choice scenario, which is given in Equation 7.2.

$$
\begin{aligned}
\mathrm{U}_{3R.1}(L1) &= -0.65\cdot HGV_1 - 0.29\cdot CAR_1 + \varepsilon_{3R.1} \\
\mathrm{U}_{3R.1}(L2) &= -0.64 - 0.98\cdot HGV_2 - 0.35\cdot CAR_2 + \varepsilon_{3R.1} \\
\mathrm{U}_{3R.1}(L3) &= -2.33 + 0.08\cdot CAR_3 + \varepsilon_{3R.1}
\end{aligned}
\tag{7.2}
$$

The relative low ASC parameter of -2.33 for the third additional lane clearly reflects the hesitance of drivers to change towards this lane. From these utility functions it can be derived that the attractiveness of lane 3 is highly dependent on the traffic crowdedness of the other lanes. Hence, just as for left turning traffic not supporting an equal spread in the sorted area. This is visualized in Figure 7.20 & 7.21. These figures clearly highlight the lack of utility for a driver to change to the third additional lane whenever traffic crowdedness in the other lanes is proportional to lane 3.

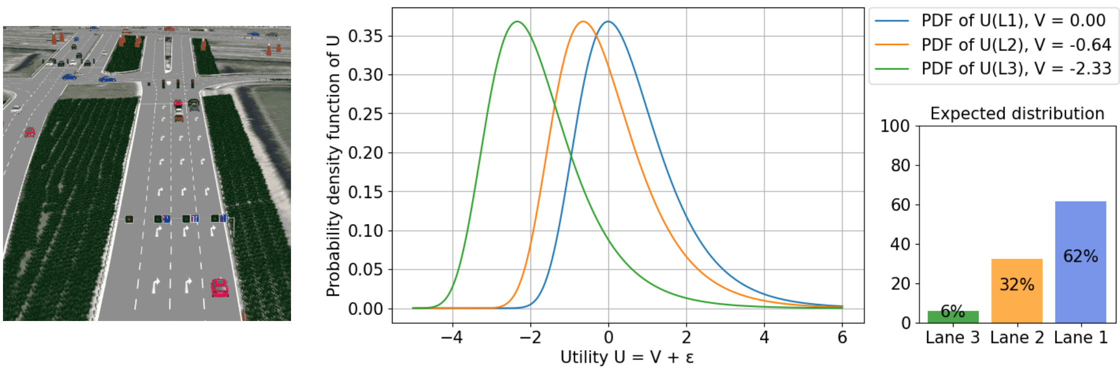


Figure 7.20. – I. Expected Distribution of Drivers in the Sorted Area Derived from a Specific Traffic Situation in the 3R.1 Choice Scenario

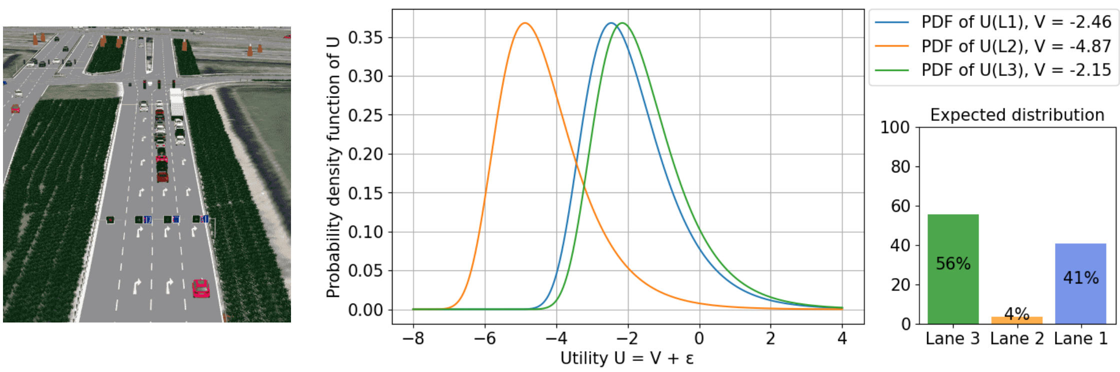


Figure 7.21. – II. Expected Distribution of Drivers in the Sorted Area Derived from a Specific Traffic Situation in the 3R.1 Choice Scenario

7.9.3. Through-turning traffic

No counterpart choice scenarios have been incorporated in the stated-choice experiment for through-going traffic, therefore behavioral differences between pre-signals and conventional signalized intersections cannot be measured directly. This choice was made to protect the feasibility of the research, and because of the similarity in choices drivers have to make upstream the signalized intersection, irrespective of the pre-signal. However, previous results revealed some behavioral insights which can be used to reflect upon the pre-signal's potential. The initial central position of trough-going drivers in the sorted area, is with respect to turning traffic, a positive starting point for a more equal spread of drivers. The results have shown that through-going drivers faced discomfort on both sides of their position, a strong discomfort for left lane changes on their left side, and a strong discomfort for heavy good vehicles with a moderate keep-right desire on their right side. The efficacy of pre-signals for through-traffic cannot be derived from such reasoning, but rather from the willingness to spread to the additional third and fourth lane of the sorted area. This will be done by taking a closer look to the utility functions of the through-going choice scenarios.

The 3T.2 choice scenario

$$
\begin{aligned}
\mathrm{U}_{3T.2}(L1) &= -1.13 - 1.14 \cdot HGV_1 - 0.25 \cdot CAR_1 + \varepsilon_{3T.2} \\
\mathrm{U}_{3T.2}(L2) &= -1.02 \cdot HGV_2 - 0.37 \cdot CAR_2 + \varepsilon_{3T.2} \\
\mathrm{U}_{3T.2}(L3) &= -1.91 - 0.16 \cdot CAR_3 + \varepsilon_{3T.2}
\end{aligned}
\tag{7.3}
$$

The utility functions in Equation 7.3 show that drivers account discomfort for lane changing, and more heavily to left lane changes. This prevents drivers from spreading in the sorted area, unless traffic crowdedness in lane 2 compensates for this dis-utility. However, ASCs are nearly half the magnitude of the ones found for turning directions, therefore traffic crowdedness on the starting lane, i.e. lane 2, will incline drivers to spread much earlier. Hence, supporting the efficacy of pre-signals. This is shown in Figure 7.22 & 7.23.

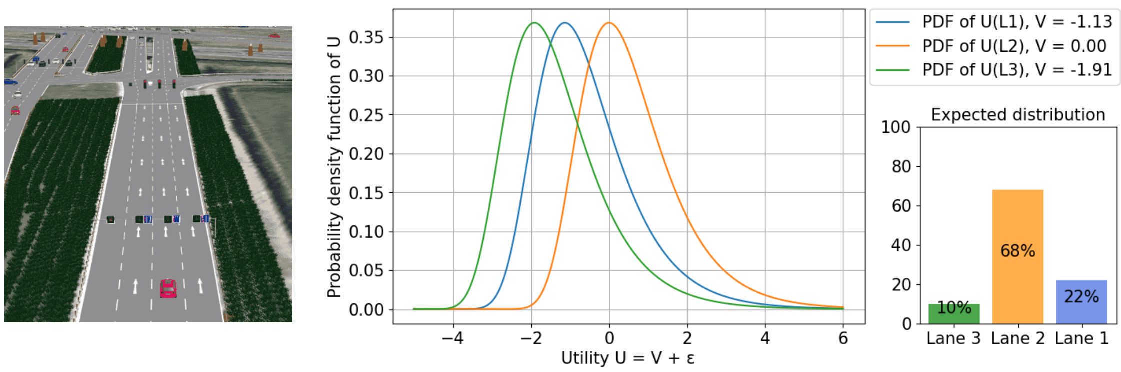


Figure 7.22. – II. Expected Distribution of Drivers in the Sorted Area Derived from a Specific Traffic Situation in the 3T.2 Choice Scenario

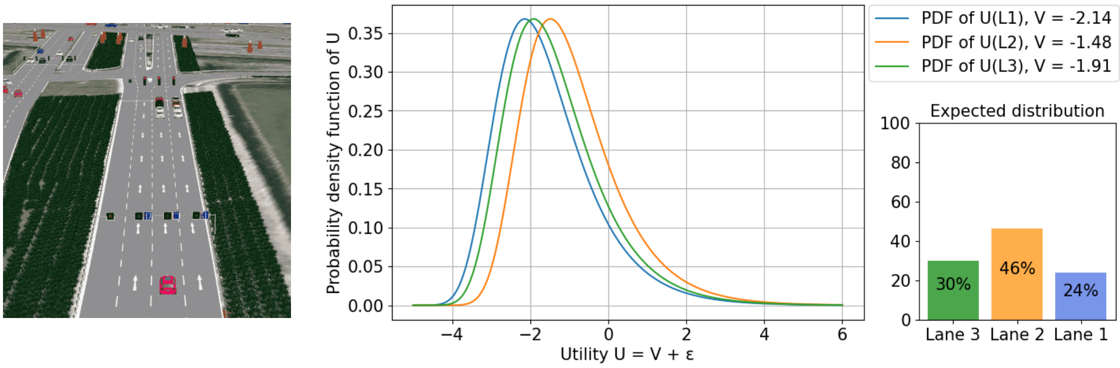


Figure 7.23. – II. Expected Distribution of Drivers in the Sorted Area Derived from a Specific Traffic Situation in the 3T.2 Choice Scenario

The 3T.3 choice scenario

$$
\begin{aligned}
\mathrm{U}_{3T.3}(L1) &= -1.45 - 1.04 \cdot HGV_1 - 0.21 \cdot CAR_1 + \varepsilon_{3T.3} \\
\mathrm{U}_{3T.3}(L2) &= 1.14 - 2.55 \cdot HGV_2 - 0.44 \cdot CAR_2 + \varepsilon_{3T.3} \\
\mathrm{U}_{3T.3}(L3) &= -0.29 \cdot CAR_3 + \varepsilon_{3T.3}
\end{aligned}
\tag{7.4}
$$

Unlike the 3T.2 choice scenario, drivers in the 3T.3 choice scenario are not positioned centrally between their alternatives to choose from, hence drivers have to change multiple lanes to reach the most right lane, i.e. lane 1. Although the positive ASC parameter of 1.14 for lane 2 reflects a strong keep-right desire, drivers are still hesitated to change to lane 1. Again, the attractiveness of lane 1 is highly dependent on the traffic crowdedness of the other lanes. When compared to the 3T.2 choice scenario, it takes a lot more traffic on lane 2 and lane 3 before drivers are inclined to opt for lane 1. Hence, not supporting an equal spread in the sorted area. This is shown in Figure 7.24 & 7.25.

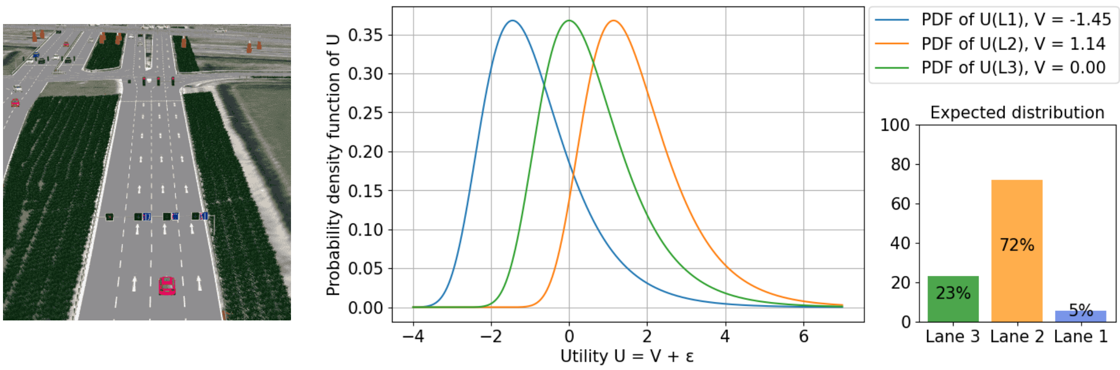


Figure 7.24. – I. Expected Distribution of Drivers in the Sorted Area Derived from a Specific Traffic Situation in the 3T.3 Choice Scenario

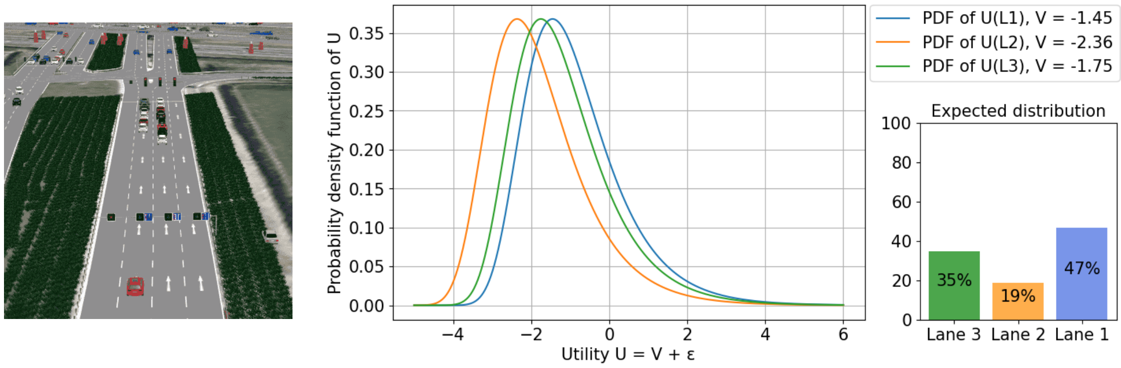


Figure 7.25. – II. Expected Distribution of Drivers in the Sorted Area Derived from a Specific Traffic Situation in the 3T.3 Choice Scenario

The 4T.2 choice scenario

$$
\begin{aligned}
\mathrm{U}_{4T.2}(L1) &= -0.45 - 2.92 \cdot HGV_1 - 0.38 \cdot CAR_1 + \varepsilon_{4T.2} \\
\mathrm{U}_{4T.2}(L2) &= -2.38 \cdot HGV_2 - 0.37 \cdot CAR_2 + \varepsilon_{4T.2} \\
\mathrm{U}_{4T.2}(L3) &= -2.12 - 0.32 \cdot CAR_3 + \varepsilon_{4T.2} \\
\mathrm{U}_{4T.2}(L4) &= -4.34 - 0 \cdot CAR_4 + \varepsilon_{4T.2}
\end{aligned}
\tag{7.5}
$$

The only difference between the 4T.2 and 3T.2 choice scenario is an additional fourth lane on the left side of the driver. Results obtained from the 3T.2 choice scenario were promising for the efficacy of pre-signals in the sense of an equal spread distribution in the sorted area. This was mostly due to the central position of the driver, however the fourth additional lane in the 4T.2 choice scenario requires two left lane changes. Drivers accounted for this heavily, which is reflected by the highly negative ASC parameter of -4.34 for lane 4. Combine this with the found keep-right desire of drivers, and the willingness to spread left-wise decreases against the 3T.2 choice scenario. Figure 7.26 to 7.28 show that drivers are only inclined to use lane 4 when there is a significant amount of traffic on the other lanes. Hence, not supporting an equal spread in the sorted area.

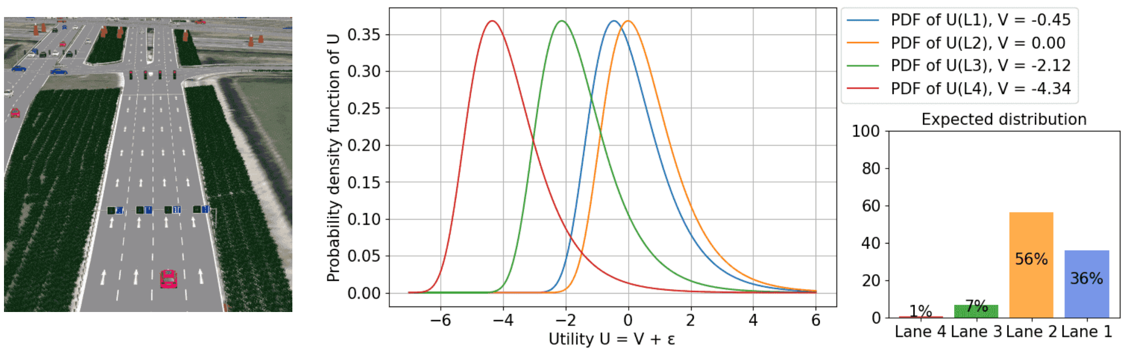


Figure 7.26. – I. Expected Distribution of Drivers in the Sorted Area Derived from a Specific Traffic Situation in the 4T.2 Choice Scenario

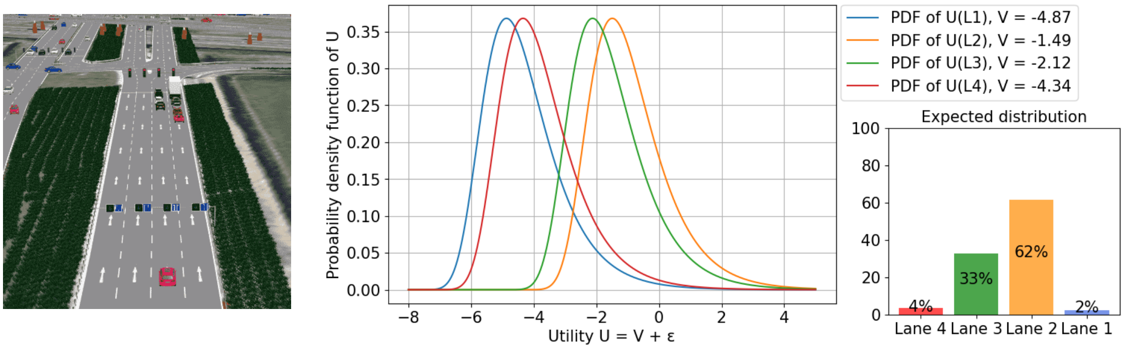


Figure 7.27. – II. Expected Distribution of Drivers in the Sorted Area Derived from a Specific Traffic Situation in the 4T.2 Choice Scenario

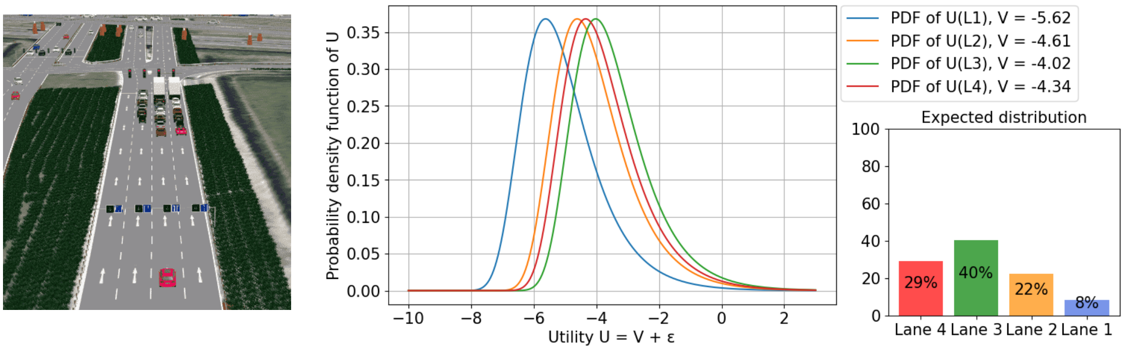


Figure 7.28. – III. Expected Distribution of Drivers in the Sorted Area Derived from a Specific Traffic Situation in the 4T.2 Choice Scenario

The 4T.3 choice scenario

$$\begin{aligned}
\mathrm{U}_{4T.3}(L1) &= -1.63 - 1.02 \cdot HGV_1 - 0.35 \cdot CAR_1 + \varepsilon_{4T.3} \\
\mathrm{U}_{4T.3}(L2) &= 0 - 2.50 \cdot HGV_2 - 0.36 \cdot CAR_2 + \varepsilon_{4T.3} \\
\mathrm{U}_{4T.3}(L3) &= 0.32 \cdot CAR_3 + \varepsilon_{4T.3} \\
\mathrm{U}_{4T.3}(L4) &= -1.57 - 0.36 \cdot CAR_4 + \varepsilon_{4T.3}
\end{aligned} \tag{7.6}$$

The results obtained from the 4T.2 choice scenario did not support the efficacy of pre-signals, which are arguably the most severe in the sense of an inefficient spatial utilization of lane 4. The only difference between the 4T.2 and 4T.3 choice scenario is the initial position of the driver, which is lane 3 instead of lane 2. This shifted position to the left also shifts the distribution of drivers in the sorted area along with it. This favors a more equal spread in the sorted area as the need for two left lane changes expires, and given that drivers account less heavier for right lane changes than for left lane changes. The ASCs for lane 1 and lane 4 are about equal, therefore suggesting that two right lane changes equal one left lane change. Hence, drivers will spread more evenly between those two outer lanes. However, this does not increase the willingness of drivers to spread to the outer lanes, since this is reflected by the magnitude of the ASCs. Given that these are slightly lower compared to the 4T.2 choice scenario, drivers will spread to the outer lanes relatively early. Nevertheless not soon enough for an equal spread in the sorted area, hence not supporting the efficacy of pre-signals. This is shown in Figure 7.24 & 7.25.

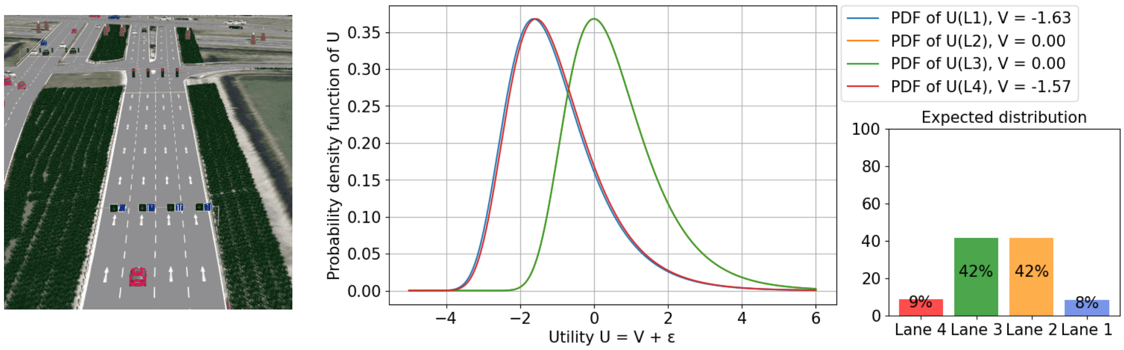


Figure 7.29. – I. Expected Distribution of Drivers in the Sorted Area Derived from a Specific Traffic Situation in the 4T.3 Choice Scenario

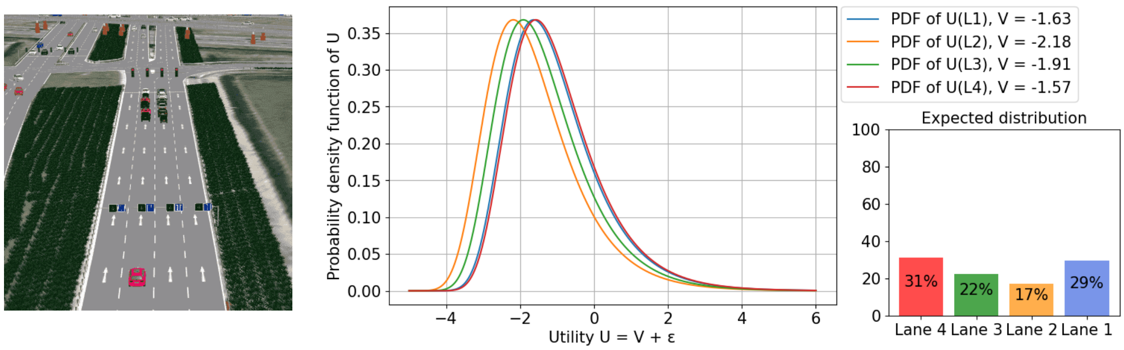


Figure 7.30. – II. Expected Distribution of Drivers in the Sorted Area Derived from a Specific Traffic Situation in the 4T.2 Choice Scenario

7.9.4. Summary of findings

Figure 7.31 summarizes the findings of Section 7.9. It was found that only the 2R.1, 2L.4, and 4T.2 choice scenarios contributed to an equal spread in the sorted area, therefore supporting the efficacy of pre-signals. The underlying reason for this success is the absence of multiple lane changes in order to reach the outer lanes. Since driver heavily accounted for multiple lane changes, it requires traffic crowdedness on the other lanes being more crowded with respect to the outer lane. Except for the three mentioned choice scenarios, this led to such highly imbalanced traffic conditions in the sorted area, therefore decreasing the efficiency of pre-signals.

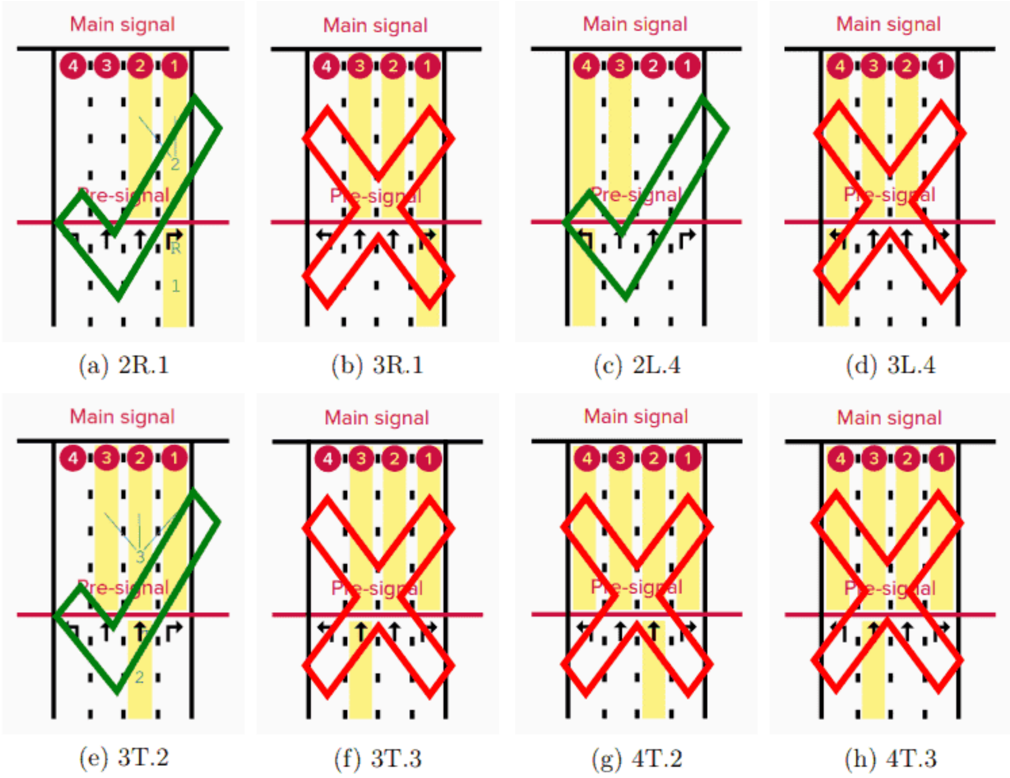


Figure 7.31. – Summary of Pre-Signal Choice Scenarios that Support the Efficacy of Pre-Signals in terms of An Equal Spread in the Sorted Area

7.10. Conclusion

This chapter started off with processing the acquired pilot study's data into a set of prior estimates, which were used to redesign the main experiment's profiles. The unexpected difficulties in the pilot study distribution emphasized the need to adopt changes into the main experiment's questionnaire design. These mostly concerned the application of static images instead of video based questions, a reformulation of some questions, and a revised questionnaire distribution setup. The main objective of this chapter was to formulate and execute the data analysis strategy for acquiring and assessing the main experiment's model estimations. Thereby, it tried to answer the following three research questions:

- What trade-offs between the relevant lane-changing factors make human drivers in their desired lane choice downstream the pre-signal?
- How are these trade-offs affected by the driver's intended turning direction and the number of lanes in the sorted area?
- To what extent does the drivers' preferred lane choice downstream the pre-signal differ from one of a conventional signalized intersection without a pre-signal, and what are the implications of these differences for the applicability and efficiency of pre-signals in general?

The data analysis strategy concerned an analysis from the perspective of three levels: model-wise, alternative-wise, and parameter-wise. The model analysis was based on an hypothesis testing strategy in which the model performance was assessed against the base model for all choice scenarios. Surprisingly, only the M1 & M1a models, which included the TRV parameter, were the consistent better performers against the base model. Although the M3 & M3a models did not manage to be significantly better at a 95% significance levels, it did on a slightly lower significance level of 70%-90%, and was increasing along with an increasing choice set size. This highlights the importance of non-myopic drivers who tend to have a higher keep right desire compared to myopic drivers.

The results of the main experiment were greatly appreciated since they reflected some general aspects of driving behavior that must had to be present. Otherwise it would not make sense to base research findings on such invalid results. Take as an example the keep-right desire of drivers, or an increasing discomfort along with increasing traffic crowdedness. Other behavioral findings concerned a relative high discomfort for the presence of heavy good vehicles compared to cars, which increased when they were the trailing vehicle in the queue, or when they were positioned in lanes closes to the driver. The lane-changing aspect also turned out to be a major contributing factor to the spread behavior of human drivers. A strong keep-right desire was found when drivers are positioned in the most left lane of the sorted area, while this moderated slightly when drivers were positioned more centrally. On the other hand, drivers felt a much lower discomfort for right lane changes compared to left lane changes. This gap increased in cases where the target lane was the most left lane of the sorted area. One could even argue here that two right lane changes equal one left lane change in terms of associated discomfort. This does not withhold drivers from spreading left, it just requires the driver's right side being more crowded with respect to its left side.

The results obtained from pre-signal choice scenarios and counterpart choice scenarios were compared to each other with the aim to assess the pre-signals' efficacy. When it comes to the appreciation of traffic crowdedness, there were no clear signs that the pre-signal affects the driver in their associated discomfort with HGVs and cars. The contrary was found te be true for the lane-changing aspect, of which its dimensions varied between choice scenarios. Hence, having a profound impact on the efficacy of pre-signals for regular traffic. It was found that only the 2R.1, 2L.4, and 3T.2 choice scenarios contributed to an equal spread in the sorted area, therefore supporting the efficacy of pre-signals. The underlying reason for this success is the absence of multiple lane changes for reaching the outer lanes. Either because of a central starting position of the driver downstream the pre-signal, or due to just a limited sorted area size of only two lanes. Although the latter seems to be rather arbitrary, it contradicts with some of the core elements of pre-signals, i.e. to provide traffic downstream the pre-signal with more pre-sorting lanes than upstream the pre-signal. Other choice scenarios were not able to achieve a (near to) equal spread in the sorted area, because traffic crowdedness on the lanes close to the driver would need to reach such highly imbalanced levels before a considerable share of drivers spread towards the most outer lane of the sorted area. This results in a relatively low spatial utilization of this outer lane, hence decreasing the efficiency of pre-signals.

Part IV. Discussion & Conclusion

8. Discussion

This chapter focuses on the reflection of the research in its entirety. When research outcomes are projected on traffic situations other than the exactly presented cases in this research, it is critical to be aware of the strengths and limitations of the research approach, otherwise wrong projections are most likely inevitable. Drawbacks of the research methodology have eventually a major contribution to the general credibility of the results in terms of their reliability and validity. Reliability in the sense of the outcomes being trustworthy and accurately, and validity in the sense of research outcomes measuring what they supposed to measure. A reflection on both is given in Section 8.1 & 8.2 respectively. Finally, some general limitations of the study and implications for pre-signals are given in Section 8.3 & 8.4 respectively.

8.1. Reliability of research outcomes

Reliability has been controlled for throughout the design of the stated-choice experiment. Mainly by implementing efficient designs instead of the more common traditional approach. Priors, the careful guesses of the base models' parameters, were used to balance utilities among alternatives such that the information richness of a respondent's choice increased heavily. As a result, standard errors of the estimates decreased and the minimum data size requirements could be calculated in order to guarantee statistical significance. Hence, it was possible to assess the reliability of parameter estimates for each variable individually. The fact that the research outcomes cannot be criticized on their reliability due to a strategic research methodology is argued to be greatest strength of the research.

However, this is only valid in case when the priors were representative for the final parameter estimations. Therefore, an independent samples t-test is used to investigate whether the priors and final estimates, which are derived from two independent samples, came from the same population. If they do, then their estimates should be approximately equal. The priors' sample is the pilot study data set, and the sample of the final parameter estimations is the main experiment data set. The test statistic follows the t-distribution with $\nu = n_1 + n_2 - 2$ degrees of freedom, where n_1 and n_2 are the sample sizes of both samples. It is calculated by

$$t = \frac{(x_1 - x_2) - (\mu_1 - \mu_2)}{SE}. \tag{8.1}$$

The null hypothesis assumes $\mu_1 = \mu_2$ and therefore

$$t = \frac{(x_1 - x_2)}{SE}. \tag{8.2}$$

SE is the standard error of the difference between the two sample means. Under the variance sum law, the variance of a difference between two independent samples is equal to the sum of their variances. The sample sizes of the pilot study and main experiment are unequal, therefore

$$\begin{aligned} &SE = \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n2}}, \text{ with } s_1^2 \text{ and } s_2^2 \text{ replaced by } s_{pooled}^2, \text{ where} \\ &s_{pooled}^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}. \end{aligned} \tag{8.3}$$

Table C.2 in Appendix C.2 provides the results of the executed independent samples t-test. The null hypothesis must be rejected when the p-value is less than 0.05, suggesting a significant evidence of a difference between the prior and the final estimated parameter. The results show only one case where the null hypothesis must be rejected. This concerns the $BETA_{CAR2}$ estimate in the 2R.1 choice scenario, while priors were a representative guess for all other parameters. Thus, it can be concluded that reliability concerns do not play any role, and that the relatively small pilot study did not negatively affect the reliability of the research outcomes.

8.2. Validity of research outcomes

Unlike the absence of reliability concerns, validity issues do need to be taken into account when it comes to answering the main research question. Although the revealed spread behavior in the sorted area has been found to support the pre-signal's efficacy for only three choice scenarios, there still persist a difference between what has been measured in the research outcomes versus what actually will materialize in real traffic situations. This gap is expected to be predominately originated from the presence of the hypothetical bias, the lack of learning effects in the stated-choice experiment, and to a lesser extent from the IIA and IID assumption of MNL choice models. These issues have been controlled as much as possible with respect to the research feasibility. How they are still expected to impact the validity of results is elaborated upon below.

The main experiment results were greatly appreciated by the researcher since they reflected some general aspects of driving behavior that someone would have expected to find, e.g. a general keep-right desire, or an increasing discomfort with increasing traffic crowdedness. This already emphasize the credibility of the research outcomes, but it definitely does not guarantee valid results yet. Take for example the research methodology where the decision was made to adopt stated-preference data instead of revealed preference data. This inevitably impacted validity due to the hypothetical bias. The question that arose here was: do stated preferences in hypothetical choice experiments reflect their choices and behavior in real traffic conditions? Although this gap was controlled as much as possible, it still questions validity. Since the size of the hypothetical bias cannot be measured due to the absence of revealed preference data from practice, implications for validity cannot be made specifically. To compensate for this, conclusion about the estimated results were made on a less comprehensive scale compared to the much more detailed estimates. Hence, general trends were extracted from the estimated results rather than precise quantitative formulations of behavioral trade-offs. Sum this up to the basic driving behavior characteristics that were present, and the research outcomes have been found valid enough for such type of conclusions about the implications of the pre-signals' applicability and efficiency in general.

Besides the presence of the hypothetical bias, the decision to prefer the MNL above the ML choice model inevitably impacted the research outcomes, but eventually a lot less than expected. Among other things, this is the result of a relative low presence of preference heterogeneity among respondent's characteristics, therefore reducing the impact of the IIA assumption. A low preference heterogeneity can be confirmed by the statistical insignificance of the models which reflected respondent's characteristics. Furthermore, the ML model outcomes would have been too detailed for the line of reasoning that is applied in the formulation of results. Regarding the IID assumption of the MNL model, individual taste heterogeneities for the explanatory variables could not be observed, although those were expected to occur. If the ML would have been applied, then the model performance would most likely increase, because parameter estimates would have been described by a normal distribution instead of a single average. Again, it is questionable if such a richer representation of variation would actually be useful given the more general formulation of the results.

Respondents had to state their desired lane choice repeatedly, without experiencing any consequences of their choices, therefore ignoring the learning curve of drivers. In real traffic, drivers are most likely to adapt their lane choice based on previous experiences and additional gained knowledge. Respondents in the questionnaire were not able to undergo such a process, therefore research outcomes do not precisely measure what they are supposed to measure. This drawback in the research methodology is assumed to have to most impact on validity. Obviously, this could have been prevented by e.g. extending the video based questions in length to a position after the pre-signal, or by adopting a driving simulator. These options were considered unfeasible due to the data size requirements and the limited time period of the research. Some implications that are expected to arise here are summed below.

- The willingness to spread left-wise could reduce further when drivers undergo the discomfort of additional required lane changes downstream their route. This issue was reflected by the MYP variable, which was in most case close to significance, and is expected to dominate much more when drivers are well-educated.
- Their could exists a significant difference in the general willingness to spread for fixed-time and real-time adaptive pre-signal controllers. If drivers understand that the green phase of a real-time adaptive pre-signal ends after the last vehicle left the sorted area, they could anticipate on this by not feeling the urge to spread anymore.
- Familiarity with the pre-signal concept might further increase the general willingness to spread. Although this has not been tested in this research, it is not unlikely that once drivers understand the main objective of pre-signals, they may (partially) steer their behavior according to the need of the pre-signal.

Another aspect that must be taken into account, is the absence of a context provided to the respondent while executing the stated-choice experiment. This argues for a difference in driving behavior for e.g. commuting versus leisure trips, or being in a hurry or not. Since such information was not provided to the respondents, they most likely took their own viewpoint, therefore aligning well to real mixed traffic conditions. Although this is not expected to make the research outcomes invalid, it is important to be aware that pre-signals might perform differently in heavy commuting traffic compared to more leisured traffic during weekends.

Finally, respondents were not able to interact with traffic dynamically. Although this has been found to have a positive effect on reliability of parameter estimates, caution has to be preserved while reflecting on validity. This mainly holds when multiple pre-sorting lanes upstream the pre-signal have been dedicated to one traffic stream. Then, drivers interact not solely with traffic queues downstream their route, but also with the vehicles positioned next to the driver. In this research, the impact of the driver's lateral position at the pre-signal has been tested without the interference of traffic dynamics. Therefore, research outcomes are not valid for pre-signals with multiple pre-sorting lanes for one traffic stream. Nevertheless, research outcomes can be reflected on such cases, which is elaborated upon in Section 8.3.2.

8.3. Additional limitations of the study

8.3.1. The hypothetical traffic environment

The innovative characteristic of the pre-signal concept for regular traffic forced the researcher to design a hypothetical traffic environment. The design of this 3D environment was mainly based on recommendations from literature, which concerned the length of the sorted area of 120 meters and the incorporation of a keep-clear area of 50 meters. Both lengths were fixed throughout the research, hence it was not possible to investigate the impact of the sorted area length on the drivers' spread behavior. Such insights can be useful to investigate whether the willingness of drivers to execute multiple lane changes increase along with an increasing sorted area length. Since this was the core problem for the efficacy of pre-signals, it could change the current negative attitude towards the efficacy of pre-signals. Furthermore, some additional design choices have been incorporated in the hypothetical traffic environment to increase the ability of respondents to understand the pre-signal concept. These concerned the decision to apply dynamic lane marking in the sorted area, and the implementation of self-created traffic signs. It is unclear if and how this influenced the desired lane choice of respondents. In any absence of (one of) these elements, the reader must be aware of their presence since they might have nudged respondents to change lanes.

The same line of reasoning holds for the decision to introduce a fixed location at which respondents had to make their desired lane choice. Although it was found that their choices were not dependent on the distance to the queue, this location will vary for all individuals in real traffic. If respondents felt constrained to execute multiple lane changes, e.g. due to limited longitudinal space, then it might explain the hesitation of drivers towards it. This is not expected to occur since respondents were facilitated with a minimum longitudinal displacement of 30 meters per lane change, which was found sufficient enough from observed driving behavior (Li *et al.*, 2019). Whether it actually was sufficient cannot be tested, hence readers must be aware of this assumption.

8.3.2. The fixed set of choice scenarios

A set of 10 choice scenarios have been incorporated in the stated-choice experiment, which are given in Figure 5.9. They reflected a sorted area size of 3 & 4 lanes for through-going traffic, and 2 & 3 lanes for turning-traffic. Unlike the variety in sorted area utilization, the pre-sorting lanes upstream the pre-signal did not vary. Hence, all results rely on the principle of 1 right-turning, 2 through-going, and 1 left-turning pre-sorting lane upstream the pre-signal (1L-2T-1R). In other traffic conditions, this designation might be changed to e.g. 1L-1T-1R, 1L-1T-2R, or 2L-2T-2R. Due to the strategic setup of choice scenarios, research outcomes can be reflected upon these changed dynamics. Hereby it is expected that the pre-signal will not yield an equal spread in the sorted area whenever multiple lane changes are required to reach the outer lanes. Then, it seems actually quite interesting to implement a pre-signal in the form of 1L-1T-1R or 1L-2T-1R, as shown in Figure 8.1. This figure presents the only two types of pre-signal systems that are expected to yield an equal spread in the sorted area. However, turning-traffic cannot use the entire sorted area, which will undoubtedly confuse the driver in real traffic environments, hence unsafe and not preferred to implement.

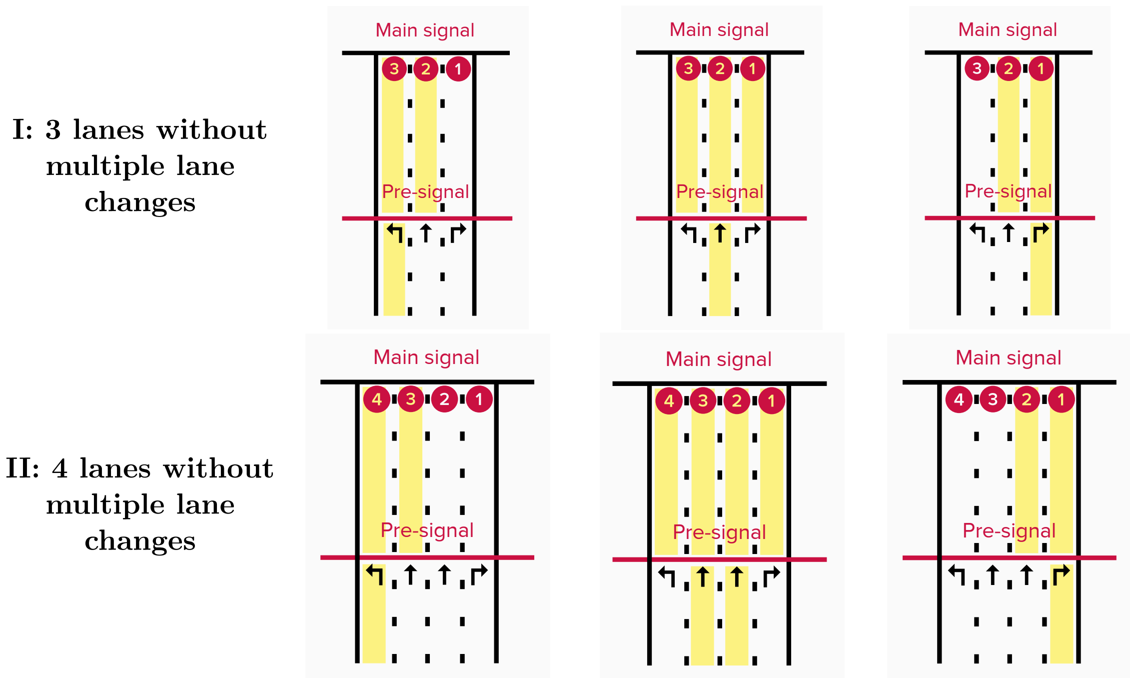


Figure 8.1. – Pre-Signal Systems that are Expected to Support an Equal Spread in the Sorted Area

There also persist no need for multiple lane changes in case when multiple pre-sorting lanes are dedicated to turning directions, i.e. in the form of 2L-1T-1R or 1L-1T-2R. The former is shown in Figure 8.2. Despite the absence of multiple lane changes, such pre-signal systems are not expected to yield an equal spread in the sorted area. This is mainly due to drivers in the outer pre-sorting lane being constraint by vehicles in the lane next to the driver from spreading towards the middle of the sorted area. It is important to note that the magnitude of this affect has not been investigated in the research. In addition, the same problem arises that drivers cannot use the entire sorted area.

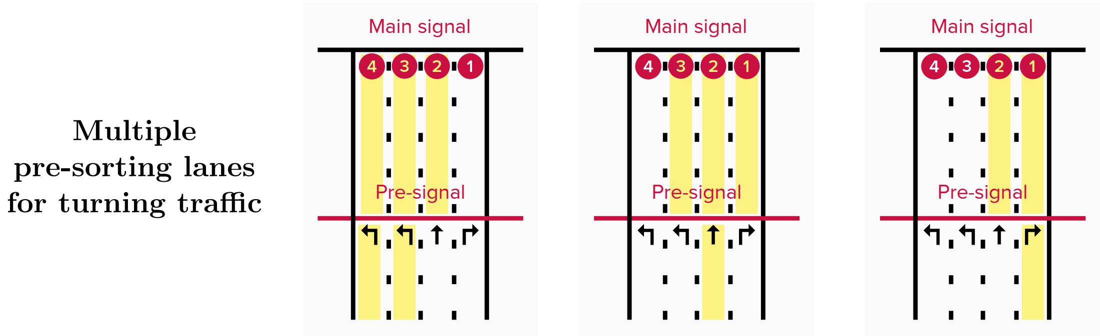


Figure 8.2. – Pre-Signal System with Multiple Pre-Sorting Lanes for Turning Traffic

8.3.3. The scope limitation to the single-movement pre-signal type

Figure 2.1 & 2.2 presented four types of pre-signals. The single- and multi-movement systems allow respectively only one and multiple traffic streams in the sorted area simultaneously. The full- and part-utilization type differ in sorted area design, where the part-utilization type dedicates a separate lane for a particular traffic stream, which is not able to spread in the sorted area. The scope has been set to the single-movement pre-signals systems with a full-utilization design of the sorted area. However, research outcomes can be reflected upon the single-movement systems with a part-utilization design.

Unfortunately, any part-utilization design of 4 pre-sorting lanes upstream the pre-signal yield the requirement for one traffic stream to execute multiple lane changes to reach the outer lane of the sorted area. In addition, the other traffic stream that is allowed to spread in the sorted area faces the same problem as shown in Figure 8.2. Hence, drivers in the outer pre-sorting lane will be constrained by vehicles in the lane next to the driver from spreading towards the middle of the sorted area. This is shown in Figure 8.3.I. However, this phenomenon will not occur when the number of pre-sorting lanes decrease from 4 to 3. This is shown in Figure 8.3.II. In this case, it is questionable whether such a pre-signal design serves its pure objective.

8.3.4. Heavy good vehicles in the sorted area

Within the stated-choice experiment, it has been assumed that HGVs always position themselves in the two most right lanes of the sorted area. Since HGVs are supposed to drive on the right side of the road, it seems quite reasonable to assume that the willingness of HGVs to spread right is greater than that of car drivers. However, HGVs require a longer longitudinal displacement for a lane change, hence they might be restricted from their desired

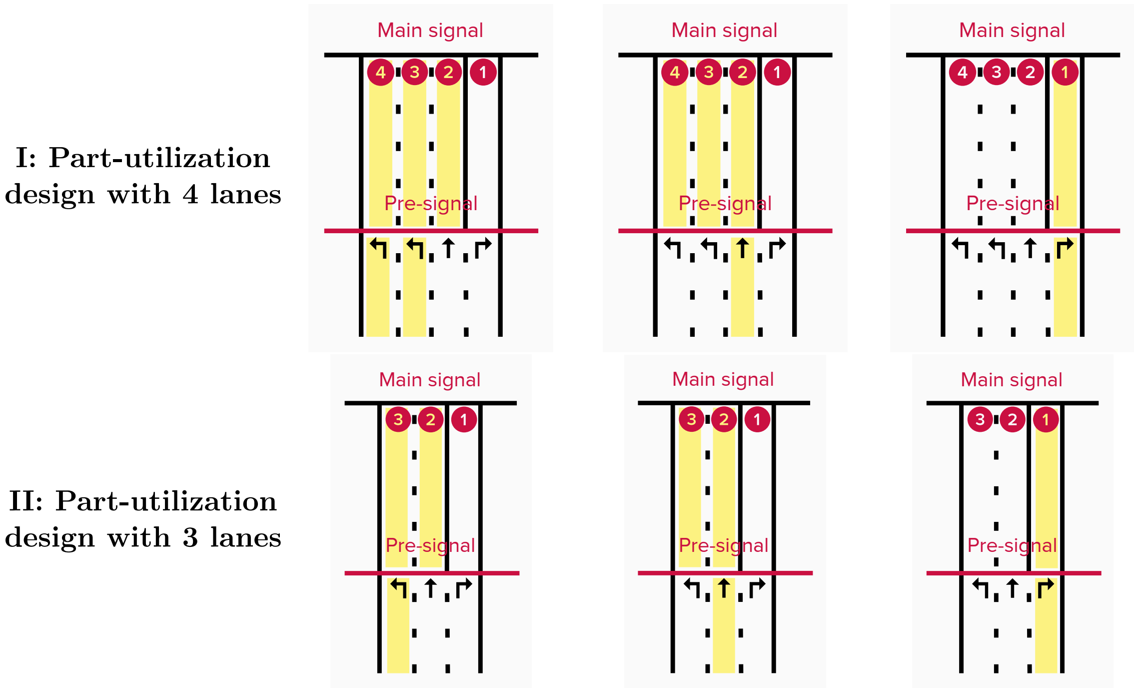


Figure 8.3. – Part-Utilization Pre-Signal System Designs with 3 and 4 Pre-Sorting Lanes

target lane in crowded traffic conditions. This is expected to occur more often for left-turning traffic since they are pushed to the left side of the sorted area. Although this has not been investigated, it is important to be aware of this phenomenon that might occur.

8.3.5. The driving style assessment of respondents

Although driving styles will undoubtedly matter in real traffic, the model level results have shown that there was no persistent behavioral difference for the self-assessed driving styles. This is expected to be the result of the simplified self-assessment method in the stated-choice experiment. The well-known multi-dimensional driving style inventory of BenAri *et al.* (2004) has been simplified to maintain the questionnaire length feasible and to prevent respondents from exhaustion. Instead of incorporating all 44 elements, respondents just had to rate their own driving style according to some characteristics of six pre-defined driving styles. Although this might not have been the most proper approach, it does not impact the efficacy of pre-signals by any means, since it would only provide a more profound insight in the behavioral difference between different types of respondents.

8.4. Some implications in general

Irrespective of the research outcomes, pre-signals face some additional challenges when it comes to a successful implementation for regular traffic. To the researchers opinion, traffic safety concerns, for particularly fixed-time pre-signal controllers, may hamper this process. Imagine for example what will happen in case that a driver does not succeed to saturate from the main intersection during its fixed green time. As a result, the driver gets stuck in the sorted area while another traffic stream fills the sorted area from behind. Does this supposed to mean that the stuck driver needs to adjust his turning direction with the new phase of the main signal?

Further traffic safety issues arise from the findings of Section 8.3.1 & 8.3.3. These findings show that it is not possible to design a pre-signal system that is able to yield an equal spread in the sorted area while also using the entire sorted area for all traffic directions. This introduces additional challenges in terms of preventing drivers from being confused about the available lanes in the sorted, and from being distracted from their driving task. Furthermore, the cost aspect of dynamic signing in this case is something that also needs to be taken into account. When it comes to the sustainable safety principle, allowing drivers to use the entire sorted area at any time, will secure predictability in pre-signal designs and the state awareness of drivers.

Finally, an issue that previous literature neglected concerns the potential of pre-signals in mixed traffic. The latter could actually be in favor of pre-signals when automated vehicles compensate for the imperfect spread behavior of human drivers. Obviously, the potential of pre-signals decays as traffic operates at (near) full connectivity. Thus, traffic engineers need to critically weigh up the pre-signal's potential against the implications it faces in real traffic.

9. Conclusion

This research aimed to identify how human drivers are affected in their preferred lane choice downstream the pre-signal, with the objective of reflecting these findings against potential implications for the applicability and efficiency of pre-signals for regular traffic. Such implications originated from the anticipation of a behavioral assumption that previous literature applied in their simulation studies. This assumption included an equal spread of drivers in the sorted area. If incorrect, it was hypothesized that it would degrade the efficacy of pre-signals. The main research questions sounded:

General main research question:

How does drivers' lane selection downstream of pre-signals impact the efficacy of pre-signal implementation for regular traffic?

Sub-main research questions:

How do drivers choose their preferred lanes downstream of pre-signals?

To what extent do drivers' lane choice strategies affect the efficiency and applicability of pre-signals for regular traffic?

9.1. Conclusion

The results have shown that pre-signals do not affect drivers in their appreciation of traffic crowdedness. In general, drivers account for heavy good vehicles more than twice as heavily than for cars. Besides that, the discomfort for heavy good vehicles increases whenever it concerns the trailing vehicle, and when these vehicles are positioned in lanes closer to the driver. This further emphasizes the tendency to avoid heavy good vehicles. Regarding the discomfort for cars, drivers account about twice as heavily whenever there is no option to avoid heavy good vehicles.

Although it was found that pre-signals do not affect drivers in their appreciation of traffic crowdedness, substantiation differences have been found in the discomfort associated with lane changing. This led to the lane-changing aspect being the predominant factor to assess potential implications for the pre-signals' efficiency and applicability for regular traffic. Drivers maintain a high-keep right desire when they are positioned in the most left lane of the sorted area, and this slightly moderates when drivers are positioned more centrally. This was the result of a much lower discomfort for right lane changes than for left lane changes, and an increase of this gap increases whenever the target lane of the driver equals the most left lane of the sorted area. In addition, drivers are the most hesitated to execute multiple left lane changes. This together does not withhold drivers from spreading left-wise in the sorted area, it just requires the driver's right side being more crowded with respect to its left side.

The results have shown that only the 2R.1, 2L.4, and 3T.2 choice scenarios contribute to an equal spread in the sorted area, hence acknowledging the efficacy of pre-signals. The underlying reason for this success is the absence of multiple lane changes to reach the outer lanes of the sorted area. This critical bottleneck lies at the heart of the entire pre-signal paradigm, imposing a barrier that significantly obstructs the equal spread of drivers and eventually the efficiency of the system. Those particular choice scenarios succeeded in this, either because of a central starting position of the driver, or due to a limited sorted area size of two lanes. Although the latter seems to be rather arbitrary, it contradicts with some of the core elements of pre-signals, i.e. to provide traffic downstream the pre-signal with more pre-sorting lanes than upstream of the pre-signal. Then, it is questionable whether pre-signals can improve the capacity of the main intersection, because literature has only provided evidence for this to increase with at least three lanes included in the sorted area for all traffic directions. Other choice scenarios were not able to achieve a (near to) equal spread in the sorted area, since traffic crowdedness on the lanes close to the driver would need to reach such highly imbalanced levels before a considerable share of drivers would spread to the most outer lane of the sorted area. As a result, it yield a relative low spatial utilization of this outer lane, hence decreasing the efficiency of pre-signals.

These results emphasize the limited support for the behavioral assumption that previous researchers incorporated in their simulation studies to highlight the potential of pre-signals to increase the intersection's capacity significantly. Although this research did not explicitly test the consequences of the obtained driving behavior with respect to the intersection's capacity, such previous statements about the potential of pre-signals should be questioned at this point. The upcoming sections elaborate upon the recommendations for practice and science.

9.2. Recommendations

9.2.1. Recommendations for practice

Despite the thin support for the applicability of pre-signals at the moment, this research also highlighted some opportunities that traffic engineers can use to decide whether or not to implement pre-signals. These recommendations follow from pre-signal designs and traffic conditions where it is expected to achieve the highest efficacy for pre-signals. Hereby, traffic engineers face two options. The first option is recommended and includes the decision to let all traffic directions utilize the entire sorted area. The other option leaves the possibility to change the available lanes in the sorted for each traffic direction. Although the latter option is able to achieve a pre-signal design that is expected to yield an equal spread in the sorted area, it also yields the least safe approach with secondary implications. Both of these options are discussed below.

Option 1: all traffic directions must use the entire sorted area.
Literature has only provided evidence for an increased capacity intersection when at least three lanes are included in the sorted area for all traffic directions. On the other hand, results have shown that with at least 3 lanes in the sorted area, it is impossible to yield an equal spread under option 1. This is the result of the need of multiple lane changes for the turning directions to reach the outer lanes of the sorted area, as shown in Figure 9.1. Despite the lack of an equal spread, it has been considered as the general preferred option, which is based on the principles of sustainable safety. This option secures predictability in the pre-signals' design, and protects the state awareness of drivers. As a result, this predictability prevents drivers from being distracted from their driving task. Once drivers approach a pre-signal, they can rely on their previous experiences, which are all similar: the driver is allowed to use the entire sorted area.

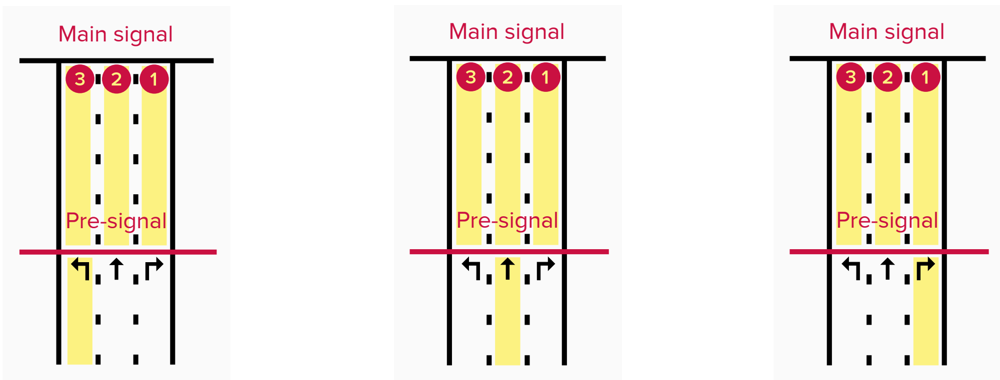


Figure 9.1. – Recommended design of the Pre-Signal System when All Traffic Directions Must Use the Entire Sorted Area

Whenever this option is considered, traffic engineers must be aware that the pre-signal is less efficient for turning directions than for through-going traffic due to a lower spatial utilization of the third additional lanes. Hence, it might seem an attractive solution if an intersection faces heavy through-going traffic. Please note that this has not been particularly confirmed by any simulation studies.

Option 2: parts of the sorted area are dedicated to a particular traffic direction.
Unlike option 1, this option does yield an equal spread in the sorted area, because sorted area lanes can be dedicated to traffic stream such that they avoid the need of multiple lane changes. From all single-movement and part-utilization pre-signals designs, only two designs have been found that support an equal spread in the sorted area. These are given in Figure 9.2 for both 3 and 4 sorted area lanes. Despite the equal spread, they yield secondary implications which are not desirable for practice. These include traffic safety issues and elevated costs through dynamic road signing. Unlike option 1, the lack of predictability in pre-signal design poses challenges for traffic engineers. Challenges that arise here concern the need to limit the driving task and to clearly inform the driver about the available lanes in the sorted area. If misunderstood, those drivers get stuck at the main signal's red light,

forcing them to run the red light, then coming short in the infrastructure downstream the main intersection to facilitate the additional occupied lane.

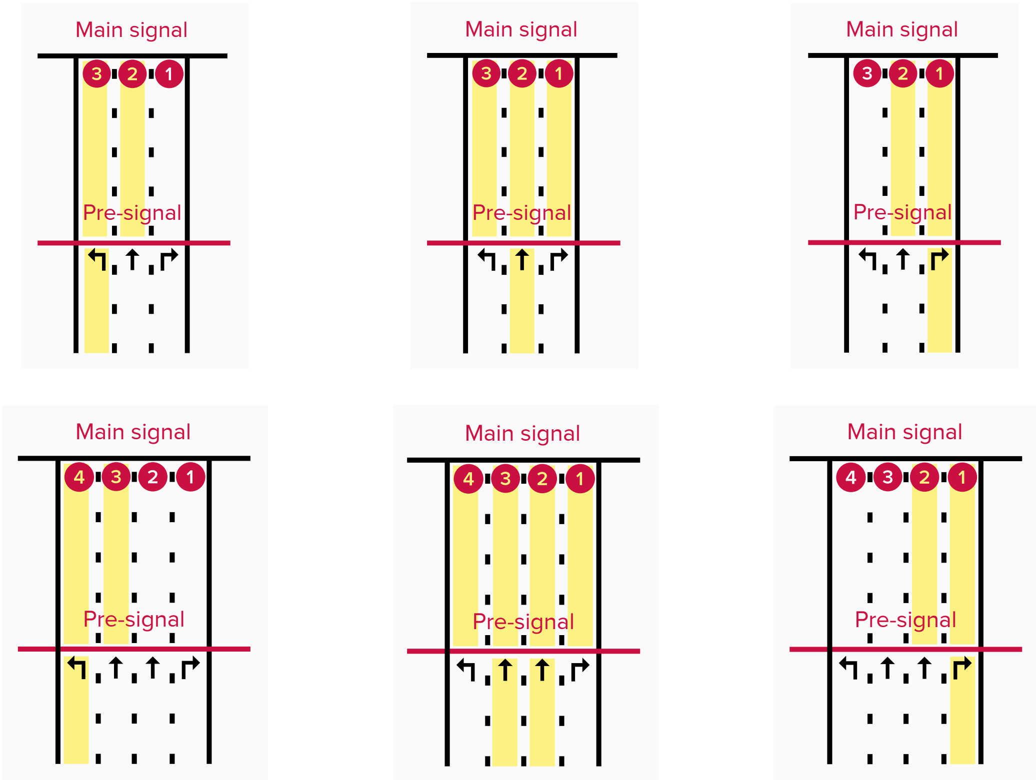


Figure 9.2. – Recommended design of the Pre-Signal System when Traffic Directions are Dedicated to Parts of the Sorted Area

To conclude, the design of a pre-signal system that achieves both an equal spread and uses the entire sorted area for all traffic directions proves unfeasible.

9.2.2. Recommendations for science

This research stepped into the research gap of pre-signals that withheld the innovative concept from being validated with the interaction of human involvement. To the knowledge of the researcher, it is the first study that investigated driving behavior at pre-signals for regular traffic. That the support for pre-signals is rather limited after this research further emphasizes the urgency of incorporating behavioral science before such an innovation can be judged properly. Although previous simulators were wrong about their behavioral assumptions, it does not necessarily need to withhold future researchers to investigate the potential of pre-signals. This research also highlighted some opportunities for pre-signals, which require additional research. The next recommended step for future researches is to implement the estimated utility functions of this study into a new simulation model, and to compare the intersection performances by making use of a before-after-analysis. The selection of a specific intersection design can be based on the recommendations for practice as given in

Section 9.2.1. By doing so, implications for the pre-signals' applicability and efficiency can be based on a quantitative analysis, instead of the more general qualitative approach that has been taken in this research.

Regarding the characteristics of drivers, it was found that non-myopic drivers tend to have a higher-keep right desire than myopic drivers. This emphasized the importance of the learning curve of drivers, which has not been taken into account in this research. It is recommended to further investigate the shift in driving behavior that may occur when drivers are well-experienced with the pre-signal concept.

Driving behavior in this research has been studied without the consideration of a variable length of the sorted area, the type of pre-signal controller, and a part-utilization of the sorted area. Nevertheless, it was argued that the general willingness of drivers to spread would decrease in case of a real-adaptive controller, and that a less equal spread would be achieved in case of any part-utilization pre-signal type. However, it might be interesting to investigate whether the willingness to spread of drivers would increase along with an increasing sorted area length. If so, then it might shift the current negative outlook for pre-signals in a more positive direction. Future researchers are recommended to investigate whether or not drivers anticipate differently on such design changes.

Finally, literature currently neglect any concerns regarding the implementation risks of pre-signals. Aspects such as traffic safety, cost efficiency, connectivity, and human factors have not been researched yet, while these are often dominant aspects when it comes to an actual implementation in real traffic.

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Appendices

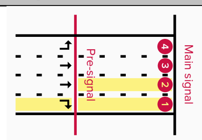
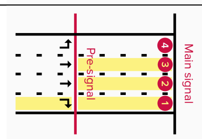
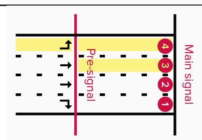
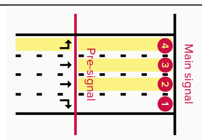
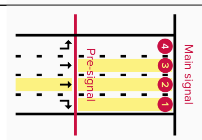
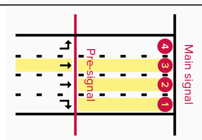
Appendix A.

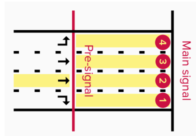
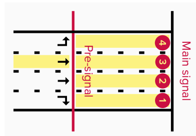
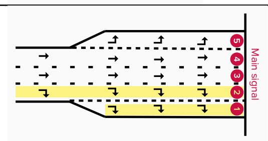
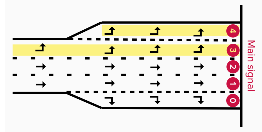
Mathematical formulation of utility functions and profiles

This appendix includes the full package of mathematical formulations regarding the utility functions, and the construction of profiles for both the pilot study and the main experiment.

A.1. Pilot study: utility functions

Table A.1. – Utility Functions per Choice Scenario

Choice scenario	**Utility functions**	**Schematic representation**
2R.1	$\mathrm{U}_{2R.1}(L1) = \beta_{HGV,1} \cdot HGV_1 + \beta_{CAR,1} \cdot CAR_1 + \varepsilon_{2R.1}$ $\mathrm{U}_{2R.1}(L2) = ASC_2 + \beta_{HGV,2} \cdot HGV_2 + \beta_{CAR,2} \cdot CAR_2 + \varepsilon_{2R.1}$	
3R.1	$\mathrm{U}_{3R.1}(L1) = \beta_{HGV,1} \cdot HGV_1 + \beta_{CAR,1} \cdot CAR_1 + \varepsilon_{3R.1}$ $\mathrm{U}_{3R.1}(L2) = ASC_2 + \beta_{HGV,2} \cdot HGV_2 + \beta_{CAR,2} \cdot CAR_2 + \varepsilon_{3R.1}$ $\mathrm{U}_{3R.1}(L3) = ASC_3 + \beta_{CAR,3} \cdot CAR_3 + \varepsilon_{3R.1}$	
2L.4	$\mathrm{U}_{2L.4}(L3) = ASC_3 + \beta_{HGV,3} \cdot HGV_3 + \beta_{CAR,3} \cdot CAR_3 + \varepsilon_{2L.4}$ $\mathrm{U}_{2L.4}(L4) = \beta_{HGV,4} \cdot HGV_4 + \beta_{CAR,4} \cdot CAR_4 + \varepsilon_{2L.4}$	
3L.4	$\mathrm{U}_{3L.4}(L2) = ASC_2 + \beta_{HGV,2} \cdot HGV_2 + \beta_{CAR,2} \cdot CAR_2 + \varepsilon_{3L.4}$ $\mathrm{U}_{3L.4}(L3) = ASC_3 + \beta_{HGV,3} \cdot HGV_3 + \beta_{CAR,3} \cdot CAR_3 + \varepsilon_{3L.4}$ $\mathrm{U}_{3L.4}(L4) = \beta_{CAR,4} \cdot CAR_4 + \varepsilon_{3L.4}$	
3T.2	$\mathrm{U}_{3T.2}(L1) = ASC_1 + \beta_{HGV,1} \cdot HGV_1 + \beta_{CAR,1} \cdot CAR_1 + \varepsilon_{3T.2}$ $\mathrm{U}_{3T.2}(L2) = \beta_{HGV,2} \cdot HGV_2 + \beta_{CAR,2} \cdot CAR_2 + \varepsilon_{3T.2}$ $\mathrm{U}_{3T.2}(L3) = ASC_3 + \beta_{CAR,3} \cdot CAR_3 + \varepsilon_{3T.2}$	
3T.3	$\mathrm{U}_{3T.3}(L1) = ASC_1 + \beta_{HGV,1} \cdot HGV_1 + \beta_{CAR,1} \cdot CAR_1 + \varepsilon_{3T.3}$ $\mathrm{U}_{3T.3}(L2) = ASC_2 + \beta_{HGV,2} \cdot HGV_2 + \beta_{CAR,2} \cdot CAR_2 + \varepsilon_{3T.3}$ $\mathrm{U}_{3T.3}(L3) = \beta_{CAR,3} \cdot CAR_3 + \varepsilon_{3T.3}$	

4T.2	$U_{4T.2}(L1) = ASC_1 + \beta_{HGV,1} \cdot HGV_1 + \beta_{CAR,1} \cdot CAR_1 + \varepsilon_{4T.2}$ $U_{4T.2}(L2) = \beta_{HGV,2} \cdot HGV_2 + \beta_{CAR,2} \cdot CAR_2 + \varepsilon_{4T.2}$ $U_{4T.2}(L3) = ASC_3 + \beta_{CAR,3} \cdot CAR_3 + \varepsilon_{4T.2}$ $U_{4T.2}(L4) = ASC_4 + \beta_{CAR,4} \cdot CAR_4 + \varepsilon_{4T.2}$	
4T.3	$U_{4T.3}(L1) = ASC_1 + \beta_{HGV,1} \cdot HGV_1 + \beta_{CAR,1} \cdot CAR_1 + \varepsilon_{4T.3}$ $U_{4T.3}(L2) = ASC_2 + \beta_{HGV,2} \cdot HGV_2 + \beta_{CAR,2} \cdot CAR_2 + \varepsilon_{4T.3}$ $U_{4T.3}(L3) = \beta_{CAR,3} \cdot CAR_3 + \varepsilon_{4T.3}$ $U_{4T.3}(L4) = ASC_4 + \beta_{CAR,4} \cdot CAR_4 + \varepsilon_{4T.3}$	
2R.1_C	$U_{2R.1\_C}(L1) = ASC_1 + \beta_{HGV,1} \cdot HGV_1 + \beta_{CAR,1} \cdot CAR_1 + \varepsilon_{2R.1\_C}$ $U_{2R.1\_C}(L2) = \beta_{HGV,2} \cdot HGV_2 + \beta_{CAR,2} \cdot CAR_2 + \varepsilon_{2R.1\_C}$	
2L.4_C	$U_{2L.4\_C}(L3) = \beta_{HGV,3} \cdot HGV_3 + \beta_{CAR,3} \cdot CAR_3 + \varepsilon_{2L.4\_C}$ $U_{2L.4\_C}(L4) = ASC_4 + \beta_{HGV,4} \cdot HGV_4 + \beta_{CAR,4} \cdot CAR_4 + \varepsilon_{2L.4\_C}$	

A.2. Pilot study: profiles

Table A.2. – By Ngene Generated Profiles per Choice Scenario with Manually Inserted TRV_{HG} Levels

Design choice scenario 2R.1						
Choice scenario	**L1.HGV$_1$**	**L1.CAR$_1$**	**L2.HGV$_2$**	**L2.CAR$_2$**		
1	3_0	4	0_0	0		
2	0_0	4	0_0	12		
3	1_1	2	1_3	4		
4	2_1	2	1_1	8		
5	2_1	6	0_1	4		
6	1_1	6	0_2	8		
7	0_0	8	1_3	0		
8	3_0	8	1_2	12		
Design choice scenario 3R.1						
Choice scenario	**L1.HGV$_1$**	**L1.CAR$_1$**	**L2.HGV$_2$**	**L2.CAR$_2$**	**L3.CAR$_3$**	
1	0_0	8	0_0	4	2	
2	1_1	4	1_3	4	0	
3	2_0	2	1_3	0	2	
4	3_1	4	0_0	8	0	
5	2_1	6	0_0	12	0	
6	1_1	6	1_1	8	2	
7	3_1	2	0_1	4	6	

8	1_0	6	0_1	0	4	
9	2_0	8	1_3	0	4	
10	0_0	4	0_2	8	6	
11	0_0	2	1_2	12	4	
12	3_1	8	1_2	12	6	
Design choice scenario 2L.4 & 2L.4_C						
Choice scenario	**L3.HGV$_3$**	**L3.CAR$_3$**	**L4.HGV$_4$**	**L4.CAR$_4$**		
1	3_0	4	0_0	0		
2	0_0	4	0_0	12		
3	1_1	2	1_3	4		
4	2_1	2	1_1	8		
5	2_1	6	0_1	4		
6	1_1	6	0_2	8		
7	0_0	8	1_3	0		
8	3_0	8	1_2	12		
Design choice scenario 3L.4						
Choice scenario	**L2.HGV$_2$**	**L2.CAR$_2$**	**L3.HGV$_3$**	**L3.CAR$_3$**	**L4.CAR$_4$**	
1	0_0	3	0_0	4	4	
2	1_1	1	1_0	4	0	
3	2_1	0	1_3	0	4	
4	3_0	1	0_0	8	0	
5	2_1	2	0_1	12	0	
6	1_1	2	1_3	8	4	
7	3_1	0	0_1	4	12	
8	1_0	2	0_1	0	8	
9	2_0	3	1_3	0	8	
10	0_0	1	0_2	8	12	
11	0_0	0	1_2	12	8	
12	3_1	3	1_2	12	12	
Design choice scenario 3T.2						
Choice scenario	**L1.HGV$_1$**	**L1.CAR$_1$**	**L2.HGV$_2$**	**L2.CAR$_2$**	**L3.CAR$_3$**	
1	0_0	8	0_0	4	4	
2	1_1	4	1_3	4	0	
3	2_0	2	1_3	0	4	
4	3_1	4	0_0	8	0	
5	2_1	6	0_0	12	0	
6	1_1	6	1_1	8	4	
7	3_1	2	0_1	4	12	
8	1_0	6	0_1	0	8	
9	2_0	8	1_3	0	8	

10	0_0	4	0_2	8	12	
11	0_0	2	1_2	12	8	
12	3_1	8	1_2	12	12	
Design choice scenario 3T.3						
Choice scenario	**L1.HGV$_1$**	**L1.CAR$_1$**	**L2.HGV$_2$**	**L2.CAR$_2$**	**L3.CAR$_3$**	
1	0_0	3	0_0	4	4	
2	1_1	1	1_0	4	0	
3	2_1	0	1_3	0	4	
4	3_0	1	0_0	8	0	
5	2_1	2	0_1	12	0	
6	1_1	2	1_3	8	4	
7	3_1	0	0_1	4	12	
8	1_0	2	0_1	0	8	
9	2_0	3	1_3	0	8	
10	0_0	1	0_2	8	12	
11	0_0	0	1_2	12	8	
12	3_1	3	1_2	12	12	
Design choice scenario 4T.2						
Choice scenario	**L1.HGV$_1$**	**L1.CAR$_1$**	**L2.HGV$_2$**	**L2.CAR$_2$**	**L3.CAR$_3$**	**L4.CAR$_4$**
1	1_1	2	1_0	4	4	2
2	2_1	4	0_0	12	4	0
3	3_1	6	0_0	8	0	2
4	1_1	8	0_1	4	8	0
5	2_0	6	1_3	0	12	0
6	0_0	4	1_1	8	8	2
7	0_0	8	0_1	0	4	6
8	3_0	4	1_3	0	0	4
9	0_0	6	1_2	12	0	4
10	2_1	2	0_2	4	8	6
11	1_1	2	0_2	8	12	4
12	3_0	8	1_3	12	12	6
Design choice scenario 4T.3						
Choice scenario	**L1.HGV$_1$**	**L1.CAR$_1$**	**L2.HGV$_2$**	**L2.CAR$_2$**	**L3.CAR$_3$**	**L4.CAR$_4$**
1	1_1	0	1_0	4	4	4
2	2_1	1	0_0	12	4	0
3	3_1	2	0_0	8	0	4
4	1_0	3	0_1	4	8	0
5	2_0	2	1_3	0	12	0
6	0_0	1	1_1	8	8	4
7	0_0	3	0_1	0	4	12

8	3_0	1	1_3	0	0	8
9	0_0	2	1_2	12	0	8
10	2_1	0	0_2	4	8	12
11	1_1	0	0_2	8	12	8
12	3_1	3	1_3	12	12	12

A.3. Main experiment: profiles

Table A.3. – By Ngene Generated Profiles per Choice Scenario with Manually Inserted TRV_{HG} Levels

Design choice scenario 2R.1						
Choice Scenario	**L1.HGV$_1$**	**L1.CAR$_1$**	**L2.HGV$_2$**	**L2.CAR$_2$**		
2	1_1	4	1_0	4		
3	0_0	6	1_3	0		
4	2_0	2	0_0	12		
5	0_0	2	0_1	4		
6	3_1	8	1_3	12		
7	1_0	6	0_1	8		
Design choice scenario 2R.1_C						
Choice Scenario	**L1.HGV$_1$**	**L1.CAR$_1$**	**L2.HGV$_2$**	**L2.CAR$_2$**		
1	2_0	8	1_0	8		
4	1_1	6	1_3	4		
5	3_0	4	1_0	12		
7	0_0	2	1_3	0		
8	0_0	2	0_1	4		
9	2_0	2	0_1	12		
Design choice scenario 3R.1						
Choice Scenario	**L1.HGV$_1$**	**L1.CAR$_1$**	**L2.HGV$_2$**	**L2.CAR$_2$**	**L3.CAR$_3$**	
1	0_0	2	0_0	4	0	
2	2_0	4	1_3	0	4	
3	2_0	4	0_0	12	2	
4	1_1	8	0_1	12	6	
5	3_1	2	1_3	8	6	
6	3_1	6	0_1	0	0	
7	1_0	6	1_2	8	2	
8	0_0	8	1_2	4	4	
Design choice scenario 2L.4						

Choice Scenario	**L3.HGV$_3$**	**L3.CAR$_3$**	**L4.HGV$_4$**	**L4.CAR$_4$**		
1	1_0	6	0_0	4		
2	0_0	4	0_0	8		
3	3_1	4	1_1	12		
4	0_0	8	1_3	4		
5	1_1	2	1_3	0		
6	2_0	2	0_1	0		
Design choice scenario 2L.4_C						
Choice Scenario	**L3.HGV$_3$**	**L3.CAR$_3$**	**L4.HGV$_4$**	**L4.CAR$_4$**		
1	2_0	8	1_0	8		
2	0_0	4	1_3	0		
3	3_1	2	1_3	8		
6	0_0	8	0_0	12		
8	0_0	2	0_1	4		
9	2_1	2	0_1	12		
Design choice scenario 3L.4						
Choice Scenario	**L2.HGV$_2$**	**L2.CAR$_2$**	**L3.HGV$_3$**	**L3.CAR$_3$**	**L4.CAR$_4$**	
1	0_0	0	1_0	12	4	
2	2_1	3	0_0	8	12	
3	1_0	1	0_1	4	0	
4	3_1	1	1_3	0	8	
5	1_0	2	0_1	0	0	
6	2_1	0	0_2	8	12	
7	3_0	2	1_3	4	8	
8	0_0	3	1_2	12	4	
Design choice scenario 3T.2						
Choice Scenario	**L1.HGV$_1$**	**L1.CAR$_1$**	**L2.HGV$_2$**	**L2.CAR$_2$**	**L3.CAR$_3$**	
1	3_0	6	0_0	4	0	
2	3_0	6	0_0	0	0	
3	2_0	8	1_3	12	12	
4	1_1	8	1_1	12	12	
5	0_0	4	0_1	8	4	
6	1_1	2	1_3	0	8	
7	0_0	2	0_2	4	8	
8	2_1	4	1_2	8	4	
Design choice scenario 3T.3						
Choice Scenario	**L1.HGV$_1$**	**L1.CAR$_1$**	**L2.HGV$_2$**	**L2.CAR$_2$**	**L3.CAR$_3$**	
1	3_0	2	1_3	0	8	

2	2_1	3	1_3	8	12	
3	1_0	0	1_0	4	4	
4	0_0	0	1_0	4	8	
5	1_0	2	0_1	0	0	
6	3_0	1	0_1	12	12	
7	0_0	3	0_2	8	0	
8	2_1	1	0_2	12	4	
Design choice scenario 4T.2						
Choice Scenario	**L1.HGV$_1$**	**L1.CAR$_1$**	**L2.HGV$_2$**	**L2.CAR$_2$**	**L3.CAR$_3$**	**L4.CAR$_4$**
1	2_0	8	1_0	8	12	0
2	0_0	4	0_0	0	4	2
3	1_1	8	1_3	12	12	6
4	3_1	6	0_1	0	0	0
5	1_0	2	1_3	4	8	4
6	3_0	6	0_1	8	0	2
7	2_1	4	1_2	12	8	4
8	0_0	2	0_2	4	4	6
Design choice scenario 4T.3						
Choice Scenario	**L1.HGV$_1$**	**L1.CAR$_1$**	**L2.HGV$_2$**	**L2.CAR$_2$**	**L3.CAR$_3$**	**L4.CAR$_4$**
1	0_0	3	0_0	8	4	8
2	1_0	2	1_3	0	4	0
3	1_1	0	1_0	4	8	8
4	3_0	1	0_1	12	12	12
5	0_0	0	0_1	4	8	4
6	2_1	3	1_3	8	12	12
7	2_0	1	1_2	12	0	0
8	3_1	2	0_2	0	0	4

Appendix B.

MNL model estimation

B.1. Example of the MNL model script for the 4T.2 choice scenario

```
### Load Apollo library
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control = list(
modelName   ="MNL_4T.2",
modelDescr  ="MNL Base",
indivID     ="ID")

#### LOAD DATA
database = read.delim("DATA_4T.2.txt",header=TRUE)

### Vector of parameters
apollo_beta=c(BETA_HGV1 = 0,
              BETA_HGV2 = 0,
              BETA_CAR1 = 0,
              BETA_CAR2 = 0,
              BETA_CAR3 = 0,
              BETA_CAR4 = 0,
              ASC1 = 0,
              ASC3 = 0,
              ASC4 = 0)

### Vector with names (in quotes) of fixed parameters
apollo_fixed = c()

#### GROUP AND VALIDATE INPUTS
apollo_inputs = apollo_validateInputs()

#### DEFINE MODEL AND LIKELIHOOD FUNCTION
apollo_probabilities=function(apollo_beta, apollo_inputs,
```

```
functionality="estimate"){

### Attach inputs and detach after function exit
apollo_attach(apollo_beta, apollo_inputs)
on.exit(apollo_detach(apollo_beta, apollo_inputs))

### Create list of probabilities P
P = list()

### List of utilities
V = list()
V[['A']]  = ASC1 + BETA_HGV1 * HGV1 + BETA_CAR1 * CAR1
V[['B']]  = BETA_HGV2 * HGV2 + BETA_CAR2 * CAR2
V[['C']]  = ASC3 + BETA_CAR3 * CAR3
V[['D']]  = ASC4 + BETA_CAR4 * CAR4

### Define settings for MNL model component
mnl_settings = list(
alternatives  = c(A=1, B=2, C=3, D=4),
avail         = list(A=1, B=1, C=1, D=1),
choiceVar     = CHOICE,
V             = V)


### Compute probabilities using MNL model
P[['model']] = apollo_mnl(mnl_settings, functionality)

### Take product across observation for same individual
P = apollo_panelProd(P, apollo_inputs, functionality)

### Prepare and return outputs of function
P = apollo_prepareProb(P, apollo_inputs, functionality)
return(P)
}

#### MODEL ESTIMATION
model = apollo_estimate(apollo_beta, apollo_fixed,
apollo_probabilities, apollo_inputs)

#### MODEL OUTPUTS
apollo_modelOutput(model,modelOutput_settings=list(printPVal=TRUE))

apollo_saveOutput(model)
```

B.2. Example of the MNL model output for the 4T.2 choice scenario

```
Model name                              : MNL_4T.2
Model description                       : MNL Base
Model run at                            : 2023-08-28 14:17:33
Estimation method                       : bfgs
Model diagnosis                         : successful convergence
Optimisation diagnosis                  : Maximum found
hessian properties                      : Negative definitive
maximum eigenvalue                      : -1.608554
Number of individuals                   : 16
Number of rows in database              : 192
Number of modelled outcomes             : 192

Number of cores used                    :  1
Model without mixing

LL(start)                               : -266.17
LL at equal shares, LL(0)               : -266.17
LL at observed shares, LL(C)            : -253.94
LL(final)                               : -186.6
Rho-squared vs equal shares             :  0.299
Adj.Rho-squared vs equal shares         :  0.2651
Rho-squared vs observed shares          :  0.2652
Adj.Rho-squared vs observed shares      :  0.2416
AIC                                     :  391.19
BIC                                     :  420.51

Estimated parameters                    : 9
Time taken (hh:mm:ss)                   :  00:00:0.93
pre-estimation                          :  00:00:0.42
estimation                              :  00:00:0.26
initial estimation                      :  00:00:0.22
estimation after rescaling              :  00:00:0.04
post-estimation                         :  00:00:0.25
Iterations                              :  19
initial estimation                      :  18
estimation after rescaling              :  1
```

```
Unconstrained optimisation.

Estimates:
              Estimate       s.e.     t.rat.(0)   Rob.s.e.     Rob.t.rat.(0)
BETA_HGV1     -1.0722      0.26690    -4.0172     0.31315      -3.4238
BETA_HGV2     -0.9656      0.41036    -2.3530     0.36295      -2.6603
BETA_CAR1     -0.1460      0.10259    -1.4227     0.11876      -1.2290
BETA_CAR2     -0.3249      0.05752    -5.6495     0.06413      -5.0672
BETA_CAR3     -0.3271      0.04792    -6.8273     0.05726      -5.7130
BETA_CAR4     -0.1495      0.08897    -1.6803     0.08322      -1.7962
ASC1          -0.7127      0.67515    -1.0556     0.65494      -1.0882
ASC3           0.1964      0.42509     0.4621     0.31901       0.6157
ASC4          -1.9343      0.42360    -4.5664     0.58956      -3.2810


Overview of choices for MNL model component :
                                     A       B       C       D
Times available                   192.00  192.00  192.00  192.00
Times chosen                       28.00   52.00   74.00   38.00
Percentage chosen overall          14.58   27.08   38.54   19.79
Percentage chosen when available   14.58   27.08   38.54   19.79
```

B.3. Pilot study estimates

Table B.1. – Parameter Significance From Zero

Choice Scenario							
2R.1	**Estimate**	**s.e.**	**t.rat.(0)**	**Rob.s.e.**	**Rob. t.rat.(0)**	**Confidence level**	**S estimate D error**
BETA_HGV1	-7.1114	132.4296	-0.0537	0.5987	-11.878	99.9%	3.89
BETA_HGV2	-10.0755	132.4381	-0.07608	1.8073	-5.575	99.9%	3.30
BETA_CAR1	-0.647	0.1893	-3.41826	0.1836	-3.523	99.9%	4.40
BETA_CAR2	-1.8723	33.1074	-0.05655	0.1458	-12.845	99.9%	3.76
ASC2	6.2876	132.4442	0.04747	2.238	2.81	99.0%	5.08
2R.1_C	**Estimate**	**s.e.**	**t.rat.(0)**	**Rob.s.e.**	**Rob. t.rat.(0)**	**Confidence level**	**S estimate D error**
BETA_HGV1	-6.0105	35.6658	-0.1685	0.6249	-9.618	99.9%	3.42
BETA_HGV2	-7.76	35.6985	-0.2174	1.6069	-4.829	99.9%	3.43
BETA_CAR1	-0.432	0.1285	-3.3625	0.1347	-3.206	99.8%	5.99
BETA_CAR2	-1.5959	8.9163	-0.179	0.1179	-13.536	99.9%	3.29
ASC1	-6.4666	35.7067	-0.1811	1.6483	-3.923	99.9%	3.60
3R.1	**Estimate**	**s.e.**	**t.rat.(0)**	**Rob.s.e.**	**Rob. t.rat.(0)**	**Confidence level**	**S estimate D error**

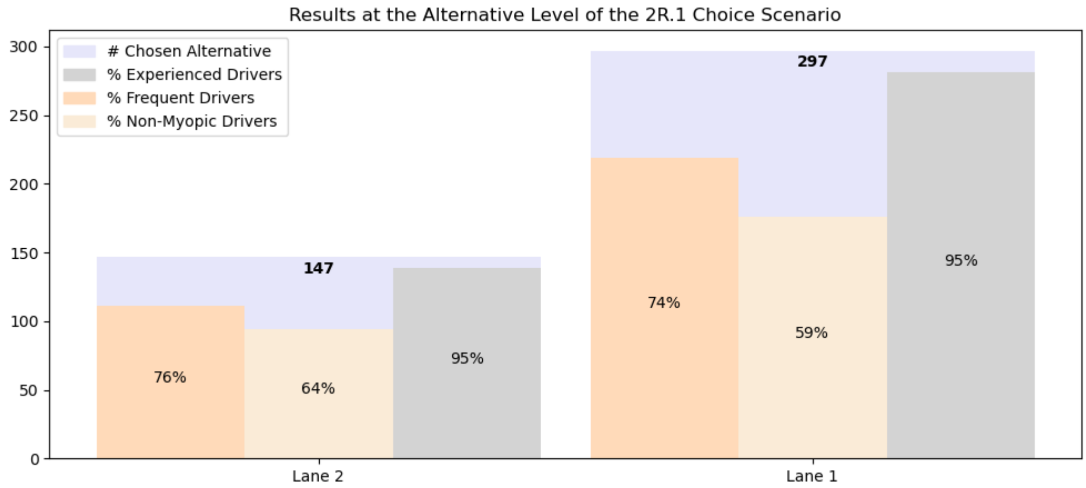
BETA_HGV1	-2.0982	0.43043	-4.875	0.3668	-5.72	99.9%	1.63
BETA_HGV2	-2.8099	0.59406	-4.73	0.7105	-3.955	99.9%	3.71
BETA_CAR1	-0.4892	0.16655	-2.937	0.147	-3.327	99.9%	4.07
BETA_CAR2	-0.2727	0.0633	-4.307	0.1053	-2.588	99.0%	4.11
BETA_CAR3	-0.7382	0.14664	-5.034	0.1598	-4.621	99.9%	2.83
ASC2	-1.9082	1.19068	-1.603	1.3515	-1.412	80.0%	9.99
ASC3	-1.665	1.14903	-1.449	1.3722	-1.213	70.0%	10.03
2L.4	**Estimate**	**s.e.**	**t.rat.(0)**	**Rob.s.e.**	**Rob. t.rat.(0)**	**Confidence level**	**S estimate D error**
BETA_HGV3	-0.8806	0.29558	-2.979	0.40127	-2.1946	95.0%	6.53
BETA_HGV4	-0.7796	0.60926	-1.28	0.78175	-0.9972	60.0%	26.17
BETA_CAR3	-0.4707	0.1147	-4.104	0.12258	-3.8398	99.9%	5.80
BETA_CAR4	-0.2049	0.07427	-2.759	0.09953	-2.0587	95.0%	6.01
ASC3	1.099	0.96554	1.138	0.95856	1.1465	70.0%	26.36
2L.4_C	**Estimate**	**s.e.**	**t.rat.(0)**	**Rob.s.e.**	**Rob. t.rat.(0)**	**Confidence level**	**S estimate D error**
BETA_HGV3	-1.7217	0.6353	-2.7102	0.5739	-2.9999	99.0%	4.20
BETA_HGV4	-3.8591	1.567	-2.4627	1.5721	-2.4547	98.0%	4.76
BETA_CAR3	-0.5076	0.116	-4.3747	0.1243	-4.0829	99.9%	4.71
BETA_CAR4	-0.4304	0.1588	-2.7102	0.1536	-2.8016	99.0%	4.88
ASC4	1.3211	1.7666	0.7478	1.8485	0.7147	50.0%	15.03
3L.4	**Estimate**	**s.e.**	**t.rat.(0)**	**Rob.s.e.**	**Rob. t.rat.(0)**	**Confidence level**	**S estimate D error**
BETA_HGV2	-1.27366	0.24588	-5.1799	0.26469	-4.8118	99.9%	3.79
BETA_HGV3	-2.40103	0.69081	-3.4757	0.43138	-5.5659	99.9%	5.87
BETA_CAR2	0.05234	0.21177	0.2472	0.19662	0.2662	0.0%	Nan
BETA_CAR3	-0.54144	0.12107	-4.4722	0.11889	-4.5542	99.9%	2.84
BETA_CAR4	-0.20665	0.05301	-3.8979	0.0656	-3.1501	99.8%	6.75
ASC2	-0.92683	0.5545	-1.6715	0.68115	-1.3607	80.0%	17.90
ASC3	1.06648	0.76741	1.3897	0.73494	1.4511	80.0%	12.81
3T.2	**Estimate**	**s.e.**	**t.rat.(0)**	**Rob.s.e.**	**Rob. t.rat.(0)**	**Confidence level**	**S estimate D / S error**
BETA_HGV1	-1.393	0.33398	-4.1709	0.42512	-3.2767	99.8%	3.25 / 5.65
BETA_HGV2	-2.0222	0.52045	-3.8856	0.60785	-3.3269	99.9%	4.61 / 5.97
BETA_CAR1	-0.3549	0.15558	-2.2814	0.24717	-1.436	80.0%	6.40 / 17.1
BETA_CAR2	-0.3219	0.05238	-6.1463	0.05704	-5.6437	99.9%	3.42 / 4.25
BETA_CAR3	-0.3684	0.05845	-6.3021	0.06015	-6.124	99.9%	2.53 / 4.25
ASC1	-0.7929	0.87845	-0.9026	0.9763	-0.8121	50.0%	41.56 / 23.05
ASC3	-1.3074	0.49729	-2.6291	0.45742	-2.8582	99.0%	7.65 / 6.23
3T.3	**Estimate**	**s.e.**	**t.rat.(0)**	**Rob.s.e.**	**Rob. t.rat.(0)**	**Confidence level**	**S estimate D error**
BETA_HGV1	-1.1635	0.25133	-4.6295	0.27476	-4.2347	99.9%	3.24
BETA_HGV2	-2.3915	0.54241	-4.409	0.32183	-7.431	99.9%	3.96

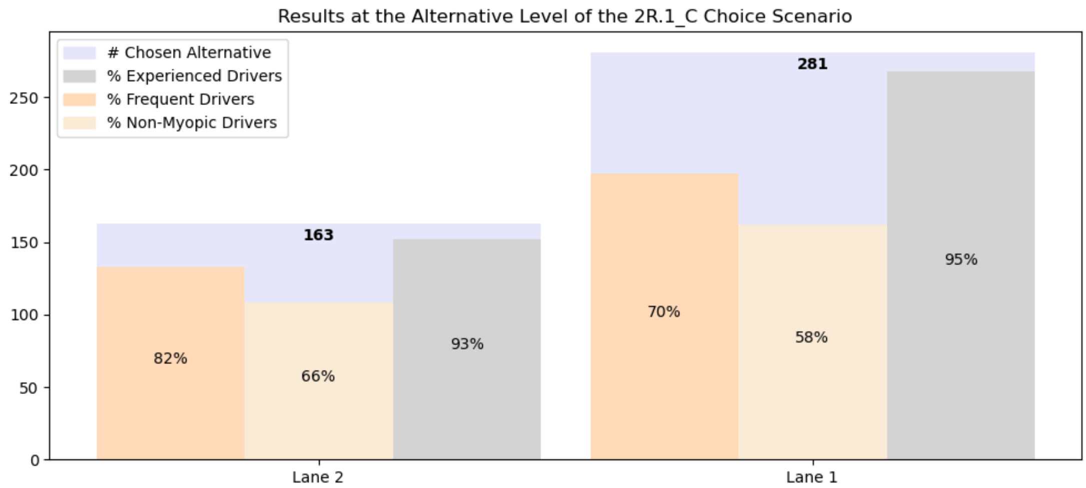
BETA_CAR1	0.349	0.224	1.5579	0.29698	1.1751	70.0%	18.15
BETA_CAR2	-0.2665	0.06595	-4.041	0.08564	-3.1119	99.8%	3.33
BETA_CAR3	-0.2251	0.05149	-4.3712	0.05647	-3.9853	99.9%	3.58
ASC1	-1.5791	0.53164	-2.9702	0.60698	-2.6015	99.0%	6.31
ASC2	0.257	0.58782	0.4372	0.43441	0.5916	0.0%	Nan
4T.2	**Estimate**	**s.e.**	**t.rat.(0)**	**Rob.s.e.**	**Rob. t.rat.(0)**	**Confidence level**	**S estimate D / S error**
BETA_HGV1	-1.0722	0.2669	-4.0172	0.31315	-3.4238	99.9%	3.13 / 7.68
BETA_HGV2	-0.9656	0.41036	-2.353	0.36295	-2.6603	99.0%	15.73 / 33.49
BETA_CAR1	-0.146	0.10259	-1.4227	0.11876	-1.229	70.0%	28.32 / 35.37
BETA_CAR2	-0.3249	0.05752	-5.6495	0.06413	-5.0672	99.9%	2.19 / 4.11
BETA_CAR3	-0.3271	0.04792	-6.8273	0.05726	-5.713	99.9%	2.05 / 2.15
BETA_CAR4	-0.1495	0.08897	-1.6803	0.08322	-1.7962	90.0%	28.32 / 33.15
ASC1	-0.7127	0.67515	-1.0556	0.65494	-1.0882	70.0%	66.97 / 35.6
ASC3	0.1964	0.42509	0.4621	0.31901	0.6157	0.0%	Nan
ASC4	-1.9343	0.4236	-4.5664	0.58956	-3.281	99.8%	5.72 / 5.26
4T.3	**Estimate**	**s.e.**	**t.rat.(0)**	**Rob.s.e.**	**Rob. t.rat.(0)**	**Confidence level**	**S estimate D error**
BETA_HGV1	-1.9767	0.46448	-4.2559	0.6093	-3.2443	99.8%	3.13
BETA_HGV2	-1.6267	0.66144	-2.4593	0.45458	-3.5785	99.9%	8.36
BETA_CAR1	-0.1727	0.36834	-0.4687	0.48006	-0.3597	0.0%	Nan
BETA_CAR2	-0.6901	0.11995	-5.7536	0.21215	-3.253	99.8%	2.54
BETA_CAR3	-0.6392	0.10779	-5.9299	0.14883	-4.2945	99.9%	2.34
BETA_CAR4	-0.614	0.09423	-6.5162	0.0892	-6.8832	99.9%	2.06
ASC1	-3.5224	0.92864	-3.7931	1.54752	-2.2762	95.0%	2.73
ASC2	-0.795	0.71019	-1.1194	0.58197	-1.366	80.0%	19.91
ASC4	-1.6828	0.59036	-2.8504	0.80128	-2.1001	95.0%	5.12

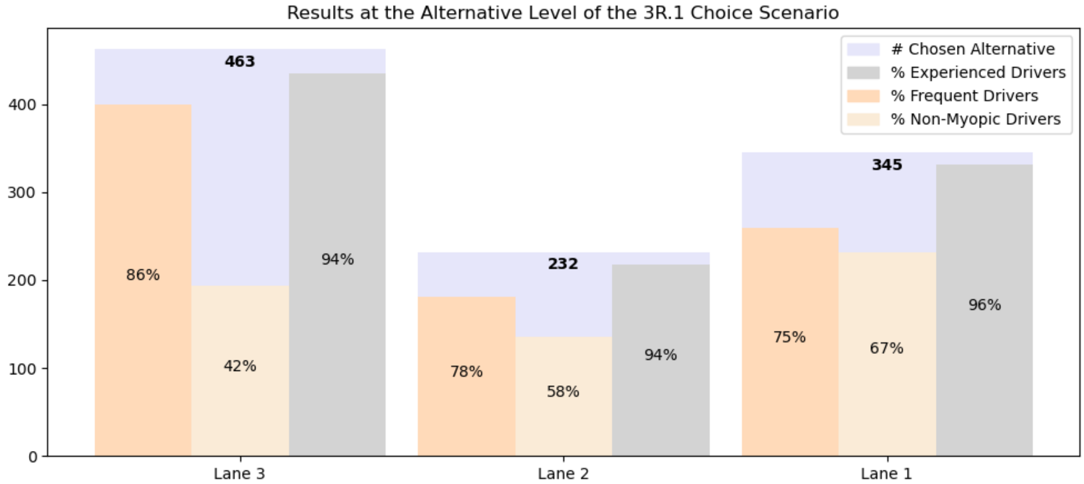
Appendix C.

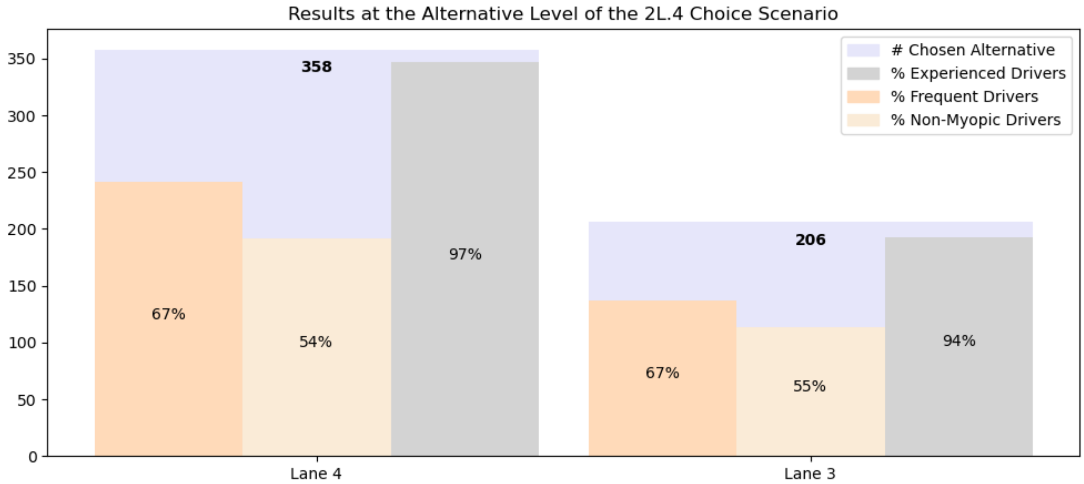
Main experiment results

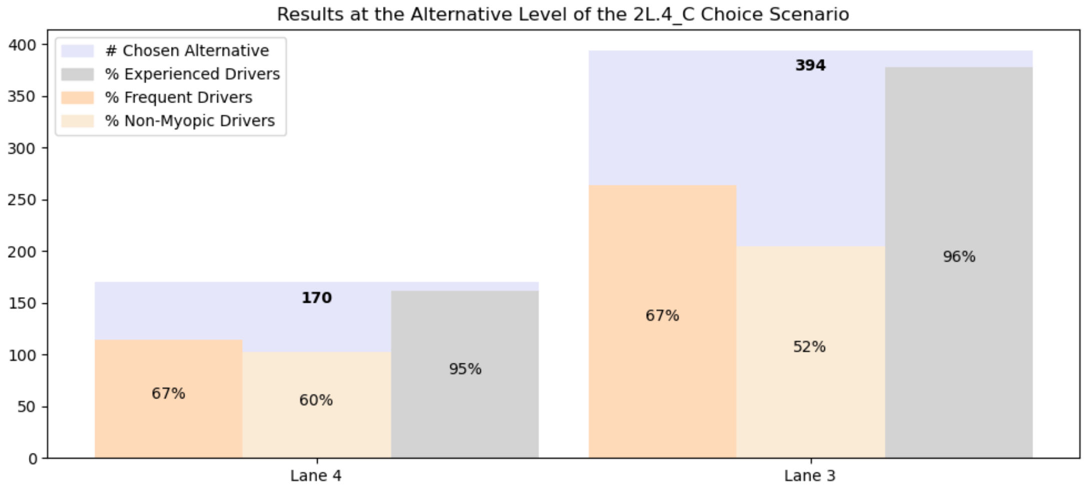
C.1. Results at the alternative level

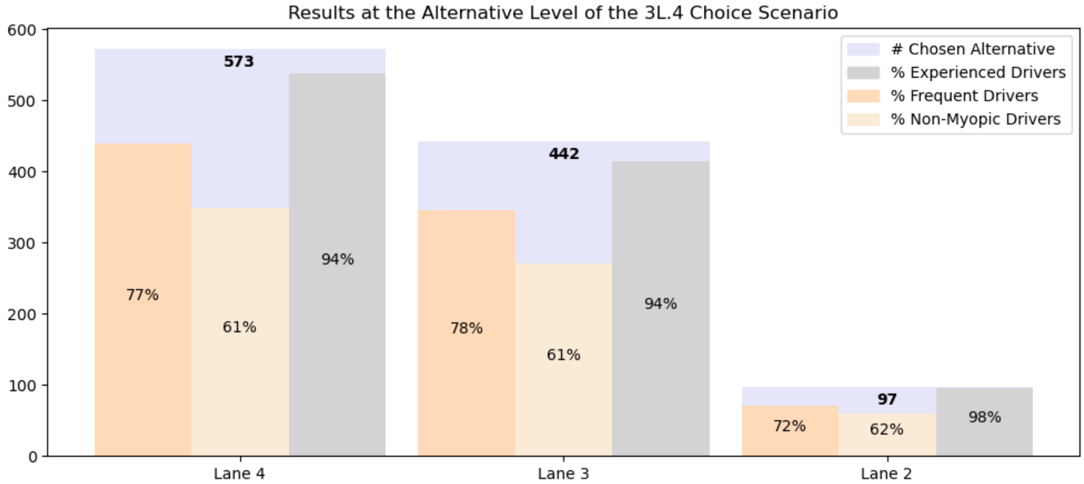


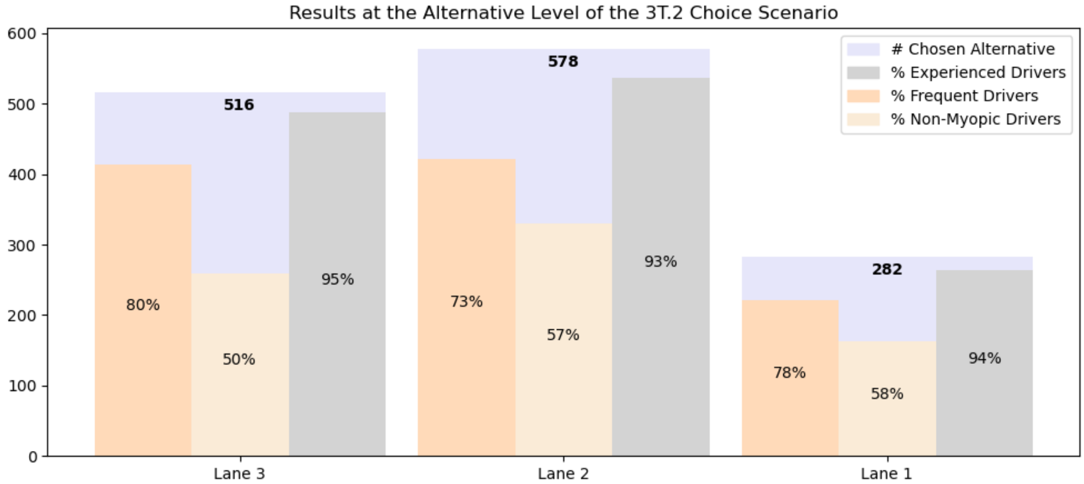


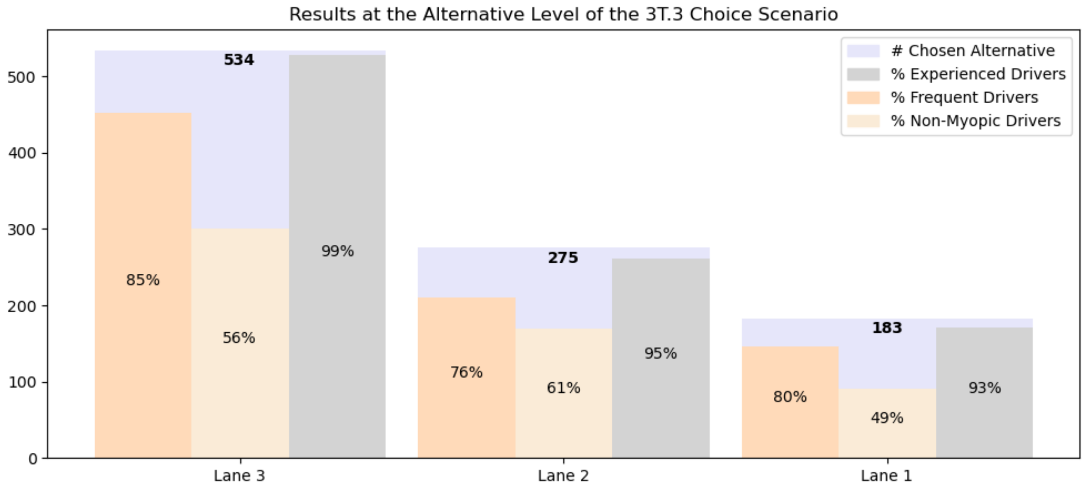

Results at the Alternative Level of the 3R.1 Choice Scenario
Chosen Alternative
% Experienced Drivers
% Frequent Drivers
% Non-Myopic Drivers
463
86%
42%
94%
232
78%
58%
94%
345
75%
67%
96%
0
100
200
300
400
Lane 3
Lane 2
Lane 1

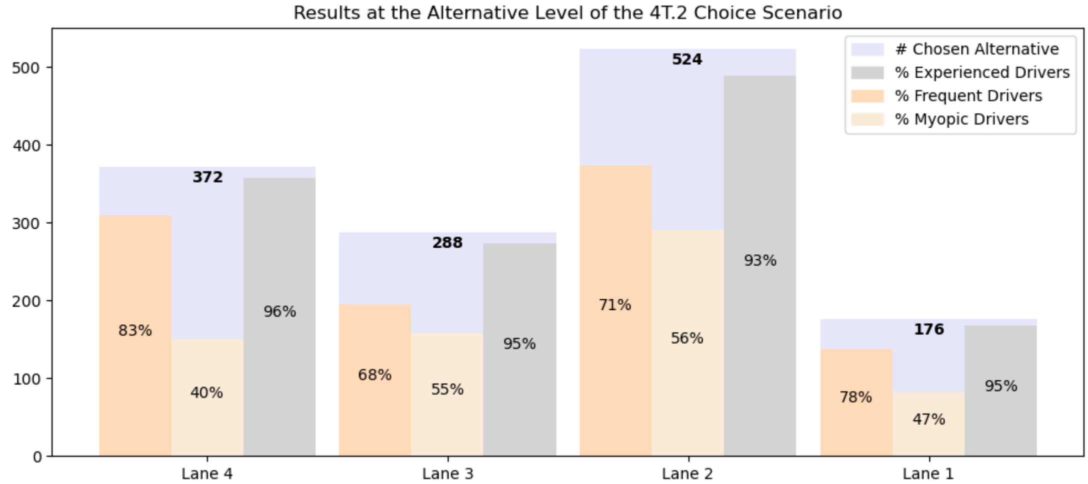

Results at the Alternative Level of the 2L.4 Choice Scenario
Chosen Alternative
% Experienced Drivers
% Frequent Drivers
% Non-Myopic Drivers
358
67%
54%
97%
206
67%
55%
94%
0
50
100
150
200
250
300
350
Lane 4
Lane 3


Results at the Alternative Level of the 2L.4_C Choice Scenario
Chosen Alternative
% Experienced Drivers
% Frequent Drivers
% Non-Myopic Drivers
170
67%
60%
95%
394
67%
52%
96%
0
50
100
150
200
250
300
350
400
Lane 4
Lane 3


Results at the Alternative Level of the 3L.4 Choice Scenario
Chosen Alternative
% Experienced Drivers
% Frequent Drivers
% Non-Myopic Drivers
573
442
97
77%
61%
94%
78%
61%
94%
72%
62%
98%
Lane 4
Lane 3
Lane 2
0
100
200
300
400
500
600


Results at the Alternative Level of the 3T.2 Choice Scenario
Chosen Alternative
% Experienced Drivers
% Frequent Drivers
% Non-Myopic Drivers
516
578
282
80%
50%
95%
73%
57%
93%
78%
58%
94%
Lane 3
Lane 2
Lane 1
0
100
200
300
400
500
600


Results at the Alternative Level of the 3T.3 Choice Scenario
Chosen Alternative
% Experienced Drivers
% Frequent Drivers
% Non-Myopic Drivers
534
275
183
85%
56%
99%
76%
61%
95%
80%
49%
93%
Lane 3
Lane 2
Lane 1
0
100
200
300
400
500



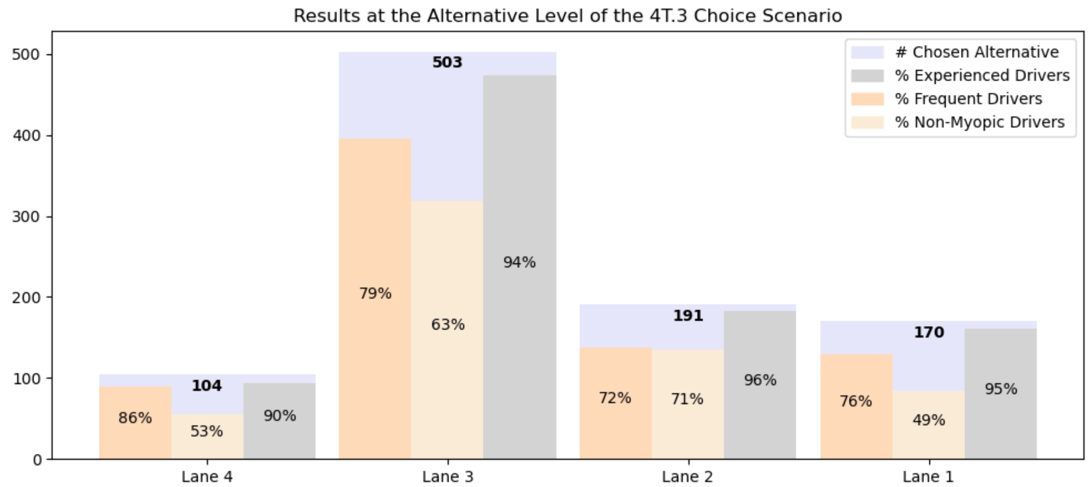


Figure C.1. – Distribution of Chosen Alternatives per Choice Scenario

C.2. Results at the parameter level

Legend color coding:

X	Y	Z	
Significantly better model	ρ^2 increase, but parameter insignificant	Estimate not significantly different from zero	No data

Table C.1. – Parameter Ratio Estimates of the Additional Explanatory Variables for All Choice Scenarios

Choice scenario	**2R.1**	**2R.1_C**	**3R.1**	**2L.4**	**2L.4_C**	**3L.4**	**3T.2**	**3T.3**	**4T.2**	**4T.3**
BETA_TRV	-0.08	-0.39	0.06	-0.53	-0.36	0.01	-0.14	-0.07	-0.11	-0.10
BETA_TRV1	-0.41	Nan	0.06				-0.13	-0.12	-0.13	-0.10
BETA_TRV2	0.47	Nan	0.05			0.05	-0.11	-0.00	-0.14	-0.07
BETA_TRV3				-0.58	Nan	-0.26				
BETA_TRV4				-0.27	Nan					
BETA_DQ			-0.03			0.00	0.05	0.06	0.02	0.00
BETA_DQ1		0.04						0.07	0.00	0.08
BETA_DQ2	0.02		-0.06			-0.05	0.02	0.04		0.00
BETA_DQ3			0.03	-0.02		0.00	0.08		0.00	
BETA_DQ4					-0.07					0.01
BETA_MYP			0.18			0.01	0.06	0.00	0.04	-0.01
BETA_MYP1	-0.06	-0.05	0.19				0.06	-0.05	0.01	-0.07
BETA_MYP2			0.14			0.01	0.06	0.05	0.05	0.03
BETA_MYP3				0.01	-0.07	0.02				
BETA_MYP4										
BETA_FREQ			0.09			0.04	-0.02	0.02	0.02	0.03
BETA_FREQ1										
BETA_FREQ2	0.07	0.08	0.01				-0.06	-0.05		
BETA_FREQ3			0.13			0.06	0.02	0.05	-0.01	0.02
BETA_FREQ4				0.04	0.00	0.03			0.06	0.09
BETA_DL			-0.10			-0.13	-0.00	0.20	0.04	0.00
BETA_DL1										
BETA_DL2	0.01	-0.07	-0.10				-0.03	0.01		
BETA_DL3			-0.09			-0.11	0.03	0.22	0.03	0.00
BETA_DL4				0.19	-0.03	-0.12			0.05	-0.09
BETA_ANGRY	-0.02	0.11	-0.06		-0.02	0.04	-0.11	0.01	-0.04	0.03
BETA_RISKY	-0.05	0.08	-0.02	0.11	0.09	0.02	0.06	0.16	0.01	-0.09
BETA_ANX.			0.14			0.09	-0.01		0.01	0.13
BETA_DISSOC.			-0.06	-0.20	-0.17		0.07		-0.04	0.08
BETA_CAREFUL	0.10	-0.02	-0.02	0.01	-0.04	0.03	0.02	0.04	-0.01	0.01
BETA_DISSTR.	0.05	0.02	0.06	0.05	-0.05	0.01	-0.04	0.08	-0.02	0.00

Table C.2. – Independent Samples t-Test Priors vs. Final Estimates with Heat Map P-Values

Parameters	Prior	s.e.	N	Final Estimate	s.e.	N	df.	s^2_{pooled}	t	P(T<=t) two-tail
Choice scenario 2R.1										
BETA_HGV1	-7.11	0.60		-3.11	0.37			48.53	-1.78	0.079
BETA_HGV2	-10.08	1.81		0.65	0.53			377.42	-1.71	0.091
BETA_CAR1	-0.65	0.18	11	0.24	0.10	74	83	4.40	-1.31	0.194
BETA_CAR2	-1.87	0.15		-0.69	0.09			2.86	-2.17	0.033
ASC2	6.29	2.24		-0.71	137.18			1225311.30	0.02	0.984
Choice scenario 2R.1_C										
Parameters	**Prior**	**s.e.**	**N**	**Final Estimate**	**s.e.**	**N**	**df.**	s^2_{pooled}	**t**	**P(T<=t) two-tail**
BETA_HGV1	-6.01	0.62		-3.60	0.37			51.67	-1.04	0.303
BETA_HGV2	-7.76	1.61		-4.05	0.58			306.17	-0.66	0.513
BETA_CAR1	-0.43	0.13	11	-0.72	0.11	74	83	2.71	0.55	0.585
BETA_CAR2	-1.60	0.12		-0.86	0.08			1.97	-1.63	0.107
ASC1	-6.47	1.65		2.57	45.21			133311.13	-0.08	0.939
Choice scenario 3R.1										
Parameters	**Prior**	**s.e.**	**N**	**Final Estimate**	**s.e.**	**N**	**df.**	s^2_{pooled}	**t**	**P(T<=t) two-tail**
BETA_HGV1	-2.10	0.43		-0.65	0.09			34.62	-0.88	0.382
BETA_HGV2	-2.81	0.59		-0.98	0.22			70.20	-0.78	0.438
BETA_CAR1	-0.49	0.17		-0.29	0.04			5.23	-0.31	0.759
BETA_CAR2	-0.27	0.06	14	-0.35	0.03	130	142	0.81	0.31	0.754
BETA_CAR3	-0.74	0.15		0.09	0.04			4.12	-1.45	0.150
ASC2	-1.91	1.19		-0.64	0.27			266.95	-0.28	0.783
ASC3	-1.67	1.15		-2.33	0.26			248.01	0.15	0.882
Choice scenario 2L.4										
Parameters	**Prior**	**s.e.**	**N**	**Final Estimate**	**s.e.**	**N**	**df.**	s^2_{pooled}	**t**	**P(T<=t) two-tail**
BETA_HGV3	-0.88	0.30		-1.11	0.14			17.49	0.19	0.850
BETA_HGV4	-0.78	0.61		-0.71	0.24			72.19	-0.03	0.978
BETA_CAR3	-0.47	0.11	14	-0.23	0.06	94	106	2.70	-0.51	0.614
BETA_CAR4	-0.20	0.07		-0.32	0.03			1.09	0.38	0.708
ASC3	1.10	0.97		-0.30	0.34			178.97	0.37	0.715
Choice scenario 2L.4_C										
Parameters	**Prior**	**s.e.**	**N**	**Final Estimate**	**s.e.**	**N**	**df.**	s^2_{pooled}	**t**	**P(T<=t) two-tail**
BETA_HGV3	-1.72	0.64		-1.92	0.39			85.71	0.07	0.941
BETA_HGV4	-3.86	1.57		-2.05	0.92			516.32	-0.28	0.781
BETA_CAR3	-0.51	0.12	14	-0.56	0.10	94	106	3.28	0.10	0.923
BETA_CAR4	-0.43	0.16		-0.46	0.12			5.75	0.05	0.963
ASC4	1.32	1.77		-1.30	0.55			593.29	0.38	0.708

Choice scenario 3L.4										
Parameters	**Prior**	**s.e.**	**N**	**Final Estimate**	**s.e.**	**N**	**df.**	s^2_{pooled}	**t**	**P(T<=t) two-tail**
BETA_HGV2	-1.27	0.25	15	-0.89	0.11	139	152	14.20	-0.37	0.712
BETA_HGV3	-2.40	0.69		-2.67	0.23			106.64	0.10	0.923
BETA_CAR2	0.05	0.21		-0.26	0.08			10.28	0.35	0.724
BETA_CAR3	-0.54	0.12		-0.33	0.04			3.23	-0.43	0.670
BETA_CAR4	-0.21	0.05		-0.36	0.03			0.67	0.68	0.499
ASC2	-0.93	0.55		-2.46	0.20			69.75	0.68	0.501
ASC3	1.07	0.77		0.18	0.15			126.38	0.29	0.773
Choice scenario 3T.2										
Parameters	**Prior**	**s.e.**	**N**	**Final Estimate**	**s.e.**	**N**	**df.**	s^2_{pooled}	**t**	**P(T<=t) two-tail**
BETA_HGV1	-1.39	0.33	15	-1.14	0.12	172	185	25.68	-0.18	0.855
BETA_HGV2	-2.02	0.52		-1.02	0.18			62.07	-0.47	0.637
BETA_CAR1	-0.35	0.16		-0.25	0.05			5.52	-0.16	0.870
BETA_CAR2	-0.32	0.05		-0.37	0.02			0.66	0.22	0.824
BETA_CAR3	-0.37	0.06		-0.16	0.02			0.82	-0.86	0.390
ASC1	-0.79	0.88		-1.13	0.17			166.45	0.10	0.923
ASC3	-1.31	0.50		-1.91	0.13			54.66	0.30	0.762
Choice scenario 3T.3										
Parameters	**Prior**	**s.e.**	**N**	**Final Estimate**	**s.e.**	**N**	**df.**	s^2_{pooled}	**t**	**P(T<=t) two-tail**
BETA_HGV1	-1.16	0.25	13	-1.04	0.10	124	135	10.94	-0.13	0.894
BETA_HGV2	-2.39	0.54		-2.55	0.22			51.39	0.08	0.939
BETA_CAR1	0.35	0.22		-0.21	0.08			8.48	0.66	0.514
BETA_CAR2	-0.27	0.07		-0.44	0.02			0.75	0.68	0.498
BETA_CAR3	-0.23	0.05		-0.29	0.02			0.47	0.33	0.740
ASC1	-1.58	0.53		-1.45	0.19			48.33	-0.07	0.947
ASC2	0.26	0.59		1.14	0.19			57.89	-0.40	0.690
Choice scenario 4T.2										
Parameters	**Prior**	**s.e.**	**N**	**Final Estimate**	**s.e.**	**N**	**df.**	s^2_{pooled}	**t**	**P(T<=t) two-tail**
BETA_HGV1	-1.07	0.27	16	-2.92	0.23	170	184	25.59	1.40	0.163
BETA_HGV2	-0.97	0.41		-2.38	0.23			48.95	0.77	0.441
BETA_CAR1	-0.15	0.10		-0.38	0.05			2.92	0.51	0.608
BETA_CAR2	-0.32	0.06		-0.37	0.02			0.88	0.19	0.848
BETA_CAR3	-0.33	0.05		-0.32	0.02			0.64	-0.05	0.958
BETA_CAR4	-0.15	0.09		-0.01	0.04			2.12	-0.38	0.708
ASC1	-0.71	0.68		-0.45	0.19			115.24	-0.09	0.925
ASC3	0.20	0.43		-2.12	0.17			47.79	1.28	0.202
ASC4	-1.93	0.42		-4.34	0.25			52.92	1.27	0.207
Choice scenario 4T.3										

Parameters	Prior	s.e.	N	Final Estimate	s.e.	N	df.	s^2_{pooled}	t	P(T<=t) two-tail
BETA_HGV1	-1.98	0.46		-1.02	0.12			29.97	-0.58	0.566
BETA_HGV2	-1.63	0.66		-2.50	0.22			63.27	0.36	0.718
BETA_CAR1	-0.17	0.37		-0.35	0.07			18.46	0.13	0.895
BETA_CAR2	-0.69	0.12		-0.36	0.03			2.03	-0.76	0.448
BETA_CAR3	-0.64	0.11	12	-0.32	0.03	121	131	1.63	-0.83	0.409
BETA_CAR4	-0.61	0.09423		-0.36	0.03			1.28	-0.73	0.464
ASC1	-3.52	0.92864		-1.63	0.21			118.92	-0.57	0.566
ASC2	-0.80	0.71		-0.11	0.15			69.24	-0.27	0.785
ASC4	-1.68	0.59036		-1.57	0.16			48.89	-0.05	0.958