Modeling Drivers' Takeover from Conditional Automation

By

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A dissertation submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

(Industrial & Systems Engineering)

at the

UNIVERSITY OF WISCONSIN-MADISON

2020

Date of final oral examination: 08/21/2020

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Abstract

Increasingly capable automation is changing the role of the driver introducing new human factors challenges. SAE Level 3 automated driving systems enable drivers to engage in non-driving related tasks, but they must resume manual control after receiving a takeover request (SAE International, 2018). The safety of such systems relies on the drivers' takeover response, making it critical to understand the underlying dynamics of drivers' takeover behavior and its influencing factors. A takeover can be described using the speed-accuracy tradeoff notion with speed referring to the timeliness of the takeover response, and accuracy being the quality of its execution. Delayed takeovers are synonymous with more extreme initial conditions, but they could also come from drivers wanting to increase their situation awareness for a higher quality takeover. With quicker takeovers, drivers might have to trade off augmenting their situation awareness for a fast response that could suffer in quality. This demonstrates the need to examine takeover time and quality together for a comprehensive assessment of the takeover response.

This dissertation used data from a driving simulator study exposing drivers to a variety of takeover conditions, including different time budgets, levels of visual demand, and event types. Chapter 3 explored the distribution of drivers' takeover times and found that the independent variables influenced the quantiles of the distribution differently. Chapter 4 proposes an evidence accumulation model with a collapsing threshold to predict drivers' takeover time and control choice. In Chapter 5, we proposed an algorithm that ties drivers' evidence accumulation to lateral control models. We also described a new metric for evaluating the stability of drivers' lateral control, the number of chain corrections.

The main theoretical contributions of this dissertation were modeling drivers' time-pressured perceptual decision making after a takeover request, along with their subsequent lateral control. The main practical contributions included highlighting the need to consider the tails of takeover time distributions for safer automated system designs. Moreover, the models developed in this dissertation can be used to create a comprehensive virtual environment that will allow the testing and validation of different automated vehicle design choices in a variety of takeover scenarios.

Table of Contents

Table of Figures

Table of Tables

Acknowledgment

It has been a privilege to have many amazing individuals accompany me during my PhD journey. Without their kind support, encouragement, and help, this dissertation would not have been possible, and it is an honor to share this moment with them.

I would like to express my deepest appreciation to my adviser, Professor John D. Lee, for his continued mentorship, guidance, and support. Thank you for always helping me see the big picture, be a critical thinker, and providing me with the exact feedback that I needed. Your wisdom, patience, and encouragement helped me develop a strong foundation, giving me confidence for any future professional endeavor.

I would like to express my sincere gratitude to my committee, Drs. Douglas Wiegmann, Bilge Mutlu, Soyoung Ahn, and Nicole Werner for their guidance, expertise, and many insightful discussions and suggestions.

I also wanted to express my appreciation to the great team at the National Advanced Driving Simulator at the University of Iowa, Drs. Daniel McGehee, Timothy Brown, and especially Chris Schwarz for his kind support and help with my endless questions.

Having a good support system who motive, challenge, and inspire you makes a huge difference in graduate school. I am forever grateful for the phenomenal members of the Cognitive Systems Lab at the University of Wisconsin-Madison Areen Alsaid, Joshua Domeyer, Varshini Kamaraj, Ja Young Lee, Rashmi Payyanadan, Mengyao Liu, Joonbum Lee, Lorelei Grepo, Shu-Yuan Liu, Morgan Price, Vindhya Venkatraman, Elease McLaurin, and Atefeh Katrahmani.

My sincere thanks to the remarkable faculty, amazing staff, and incredible students of the Industrial and Systems Engineering department at the University of Wisconsin-Madison for making my graduate school experience enjoyable and rewarding.

I gratefully acknowledge the funding received towards my PhD from Toyota Collaborative Safety Research Center (CSRC) and the Ohio State University Transportation Center (UTC).

Most importantly, a heartfelt and huge thank you to my family and friends for their unconditional love and support. A special thank you to my husband, Milad, for his continuous encouragement, support and inspiring me to simplify my complicated thoughts while sitting through every single practice presentation and being my rock. I am especially grateful to my parents Dr. Sedigheh

Zakeri, and Dr. Navid Dinparastdjadid for their many sacrifices. As a child, I witnessed them go through their PhD journey with its many challenges in a foreign country and it taught me to never give up on my dreams. I am forever indebted to them and my little brother for always believing in me, pushing me to be the best version of myself while being my biggest cheerleaders. This accomplishment would not have been possible without them.

1 Chapter 1: Introduction

Current driver assistance systems such as autonomous emergency braking (AEB), forward collision warnings, and blind-spot monitoring detection systems have significantly enhanced road safety (A. McDonald et al., 2019). With more advanced systems, drivers could also enjoy the increased comfort of being freed from routine driving tasks, allowing them to use that time for more meaningful activities. Automated vehicles also promise other bonuses such as, offering greater mobility to older drivers, people with disabilities, and the economically disadvantaged (J. D. Lee, 2019), economic benefits (Fagnant & Kockelman, 2015), increase in the flow and capacity of the road network (Kesting et al., 2008; Ntousakis et al., 2015), an increase in shared mobility (Fagnant & Kockelman, 2015), and a reduction in energy consumption (Anderson et al., 2014). An important contribution of these systems is the promise to reduce road traffic accidents (Bertoncello & Wee, 2015).

However, when discussing the term “automated driving”, it can encompass many different meanings that depend on how function allocation distributes responsibility between the automated system and the driver (Inagaki & Sheridan, 2019). The Society of Automotive Engineers (SAE) has offered the most widely accepted common language worldwide to distinguish different categories of automated driving. SAE J3016 has introduced five levels of driving automation, which characterize how responsibilities for vehicle control, monitoring of the driving environment, and fallback performance have been allocated between the automation and the driver (A. McDonald et al., 2019). SAE J3016 has introduced five levels of driving automation with level 0, being “no automation”, but still including driver support features like blind-spot detection. In brief, Level 1 includes some degree of driver lateral or longitudinal vehicle motion control like adaptive cruise control or lane-keep assist. Level 2 covers both lateral and longitudinal driver control features, but the driver is expected to monitor the driving environment and intervene when needed. With Level 3, the vehicle automation system performs the dynamic driving tasks, including all the operational and tactical functions required to safely operate a vehicle while the driver has more of a supervisory role intervening only when necessary. In Levels 4 and 5, the driver is no longer expected to intervene, and the vehicle is supposed to operate under full automation. The main difference between these two levels is that Level 4 vehicle automation has a limited operational design domain (Hancock et al., 2020).

Automated vehicles are the focus of rapid research and development with some automated functions like adaptive cruise control with lane centering, and automated parking already on the market, while prototypes of higher levels of automated vehicles are being tested on public roads (Seppelt & Victor, 2016). Although these systems promise to offer a better, safer, and more usable personal driving experience, their evaluation, feasibility, and regulation should be discussed extensively (Hancock et al., 2020). Human Factors researchers can particularly contribute to this conversation by focusing on human related research topics like the role of the driver during automation (e.g., whether the driver is in our out of the driving loop), the dynamics of a transfer of control, and design alternatives for the human machine interfaces (HMIs) to provide system transparency which includes communicating the capabilities and limitations and of the system (Seppelt & Victor, 2016). Specifically, with the transition from partial automation (Level 2) which is currently available on the market to Level 3, the changing role of the driver in which there is no longer a need to supervise the system presents a series of human factors challenges that will be explored in this dissertation.

1.1 Problem Statement

SAE J3016 has defined conditional automation for an automated driving system, SAE Level 3, as the automation performing all the dynamic driving tasks, which includes lateral and longitudinal control along with event and object detection and response (SAE International, 2018). According to this definition, the driver is free to engage in non-driving tasks when automation is active, on the condition that the driver remains ready to take control when the automated system exceeds its operational design domain limits or some other performance-relevant system failure occurs (Inagaki & Sheridan, 2019). In such cases, Level 3 automation should issue a takeover request (TOR) that provides the driver with sufficient time to take back vehicle control (SAE International, 2018). However, this raises the question of whether the driver will be prepared to be the system's fallback in all circumstances and whether the driver will be able to safely take over in a situation that exceeds the ability of the automation. Automation might make an already challenging situation more challenging. Bainbridge referred to this dilemma an irony of automation: ‘‘by taking away the easy parts of human tasks, automation can make the difficult parts … more difficult’’ (Bainbridge, 1983, p. 777).

The success of Level 3 automated vehicles may depend on drivers' takeover performance. In other words, assuming flawless performance within the operational bounds of the automated system, the safety of the takeover process, becomes an important design consideration for the human-machine-interface and the automated driving system (C. Gold et al., 2018). The Level 3 automation initiates this takeover process with a request to the driver. After a takeover request has been issued, drivers should relocate their hands and feet to the driving position, assess the situation, gain situation awareness, and formulate a response to take control and avoid a possible safety-critical event (C. Gold et al., 2013; Mok et al., 2015; Zeeb et al., 2015). Therefore, it is important to develop measures and models to ensure a safe and successful takeover maneuvers. Such measures and models can be used to evaluate how designs of SAE Level 3 automated driving systems affect drivers' takeover behavior.

Figure 1 provides a schematic timeline of the takeover process and relevant factors that need to be considered in studying takeover behavior. Since the focus of this dissertation is on SAE Level 3 automated driving systems, drivers might engage in none-driving related tasks (NDRT) while automation is on. In addition, higher levels of automation reduce drivers' interaction with, and control of, certain driving tasks, which might negatively affect the drivers' ability to intervene with a timely and appropriate response to safety-critical events. This phenomenon has been termed "Out of the Loop" (OOTL) (Merat et al., 2018). These cognitive processes will shape the drivers' takeover response because when the takeover request is issued, drivers could have different levels of situation awareness regarding the driving task, which some have labeled as "varying levels of OOTLness" in Figure 1. The term "Time budget" refers to the time between the takeover request being issued, and when the driver must respond, while "Takeover Time", is the time between when a takeover request is issued or an event becomes visible for silent failures, and the first instance of when the drivers' braking or steering input exceeds control thresholds (Dinparastdjadid et al., 2018; A. McDonald et al., 2019).

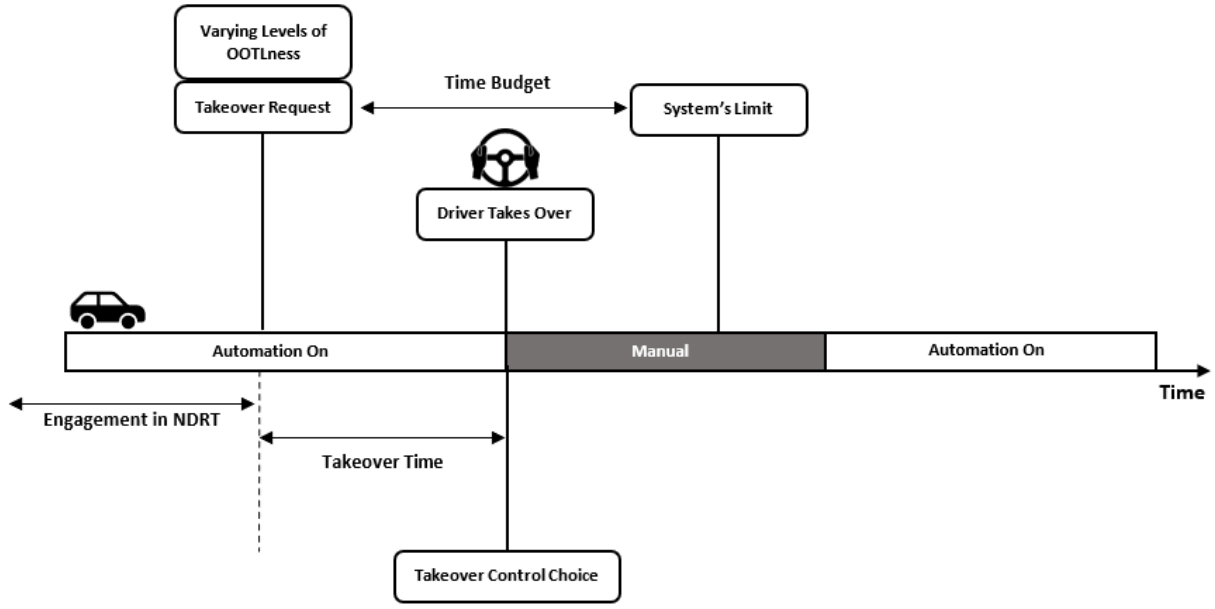


Figure 1. Schematic representation of the takeover process and relevant elements explored in this dissertation.

Among all the different measures that could be used to assess drivers' takeover response, a meta-analysis of 93 studies on takeover behavior with SAE Level 2 automation or higher, by Zhang et al., stated that takeover time (TOT) seems to be the most frequently used measure in the literature (Zhang et al., 2019). Given the variability of drivers' takeover time across different conditions and the different quantiles of driver takeover time within a condition (DinparastDjadid et al., 2019), understanding how drivers process information from the surroundings and integrate it into a coherent image that can guide safe behavior is a critical aspect of driving, specifically during a take-over situation. To the best of our knowledge, such cognitive processes proceeding the takeover performance have not been formally modeled. Modeling the decision-making process after receiving a takeover request, could be beneficial in providing a deeper understanding of how vehicle design, along with situational factors, affect driver behavior. Creating safe and efficient interactions between the human driver and the automated system will come down to specific details concerning the dynamics of human perception, interpretation of the driving scene, and decision making (Kaber & Endsley, 2004; Markkula, Romano, et al., 2018; Zeeb et al., 2015).

Having an estimate of drivers' takeover time is beneficial in assessing drivers' response capacity and in evaluating warning design considerations such as time budget (Favarò et al., 2019). However, takeover time, should not be the only measure to reflect the drivers' understanding of

the situation and readiness to take over (Louw, Kountouriotis, et al., 2015). Even though the timing of a takeover is crucial, merely resuming manual control does not guarantee that the driver will respond to the situation in a safe manner (Louw, Markkula, et al., 2017). Assessing the quality of drivers' vehicle control response in combination with the takeover time can provide a more comprehensive measure of the drivers' takeover performance.

The quality of the drivers' takeover responses has been examined through measures such as minimum time headway to an obstacle, minimum Time-To-Collision (TTC), (C. Gold et al., 2013; Louw, Kountouriotis, et al., 2015), which Hayward (1972) defined as "the time required for two vehicles to collide if they continue at their present speed and on the same path" (Hayward, 1972, p. 27), collisions (Radlmayr et al., 2014), and maximum accelerations during the transition of control (C. Gold et al., 2013; Hergeth et al., 2016; Zeeb et al., 2015). A limitation with current measures for evaluating the quality of a takeover control response is that they are often constrained to specific takeover events. For instance, in takeover scenarios involving a lane departure, the vehicle is already at an extreme lane deviation, making the measure, maximum lane deviation, inappropriate. In situations that do not involve a potential collision with an obstacle, lane departures might be more useful than minimum time to collision (Louw et al., 2019).

As with modeling the perceptual decision-making process, having mathematical models of drivers' takeover control behavior (i.e., braking and steering) could pave the way to assess the quality of drivers' takeover performance across a variety of event types and in interaction with different design and situational factors such as time budget or traffic density. The time-series profiles of drivers' control maneuvers will allow us to extract different takeover quality metrics and evaluate their effectiveness in different scenarios.

Building on this brief overview, Figure 2 shows the main components of this dissertation. These components focus on exploring and modeling when and how drivers resume manual control from SAE Level 3 automated vehicles in takeover scenarios that involve different situational, in-vehicle, and driver-related characteristics. The next section will expand on the details of the specific research questions in this dissertation.

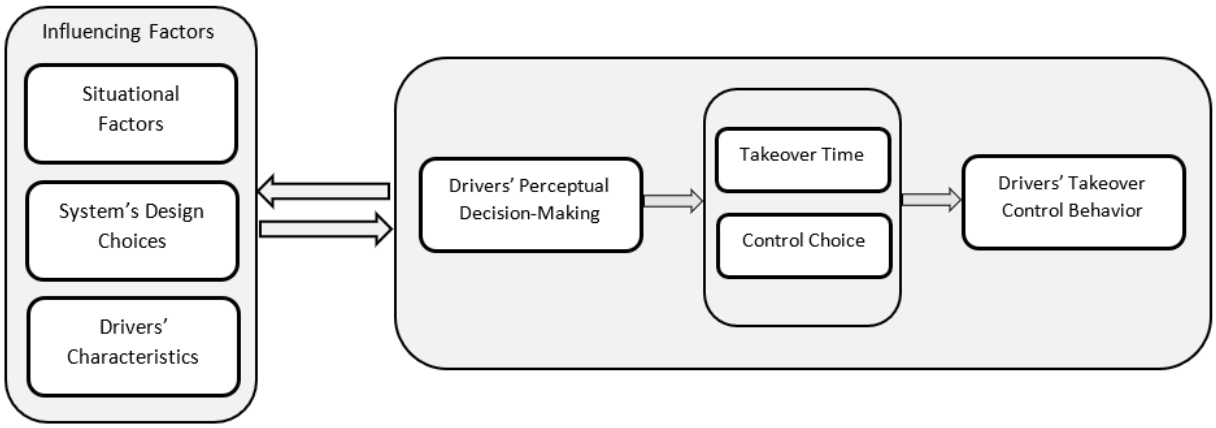


Figure 2. Overview of the main components explored in the dissertation.

1.2 Research Objectives

Taking over from automation can happen in a variety of situations and entail different situational, in-vehicle, and driver-related characteristics. To ensure the safety of alternative design options for SAE Level 3 automated driving systems, they need to be subjected to extensive testing and evaluation across a variety of traffic situations. Driving simulators provide an outlet to study various research questions, such as how drivers will interact with each design choice in different takeover scenarios. The data from these experiments can be used to develop and validate models of drivers' takeover behavior. These models can then simulate hours of driving data based on an infinite number of designs, traffic situations, and driver-related factors. This would significantly improve our understanding of the underlying dynamics of drivers' takeover behavior and improve the safety of Level 3 systems on the road.

In this dissertation, we follow a similar approach to address the three gaps that I identified in research on drivers' takeover behavior. These gaps were translated into three research questions focusing on the timeliness and quality of drivers' takeover performance across a variety of scenarios.

1. *Does mean takeover time misrepresent drivers' takeover behavior?*

Studies on driver takeover time provide a general understanding of driver behavior during a takeover, but they typically distill the drivers' response time to a single mean value. However, the mean is not always representative of the whole response time distribution and might not reflect how various factors affect different regions of the distribution. This is important because

the tails of the distribution can have a disproportionate effect on safety outcomes (Horrey & Wickens, 2007). The routine emphasis on mean response times could lead designers to neglect problems with safety-critical systems, where the tails of the distribution have an outsized influence on crash risk (Horrey & Wickens, 2007; Porter, 2015). In this dissertation, the distribution of drivers' takeover time, specifically the lower and upper quantiles of the distribution were compared to the mean response time in different takeover scenarios. (Published in the journal *Human Factors*.)

2. Can evidence accumulation models capture the underlying processes that influence drivers' takeover time and control choice?

Recent neuroscientific studies have confirmed that the underlying process of perceptual decision-making involves noisy evidence accumulation process that initiates a response when the accumulated evidence exceeds a decision threshold (Purcell et al., 2010). In the context of driving, such models explain driver reaction times in response to stimuli in traffic. The traffic stimuli include both discrete stimuli like brake lights (Ratcliff & Strayer, 2014), and also, dynamic stimuli such as the visual looming of collision threats or approaching road users (Markkula et al., 2016; Svärd et al., 2017).

To the best of our knowledge, these models have been applied to routine manual driving and safety-critical control maneuvers that lack a warning signal. In the context of a takeover scenario, especially for SAE Level 3, the effect of the takeover request needs to be considered in modeling drivers' takeover behavior. In addition, apart from takeover time distributions, another outcome of an evidence accumulation model is the decision choice. A simplified version of control choice alternatives in a takeover scenario includes braking and steering. In this dissertation, we will develop alternate models to simulate the evidence accumulation process after a takeover request and validate the model outcomes, takeover time, and control choice.

3. Is there a relationship between takeover time and lateral and longitudinal performance quality metrics? And can we model drivers' lateral takeover control based on the drivers' takeover time and the kinematics of the driving scenario?

In this dissertation, I explored the interaction between takeover time and a series of takeover performance metrics. Specifically, I expand on the notion of takeover quality to encompass not

only safety but also the experience of the takeover. For example, if the driver were to abruptly brake and stop the vehicle in response to a takeover request or have an evasive steering response, even though it would avoid a collision, it might make the driver and passengers uncomfortable. This could decrease the passenger's confidence in the system because it failed to provide the driver with an effective warning through its interface. This has the potential to negatively influence trust and future adoption of such technology (Ghazizadeh et al., 2012). Therefore, we will propose a new lateral quality metric to evaluate the safety and comfort of the takeover response together.

One of the gaps identified in the literature was the lack of event diversity in exploring different takeover quality metrics. As discussed in the previous research question, using virtual simulations will allow us to model the interaction between the automated system, driver, and the environment in a variety of situations. Building on the steering model introduced by Dinparastdjadid et al. (2018) that explored drivers' lateral control behavior when recovering from a lane departure using an SAE Level 2 automated vehicle, we will explore creating a more comprehensive steering model that will allow us to extract metrics of lateral takeover quality across a variety of takeover situations.

1.3 Overview

This dissertation has six chapters. Chapter 2 reviews the relevant literature on driver takeover and identifies the gaps and weaknesses of the existing literature. Chapters 3 through 5 will be focused on addressing the research questions, which have been summarized in Figure 3. All three chapters used empirical data from a driving simulator study to analyze and model drivers' takeover performance across a variety of takeover conditions.

As shown in Figure 2, these conditions needed to include a variety of situational factors, so we considered different hazard types that required driver intervention after taking over and two levels of traffic density, which affected the visual demand of the driving scene. In addition, the time budget, which is an element of the system's design characteristics from Figure 2 was also varied. Time budget has been the center of much debate in the literature (Alrefaie et al., 2019) and apart from further validating current findings on time budget in the literature, this experimental study provided a unique opportunity to explore the interaction between time budget with a diverse set of situational factors.

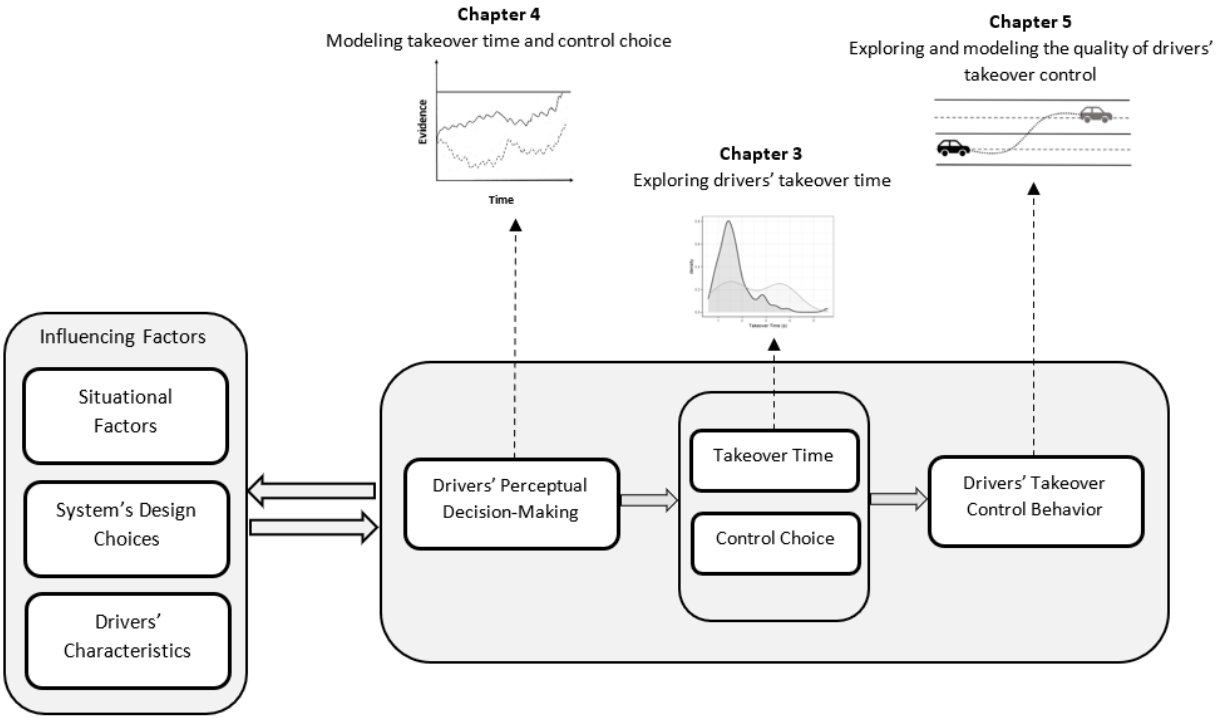


Figure 3. Overview of the analysis and models of this dissertation.

The data for this dissertation were collected at the National Advanced Driving Simulator (NADS) at the University of Iowa using the NADS-1 high-fidelity ground vehicle driving simulator. The experimental design was a 3 (time budget) x 2 (visual demand) x 5 (event type) mixed factorial design. Time budget varied between subjects with three levels of short (3 s), medium (6 s), and long (9 s). Visual demand and event type were within subject variables. The scenarios each included ten events, five in a low-demand environment, and five in a high-demand environment. These events were designed to cover a diverse range of hazards, including a revealed stopped car, a lane departure failure, a work zone, a pedestrian crossing in a work zone, and a slow lead vehicle. During each event, to distract the participants and get their eyes off the road, they were instructed to perform a trivia task where they should complete as many trivia questions as possible. This task was selected to represent the non-driving activities that drivers will likely engage in with Level 3 automated driving. Using the data from this simulator study, we were able to explore drivers' takeover performance and validate models of driver takeover behavior with Figure 3 outlining the scope of the specific analysis and modeling questions.

In Chapter 3, we explored the research question of how different quantile of drivers' takeover time distributions are affected by the independent variable (i.e., time budget, visual demand, and event type). The upper and lower quantiles of the distribution were compared to the central tendency using Bayesian quantile regression to examine whether designing for the average user is a suitable strategy in assessing the safety and quality of takeover.

Chapter 4 addresses the second research question by applying evidence accumulation models with a collapsing threshold to simulate the effect of time pressure introduced by the takeover request warning. Using the collected simulator data, we simulated drivers takeover time distributions and control choice (brake vs. steer) across the different experimental conditions

Chapter 5 focused on both analyzing and partially modeling drivers' takeover control maneuvers to address the third research question. Given that drivers' either steered or braked, the term partial modeling refers to the fact that in this dissertation will specifically focus on modeling drivers' lateral control. In evaluating drivers' takeover control, we explored both lateral and longitudinal quality metrics while also proposing a new lateral quality metric that reflects the stability of drivers' steering response.

Chapter 6 concludes this document by discussing limitations and potential future work, followed by a summary of the findings from each research question and how they contributed both theoretically and practically to our understanding of drivers' takeover behavior and the design of safer automated vehicles.

2 Chapter 2: Review of Related Literature

This chapter reviews the literature on vehicle automation, specifically SAE Level 3 automated driving systems, and the challenges facing the design of these systems to ensure drivers can have successful takeovers when needed. The chapter concludes by highlighting current gaps and weaknesses in the takeover literature.

2.1 Levels of Automation

The term “automated driving” can vary in its meaning depending on how designers allocate functions between the automated system and the driver. An incorrect or inaccurate understanding of these function allocations could lead to many human-factors related issues (Inagaki & Sheridan, 2019). Misuse and disuse of automation are one approach to describe such flawed partnerships between automation and the user that could compromise safety. The term misuse describes failures arising from the user inadvertently violating critical assumptions and relying on automation inappropriately, while failures from users rejecting the capabilities of automation have been labeled as disuse (J. D. Lee & See, 2004; Parasuraman & Riley, 1997).

As a result, many institutions such as the National Highway Traffic Safety Administration (NHTSA, 2013), the German Federal Highway Institute (Gasser & Westhoff, 2012), and the Society for Automotive Engineers (SAE, 2016) have attempted to distinguish different categories of automated driving using different approaches. SAE J3016 standard’s definition for levels of driving automation (LoDA) is the most widely accepted common language worldwide and provides a “taxonomy and definitions for terms related to on-road motor vehicle automated driving systems” (SAE, 2016). SAE J3016 has introduced five levels of driving automation, which are defined in Table 1. It should be mentioned that SAE also has a level 0, which is “no automation”.

SAE has defined the term dynamic driving task (DDT) in Table 1, with it referring to the required operational and tactical functions for the vehicle to operate on the road safely. DDT includes a series of subtasks including; 1) lateral vehicle motion control, 2) longitudinal vehicle motion control, 3) monitoring the driving environment via object and event detection, recognition, classification, and response preparation, 4) object and event response execution, 5) maneuver planning, and (6) enhancing conspicuity via lighting and gesturing, etc. The terms

object and event detection and response (OEDR) in Table 1, refer to subtasks (3) and (4) (Inagaki & Sheridan, 2019).

Table 1. SAE levels of driving automation (LoDA) Level (taken from (Inagaki & Sheridan, 2019), after (SAE, 2016)

Levels of driving automation	**Definition**
LoDA 1: Driver assistance	Automation performs either longitudinal or lateral vehicle motion control (on a sustained basis), but not complete object and event detection and response (OEDR)
LoDA 2: Partial driving automation	Automation performs both longitudinal and lateral vehicle motion control (on a sustained basis), but not complete OEDR
LoDA 3: Conditional driving automation	Automation performs the complete dynamic driving task (DDT), but not DDT fallback, within a limited operational design domain (ODD)
LoDA 4: High driving automation	Automation performs the complete DDT and DDT fallback within a limited ODD
LoDA 5: Full driving automation	Automation performs the complete DDT and DDT fallback without ODD limitation

With partial and conditional automated driving systems (SAE Level 2; L2 and Level 3; L3), the driver is responsible for the safe operation of the vehicle (SAE, 2016). With L2 automation, even though the driver is relieved from lateral and longitudinal control requirements, and the drivers' responsibility is to supervise the automation. L3 automation allows the driver to handover lateral and longitudinal control of the vehicle to the automated driving system and does not require supervision. The driver is expected to be ready to resume manual control when a request is issued by the automated system. The takeover request (TOR) is supposed to provide the driver with sufficient time to take back vehicle control (SAE International, 2018). This raises the question of whether the driver will be prepared to be the system's fallback in all circumstances and whether the driver will be able to take over safely. People using automation in other domains such as aviation (Sparaco, 1995), cruise ships (J. D. Lee & Sanquist, 2000) and paper mills (Zuboff, 1988) have also struggled with poor partnerships stemming from misuse and disuse of automation as it became more prevalent leading to unfortunate outcomes (J. D. Lee & See, 2004). Such questions will be the focus of this dissertation with the goal of contributing to the understanding of drivers' takeover behaviors in interaction with Conditional Driving Automation, L3.

2.2 Current Issues with Vehicle Automation

With advancements in software and hardware, machines are becoming more intelligent and, if applied properly, could help advance human life. In the field of vehicle automation, automated vehicles could lead to a range of benefits including, economic benefits (Fagnant & Kockelman, 2015), increase in the flow and capacity of the road network (Kesting et al., 2008; Ntousakis et al., 2015), an increase in shared mobility (Fagnant & Kockelman, 2015), and a reduction in energy consumption (Anderson et al., 2014). An important contribution of these systems is the promise to reduce road traffic accidents (Bertoncello & Wee, 2015). Companies such as Waymo and Tesla, followed by more traditional automakers like Volvo, BMW, and Audi, have been introducing automated driving systems in hopes of achieving these benefits (Dimitrakopoulos, 2017). Despite all the potential benefits of current automated systems, the human still needs to be involved in the driving task (Louw et al., 2019). Google recently reported that during 14 months of testing its self-driving cars, they were "out of automated status" 272 times, and drivers chose to cancel automated status 69 times (Google, 2015). This is just an example indicating issues surrounding drivers' safety in such automated systems and driver acceptance hinging on the need for human intervention (Wu et al., 2019).

With all the progress in machines becoming more automated, finding the balance between the roles of humans and automated systems that can lead to safe, clear, efficient, and enjoyable interactions is crucial (Flemisch et al., 2012). Aviation, a domain that has been one of the early users of automation since the twentieth century, benefited from reduced workload due to the introduction of automated functions while also suffering from issues such as mode confusion, and human-out-of-the-loop (Billings, 1997; Wiener, 1989). Bainbridge called such a notion, the "ironies of automation" where, ''by taking away the easy parts of human tasks, automation can make the difficult parts … more difficult'' (Bainbridge, 1983, p. 777). This phenomenon is similar to the Automation Conundrum by Endsley, 2017, in which she states that, as more automation is added to a system, and the more reliable and robust the automation, the less likely that human operators overseeing it will be aware of critical information and able to take over manual control when needed (Endsley, 2017b). The Lumberjack Effect is another term aiming to express the same concern by pointing out that even though more automation will aid manual performance, the same cannot be extended to recovering from automation failure (Onnasch et al., 2014). These terms, along with the literature behind it, signify the need for a balanced design

based on ability, authority, control, and responsibility between the driver and the automated vehicle (Flemisch et al., 2012).

In conditionally automated driving (L3), the driving task changes from that of continuous control in manual driving to only intervening when a takeover is issued. Driving in a conditionally automated vehicle, the drivers' mental workload is different from manual driving, and split between episodes of insufficient load, when the automated system is active and excessive load when a takeover request is suddenly issued (Wu et al., 2019). Nilsson et al. (2013) carried out a study comparing drivers' mental workload in automated driving vs. manual driving using the mental workload scale. He found that considering a 0–150-point scale, the automated mode resulted in an average mental workload of 12 points, while the average for manual driving was 37 points (Nilsson et al., 2013). Overall, automation will make routine driving easier, but as described by Bibby et al., (1975), higher levels of automation will change the role of humans from manual performance to a more supervisory role, leading to 99% boredom and 1% sudden terror (Bibby et al., 1975). On the other hand, with the moment-to-moment control of the vehicle being taken care of, there is a high chance that drivers might engage in non-driving related activities, shifting their attention away from the driving task (Carsten et al., 2012). Non-Driving related tasks will lead to the occupation of physical or psychological resources such as eyes, ears, brain, hands, and mouth. Examples of such tasks include talking on the telephone, text input, listening to the radio, and watching videos (Wu et al., 2019). Engagement in secondary tasks, also known as non- driving related tasks (NDRTs), could be due to reasons such as boredom, driver complacency, and a high trust in the automated system's capabilities giving drivers a false impression that engaging in NDRTs is safe (Banks et al., 2018).

Examining results from driving simulator studies along with real-world events involving L2 automated driving systems has shown that reduced visual attention, amplified by engagement in visual non-driving tasks, could be dangerous, especially in safety-critical events requiring the driver to takeover (Banks et al., 2018; Endsley, 2017a; Louw, Madigan, et al., 2017; Louw, Markkula, et al., 2017). Studies investigating takeover from automation suggest that engagement in non-driving related tasks during automation could affect the timeliness and safety of drivers' takeover performance (C. Gold et al., 2013; Radlmayr et al., 2014; Zeeb et al., 2015). The drivers' shift of attention from the driving task could undermine situation awareness, leaving the

driver ill-prepared to regain the attention and motor control necessary to perform a successful takeover (Endsley & Kiris, 1995; Louw, Markkula, et al., 2017).

An unfortunate example involved an Uber test-vehicle colliding with a pedestrian who was crossing its path in March 2018 (Marshall & Davies, 2018). The software responsible for interpreting the vehicle's sensors data erroneously classified the pedestrian as a "false positive." As a result, the system did not issue a takeover request to the safety driver until only a second before the impact, which was too late for a safe takeover. The safety driver was responsible for monitoring the situation and initiating an emergency response when required. However, as mentioned most drivers' fail to monitor the roadway continuously and, in this case, the safety driver was engaged in a non-driving task (watching a show on a mobile phone), causing the driver to fail in detecting the pedestrian and avoiding the collision (Louw et al., 2019).

A solution to mitigate the adverse side effects of engaging in non-driving tasks when using vehicle automation could be to simply discourage engagement and monitor that the driver is attending to the road. Examples of such systems can be found in current L2 automated vehicles, where they prompt regular contact with the steering wheel, which infers drivers' attention to the road through pressure sensors on the steering wheel (Pilot Assist II; Volvo, 2018). Some manufactures have taken it a step further and have added camera-based sensing to evaluate the drivers' attention to the driving environment (Cadillac, 2018).

In most of these systems, the automated system will disengage if the driver does not attend to the road. However, previous versions of Tesla's Autopilot, would not disengage even when drivers missed to put their hands on the steering wheel after many alerts (Louw et al., 2019). According to the U.S. National Transportation Safety Board (NTSB), in a 2018 fatal Tesla crash in Mountain View, CA, the driver of a Tesla, Model X using autopilot, did not have his hands on the steering wheel six seconds before the crash. The driver had received two visual alerts and one auditory alert prompting the driver to place his hands on the steering wheel, in the 18 minutes and 55 seconds before impact. This resulted in a total of 34 seconds of hands detected on the steering wheel 60 seconds prior to the crash, but no hands on the wheel during the last six seconds (National Transportation Safety Board, 2018). The general notion of discouraging drivers' to engage in non-driving tasks, or to prompt them to engage with driving-related tasks, though suitable for Level 2 automated vehicles might not be compatible with Level 3 automated

vehicles in which the driver is permitted to engage in non-driving related tasks when automation is active.

The discussions in this section point to the need to better understand the underlying processes of drivers' takeover behavior across a variety of takeover scenarios. The output of such research could help test and validate design alternatives for SAE Level 3 automated driving systems. In the following section, the timeline of a takeover process with its elements will be discussed providing a deeper understanding of what happens prior, during, and after a takeover request has been issued and what are the current gaps in the literature.

2.3 Takeover from Automation

This dissertation will specifically focus on drivers' takeover performance in interaction with SAE Level 3, with the assumption of the driver receiving a takeover request warning. Figure 4 shows a schematic overview of the timeline of a typical takeover scenario.

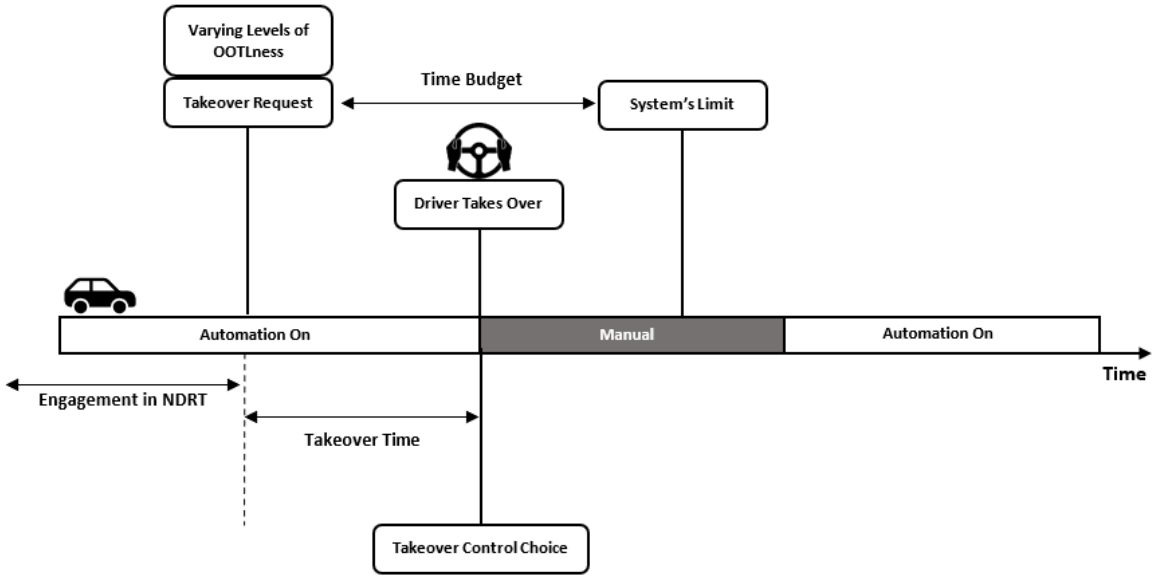


Figure 4. Schematic representation of the takeover process and relevant elements explored in this dissertation.

In Figure 4, three landmark moments have been identified, including, when the takeover request is issued, when the driver resumes manual control, and when the system would have ceded control if the driver has not taken over. Based on these three points in the takeover timeline, two critical measures reflecting the interaction between the driver and the automated system were defined: takeover time and time budget. In the following section, elements of Figure 4 will be discussed in further detail.

2.3.1 The Take-Over Request

According to the definition of conditional automation for an automated driving system, SAE Level 3, the driver is free to engage in non-driving tasks when automation is active, on the condition that the driver resumes manual control when the automated system exceeds its operational design domain limits or some other performance-relevant system failure occurs (Inagaki & Sheridan, 2019). In such cases, the system issues a takeover request (TOR) that provides the driver with sufficient time to take over (SAE International, 2018). The takeover request (TOR) can vary according to the specific modality of the takeover request, whether the signal has included one or multiple modalities, and the directionality of the warning (Petermeijer, Bazilinskyy, et al., 2017).

2.3.1.1 Modality

Even though in manual driving the drivers receive most of their information through vision and audition, with automated vehicles, due to the driver likely being engaged in secondary tasks, auditory and vibrotactile displays could potentially be more promising takeover request options (Bazilinskyy & DeWinter, 2015) due to their "gaze free" nature (Meng & Spence, 2015; Stanton & Edworthy, 1999). Visual tracking is a demanding part of the driving task requiring a high level of focal visual attention. Moreover, many non-driving related tasks that drivers engage in when automation is active are also heavily visual (e.g., texting, reading emails, or watching a movie). As a result, takeover requests such as texts, symbols, and/or icons that also demand focal visual attention could lead to a bottleneck of visual resources (Borojeni et al., 2018; Wickens, 2002). A potential solution to this matter could be using ambient light to initiate a takeover request, which relies on peripheral vision instead of focal vision (Borojeni et al., 2018). According to Wickens' multiple resource theory, using channels beyond vision like the auditory channel in combination with the visual channel might be a better solution to convey information to the driver during a takeover request. Previous studies have shown that a combination of audio-visual cues led to quicker and more accurate responses (Naujoks et al., 2016; Politis et al., 2015).

In recent years, vibration has received more interest (Petermeijer et al., 2015) and has been applied through the steering wheel or the seats. For example, for lane departure warning systems, BMW (2015) and Mercedes-Benz (2015) started using a vibrating steering wheel while Citroen (2007) and Chevrolet (General Motors, 2014) have used vibrations in the drivers' seat. Comparing the two

and considering the high probability of drivers being involved in secondary driving tasks, their hands will not always be on the steering wheel, making the seat a more promising option for delivering takeover requests using vibration.

Petermeijer et al. (2017) found reaction times for vibrotactile and auditory takeover requests are like those observed in basic psychophysical research (Woodworth & Schlosberg, 1954) and previous research in manual driving (e.g., Scott & Gray, 2008). Some studies, on the other hand, have shown contrasting results with one having in faster reaction times over the other. The specific task conditions (e.g., auditory demands, like talking on the phone) or the physical intensity of the stimulus like the vibration amplitude, or sound pressure could explain these different findings (Petermeijer, Bazilinskyy, et al., 2017). Overall auditory and vibrotactile cues are both effective options for takeover requests, especially considering that they can communicate information to the driver even when the drivers' eyes are off the road.

Another less explored means to convey the capabilities of the vehicle to the driver is the vehicle dynamics. For example, using motion cues such as the lateral movement of the vehicle has shown to negatively influence drivers' trust, implying that it could potentially be beneficial in guiding drivers' attention in the absences of threat anticipation (Domeyer et al., 2018; Morando et al., 2016). The application of brake pulses has also been used to alert drivers when the adaptive cruise control's (ACC) acceleration authority has been exceeded (J. D. Lee et al., 2007)

2.3.1.2 Number of Warning Modalities

Multimodal warnings are a combination of visual, auditory, and vibrotactile stimuli. They can offer several benefits to ensure timely detection and accurate interpretation of a warning signal. With the visual channel usually being overburdened, a multimodal signal can offload some of that burden while supporting the parallel processing of information and facilitating the fine-tuning of signal salience (Sarter, 2013).

A large-scale crowdsourcing survey among 1692 respondents on auditory, vibrotactile, and visual take-over requests from highly automated driving systems found that when the urgency of the takeover is higher, people typically prefer a multimodal takeover (Bazilinskyy et al., 2018). This finding is consistent with psychophysics research that has shown multimodal warnings to lead to higher perceived urgency than unimodal warnings (e.g., Van Erp et al., 2015). Apart from the enhanced subjective sense of urgency with multimodal warnings, they have also been found

to prompt faster reaction times. A meta-analysis of 43 studies on various types of human-machine interaction found that in comparison to visual feedback alone, visual-auditory and visual-tactile feedback elicit faster responses (Burke et al., 2006). Complimenting these findings, Diederich and Colonius (2004) found responses to trimodal stimulus combinations to be faster than those to bimodal stimuli, which in turn were faster than reactions to unimodal ones.

On the contrary to these findings, driving simulator studies by Tijerina et al. (1996) on lane departure warning systems and Lees et al. (2012) have shown that bimodal cues resulted in driver overload and higher reaction time, respectively. Another study by Lee et al. (2006) explored driver reaction times when the Adaptive Cruise Control (ACC) exceeded its functional limits, in the presence of four modes of stimuli (visual & auditory warnings, vibratory seat, and brake pulse feedback). They found that reaction times were 400 ms slower with multimodal stimuli than bimodal alert of visual and auditory cues (J. D. Lee et al., 2006). The overload and higher reaction times can be attributed to the fact that these various modes of warning signals are coming from different sources that are temporally, and spatially and semantically incongruent prompting them to be perceived as a series of cues rather than a single cue (Diaconescu et al., 2011; Petermeijer, Bazilinskyy, et al., 2017; Talsma et al., 2010).

It can be concluded that a multimodal driver-vehicle interface can redirect drivers' attention more effectively than single-mode displays, but only if they are properly integrated into a coherent signal.

2.3.1.3 Directionality

The purpose of a takeover request is to alert drivers to a limitation of the automated system and to aid them in taking over control. To achieve this, takeover request warnings need to serve a greater purpose by also providing the driver with some information about the situation and control actions to avoid possible unfortunate consequences. By doing so, the process of the driver gaining SA can be reduced, decreasing the takeover time. A non-directional warning will only alert the driver and misses the opportunity to convey extra information such as the location or direction that requires the drivers' attention, which can enhance their situation awareness (Petermeijer, Bazilinskyy, et al., 2017).

One example of a directional warning used a vertical array of three tactors to create motion either towards (upwards) or away (downwards) from the driver's head, linking the vibrotactile stimuli to

the vehicle's closing velocity in a forward-collision warning system (Gray et al., 2014). Another example, used eyeglasses and the driver seat to test left/right directional visual cues versus directional vibrotactile cues in a simulated lane change test (Nukarinen et al., 2015). In general, visual, auditory, and vibrotactile directional cues have shown to improve reaction times and situation awareness (Houtenbos et al., 2017; Prewett et al., 2012)

With directional takeover requests, there has been debate on the choice of contralateral mapping versus ipsilateral mapping (i.e., when the stimulus is in the direction that requires drivers' attention). For example, in ipsilateral mapping, if the driver needs to steer to the right, the steering wheel's stimulus should also come from the right. In contrast, in contralateral mapping, drivers are supposed to steer away from the stimulus; hence it should come from the left. Early findings from abstract laboratory studies found that ipsilateral mapping results in faster reaction times (Simon et al., 1970; Umilta & Nicoletti, 1990). In the context of driving, contralateral mapping has shown to yield faster reaction times, which could be explained by drivers having a preview of the hazard in advance allowing them to visually assess the driving scene (Beruscha et al., 2010; Müsseler et al., 2009; Wang et al., 2007). However, with conditional automation, drivers might be engaged in a secondary task when the takeover request is issued, and assessing the effectiveness of directional warnings should be further studied.

In a recent study, Petermeijer et al. (2017) investigated the effect of a directional takeover request (left, right, or non-directional) on the consistency of a drivers' response (ipsi- or contralateral), when without them knowing about the nature and presence of the directional cues. They found that almost all participants, regardless of the direction of the takeover request, overtook a stationary car on the left. This result suggests that rules and habits (in German traffic rules overtaking on the right is prohibited on highways) strongly shape behavior. Petermeijer et al. (2017) concluded that future work should address the saliency of directional takeover requests through cue saliency, instructions, or a higher level of semantics that might aid drivers in perceiving the directional warning. An important consideration with directional cues concerns the system's confidence in its suggestion since a wrong indication could lead to a dangerous or delayed response. Other alternatives to that could benefit from further investigation in this domain include the addition of directional auditory cues (e.g., left, right (Glaze et al., 2015), the application of small oscillatory

movements on the steering wheel to nudge the driver towards a specific direction (Navarro et al., 2010) and haptic steering guidance (Della Penna et al., 2010).

2.3.2 Automated System's Limit

The system limit label shown in Figure 4, includes instances where the automated system reaches its operational limits (e.g., poorly marked lane markings) or a performance-relevant system failure occurs such as an upcoming collision (e.g., with a stationary vehicle in the ego lane) requiring the driver to takeover within the given time budget to avoid a safety critical event (Inagaki & Sheridan, 2019; Zhang et al., 2019).

2.3.3 Time Budget

The timing of a takeover is a critical design parameter (Lu et al., 2017). For drivers to successfully take over control and avoid a collision, drivers need sufficient time to assess the situation (Mok et al., 2015), gain situation awareness (SA) and formulate a response. Time buffer, lead time, and time budget (Gasser & Westhoff, 2012; SAE International, 2018; Zeeb et al., 2016), are some of the names for the time allowance given to the driver to regain manual control of the vehicle after the takeover request (Lu et al., 2017). Gold et al., have defined time budget as the time available between a takeover request and the system reaching its limit, requiring driver intervention due to a critical event (C. Gold et al., 2018). In the remainder of this document, this time window will be referred to as "time budget".

Time budget has been the focus of many studies and has shown to affect drivers' information preferences, decision making (Eriksson et al., 2015), and performance during a takeover event (Van Den Beukel & Van Der Voort, 2013).

In a simulator study by Gold et al. (2013), drivers showed more abrupt steering and braking responses when there was less time available until a collision with a stationary object (5 s vs. 7 s). In the same study, they reported an average mirror-scan time of about 3 s, an average hands on steering wheel time of 1.5 s, and an average gaze reaction time of 0.5 s, with gaze reaction time being defined as the time between the issuance of the takeover request and the drivers' eye gaze moving away from the non-driving task (C. Gold et al., 2013). Mok et al., (2015) showed that few drivers in a 2 s lead-time condition were able to avoid a collision, while the 5 s and 8 s conditions they did. Further investigating the required lead-time, Samuel et al. (2016) conducted a simulator study in which they compared 4, 6, 8, and 12-second lead-times. They found for the

participants to be able to detect a latent pedestrian hazard with the same accuracy as when they were in control, a minimum lead-time (i.e., time budget) of 8 seconds was required. In addition, to fully stabilize the vehicle Merat et al. (2014) and Desmond et al. (1998) have suggested 20 sec or 40 s might be needed. In summary, some of the main findings from the literature on time budget include, allowing people 7 s (C. Gold et al., 2013), 8 s (Wandtner et al., 2018), 10 s (Melcher et al., 2015) and 12 s (Zeeb et al., 2015). NHTSA has recommended manufacturers to design their automated system's transitions based on a 7 s time budget. They state that this number, which is from Gold et al.'s (2013) study, will provide drivers with adequate time to respond to critical hazards in highly automated driving (Alrefaie et al., 2019; Campbell et al., 2018).

Drivers' response time to a takeover request should not be considered as a single value, but one that depends on factors such as traffic density, human-machine interface concepts, non-driving task type, and drivers' mental state (e.g., out of the loop distracted, or drowsy), as well as driver-specific variables such as experience and age (Zeeb et al., 2015). Zhang et al. (2019), performed a meta-analysis of 129 studies that measured the takeover time (TOT) following a critical event or a takeover request and found that the available time, the presence of hand-held devices and lack of experience with takeover requests substantially increased mean TOT, while the modality of the takeover request had a small effect on the mean TOT (Zhang et al., 2019). Another meta-analysis found that a time-budget of 5 seconds led to a mean response time of 2.1 s (SD = 0.41), while a 7 s time budget delayed driver intervention (2.9 s, SD = 0.65) (C. Gold et al., 2013). These studies provide a general understanding of driver behavior during a takeover and distill drivers' response time to a single mean value. However, the mean is not always representative of the whole response time distribution and might not reflect how various factors affect different regions of the distribution. This is especially important because the tails of the distribution can have a disproportionate effect on safety outcomes (Horrey & Wickens, 2007).

2.3.4 Takeover Time

After a takeover request has been issued, drivers should relocate their hands and feet to the driving position, assess the situation, gain situation awareness, and formulate a response to take control and avoid a possible safety-critical event (C. Gold et al., 2013; Mok et al., 2015; Zeeb et al., 2015). Gold et al., (2013), suggested gaze response time, eyes-on-road time, hands-on wheel response time, and takeover time as potential measures of response time after a takeover request.

Other possible takeover response time measures that are more task-specific including, mirror check response time (e.g., C. Gold et al., 2013; Vogelpohl, Kühn, Hummel, Gehlert, & Vollrath, 2018), hand-movement response time (e.g., Kerschbaum, Lorenz, & Bengler, 2015), and lane change response time (Eriksson et al., 2019; Petermeijer, Cieler, et al., 2017). Among all the different measures that could be used to assess drivers' takeover response, a meta-analysis of 129 studies on takeover behavior with SAE level 2 automation or higher, by Zhang et al., found that take-over time (TOT), defined as the "time that drivers take to resume control from automated driving after a critical event in the environment or after having received a takeover request, appears to be the most frequently used measure in the literature" (Zhang et al., 2019, p. 3). While studying drivers' takeover time in urgent scenarios with a short time budget is crucial, most takeovers included controlled transitions such as planned exits from a highway. A study by Stanton & Erikson (2017), found that takeovers with no time pressure led to a slower resumption of manual control, and the presence of a secondary task increased both the timing and variance of drivers' takeover time (Eriksson & Stanton, 2017).

knowing the order of magnitude of drivers' takeover time is important, especially for the design of warning interfaces. Still, takeover time alone is not the most appropriate measure of the drivers' understanding of the situation and readiness to take over (Louw, Kountouriotis, et al., 2015; Louw, Merat, et al., 2015). In other words, even though the timing of a takeover is crucial, simply resuming manual control does not guarantee that the driver will be able to successfully mitigate all risks (Louw, Markkula, et al., 2017). Examples of risky and unsafe takeover behaviors include erratic steering or brake input, abrupt lane changes, and failing to avoid surrounding traffic (Favarò et al., 2019).

2.3.5 Takeover Quality

Assessing the quality of drivers' vehicle control response in combination with the takeover time can provide a more comprehensive measure of the drivers' takeover performance. The quality of drivers' takeover control responses has been examined through measures such as minimum time headway to an obstacle (Louw, Kountouriotis, et al., 2015; Louw, Merat, et al., 2015; Merat et al., 2014; Merat & Jamson, 2009), minimum Time to Collision (TTC), (C. Gold et al., 2013; Louw, Kountouriotis, et al., 2015; Louw, Merat, et al., 2015) defined by Hayward (1972) as "the time required for two vehicles to collide if they continue at their present speed and on the same path", and maximum accelerations during vehicle control in the transition (C. Gold et al., 2013;

Hergeth et al., 2016; Zeeb et al., 2015). Other measures that have been using to evaluate the quality of drivers' lateral and longitudinal vehicle control include maximum and minimum accelerations, lateral deviations, lane departures, steering wheel reversals (Louw et al., 2019).

The quality of the drivers' takeover responses has been examined through measures such as minimum time headway to an obstacle, minimum Time to Collision (TTC), (C. Gold et al., 2013; Louw, Kountouriotis, et al., 2015), which Hayward (1972) defined as "the time required for two vehicles to collide if they continue at their present speed and on the same path" (Hayward, 1972, p. 27), occurred collisions (Radlmayr et al., 2014), and maximum accelerations during vehicle control in the transition (C. Gold et al., 2013; Hergeth et al., 2016; Zeeb et al., 2015). Other measures that have been used to evaluate the quality of drivers' lateral and longitudinal vehicle control include the maximum and minimum accelerations, lateral deviations, lane departures, and steering wheel reversals (Louw et al., 2019).

Another point of view in this literature has been drivers' evasive maneuvers. There is limited evidence on how automation affects the quality and dynamics of evasive maneuvers (Happee et al., 2017). Takeover studies have shown that, like in manual driving, evasive control actions could result in an overshoot from the target lane followed by poorly damped or oscillating stabilization (e.g., C. Gold et al., 2013).

In extreme takeover scenarios, braking alone might not be sufficient to ensure a safe and successful takeover, requiring additional steering control. However, braking seems to be drivers' initial reflexive response even when engaged in a handheld secondary task (Zeeb et al., 2017). Wu et al., (2017) found that steering responses were generally slower than braking responses during a takeover, explaining that this could be due to lateral control maneuvers demanding more cognitive and decision-making time. They also found that in takeover scenarios in which the driver is engaged in a visual non-driving task or the obstacles that need avoidance are hard to detect, increasing steering reaction time significantly (Wu et al., 2019).

A measure such as TTC, though intuitive in critical takeover scenarios requiring braking and capturing the braking performance, is not best suited to be applied to more complicated evasive maneuvers where steering inputs frequently change the projected path of the vehicle (Happee et al., 2017). Given that TTC cannot provide sufficient information on steering behavior, other measures such as Time to Line Crossing (TLC) or Standard Deviation of Lateral Position

(SDLP) have been introduced. The downside of such metrics is that they are more appropriate for slow lane and road departures, rather than rapid evasive maneuvers in which TLC and SDLP change quickly (Happee et al., 2017). The speed of the vehicle during the takeover process is another potential contributing factor to the quality of the takeover. A study by Favaro et al. (2019) suggests that establishing operational thresholds for speed could reduce the maximum drift and subsequent unintentional lane departures, ensuring a more controlled takeover (Favarò et al., 2019).

In general, a limitation with such measures is that they are often constrained to the specific experimental setup and context. For instance, in takeover scenarios involving a lane departure, the vehicle starts at an extreme lane deviation, rendering the measure, maximum lane deviation as inappropriate, or in situations that do not involve a potential collision with an obstacles lane departures might be a more useful than minTTC (Louw et al., 2019). This signifies the need to understand the underlying factors in different event types that lead to diverse takeover behaviors. Louw et al. (2017) proposed using the kinematics of the takeover scenario (i.e., the criticality at the point of takeover) as a tool to assess drivers' responses.

2.4 Non-Driving Related Tasks and Their Effect on Takeovers

Lee et al. have defined driver distraction as "a diversion of attention away from activities critical for safe driving toward a competing activity" (J. D. Lee et al., 2008, p. 7). Driver distraction can be either exogenous or endogenous, with the implications for each distraction type being different in driving. Exogenous distractions refer to external objects or events that are irrelevant to driving and can be dangerous given that in addition to the drivers' attention, they capture the drivers' gaze, drawing attention away from the road. With endogenous distraction, which is produced by the drivers' own thoughts or cognitive activity that are unrelated to the driving task, even though the drivers' eyes are on the road, looking is not always seeing (Recarte & Nunes, 2003). Recarte and Nunes (2000) examined the effects of different cognitive tasks on visual behavior and driving performance and stated that endogenous distraction could undermine visual processing. They also found that the increased workload needed by several mental tasks was reflected in a significant pupil size increment, and mental tasks affected several measures of visual search behavior (Recarte & Nunes, 2000).

Studies of manual driving show that secondary tasks can undermine driving performance and safety (Dingus et al., 2006; Engström et al., 2005; Horrey & Wickens, 2007). Likewise, engaging in visually demanding secondary tasks during manual driving can be particularly challenging (Ma & Kaber, 2005; Neubauer et al., 2012). However, the validity of these studies in the domain of automated driving should be assessed because automation decreases mental workload (Ma & Kaber, 2005; Zeeb et al., 2016), while takeover from automation might produce greater workload (Sarter & Woods, 1997). Young and Stanton (2002) have warned that automation will cause cognitive underload, which could be as serious as overload and developed the Malleable Attentional Resource theory to explain this phenomenon. This theory suggests that changes in task demand could lead to reduced attentional capacity leading to degraded performance in instances like automation failure (Young & Stanton, 2002).

However, there is a lack of consensus on the effect of non-driving tasks on drivers' takeover behavior, and the conclusions are two-fold. On the one hand, secondary tasks can diminish drivers' situation awareness. For instance, Merat et al. (2012) found that engagement in a verbal "20 Questions Task", when faced with a safety-critical event, did not affect drivers' timing to initiate a lane change. They also found that the presence of the non-driving task affected the drivers' ability to decrease the vehicle's speed to a safe level in a timely manner. On the other hand, secondary tasks could maintain the drivers' mental workload at a certain level, improving the drivers' take-over performance. For example, Neubauer et al. (2012) compared the effect of using a cell phone in automated and manual driving. They reported that cell phone use led to a decrease in response times during automated driving. In fact, they concluded that secondary tasks counteract the mental underload caused by automation and help maintain the drivers' alertness. As expected, in manual driving with a secondary task condition, delayed braking response times to an emergency event were observed. But, in the automated driving condition with a secondary task, the drivers reacted faster compared to drivers without a secondary task.

Zeeb et al. (2016) examined how naturalistic secondary tasks affect take-over time and quality. They found that even though engagement in secondary tasks influences drivers' visual and cognitive processing of the situation, it does affect the time required to achieve motor readiness (Zeeb et al., 2015, 2016). Specifically, it was hypothesized that the time required to grasp the steering wheel would be unaffected by the performance of a secondary task. All the selected tasks were expected to exert a relatively high visual and cognitive demand while also being

attractive for the driver. These tasks included writing an email, reading the news, and watching a video. In their study, a steering intervention was defined as an absolute steering wheel angle velocity larger than $0.075^{\circ}/s$ and absolute steering wheel angle acceleration larger than $5^{\circ}/s^2$. A braking intervention was recognized when the standardized brake pedal travel was greater than 10%. The takeover request in the study was a multimodal takeover request consisting of an acoustic warning and a red steering wheel icon, which appeared in both the system status display and on the touchscreen used for the secondary tasks. Their results supported the assumption that motor processes are carried out almost reflexively with little influence of the driver's mental state for normal takeover conditions and not safety-critical takeover situations. A potential reason for such discrepancies could be traced back to the different experimental conditions being examined in each study. These differences can be a combination of many factors including, different time-budgets (C. Gold et al., 2013; Van Den Beukel & Van Der Voort, 2013), traffic scenarios (Naujoks et al., 2014; Radlmayr et al., 2014), and human-machine interfaces (HMI), and the application of different non-driving related tasks. Moreover, the simulators used in these studies have varying degrees of fidelity (Louw, Markkula, et al., 2017).

Beyond the points discussed so far, a closer examination of the drivers' cognitive processing time should also be taken into consideration. Zeeb et al. (2016) found that the quality of the takeover is independent of the execution speed of motor actions, and the drivers' cognitive processing of the situation is the determining factor. Understanding drivers' cognitive processes prior to and during a takeover combined with takeover times and quality will provide a more streamlined approach to model drivers' takeover performance and inform the design of support systems.

In Figure 5, the box above the takeover request landmark points to the possibility of drivers being engaged in non-driving related tasks while being in automation. This could decrease their situational awareness regarding the driving task when the takeover request is issued. This could cause drivers to have a poor understanding of the driving situation reducing the drivers' ability to take over properly. This phenomenon has been referred to as being "Out of the Loop" and will be discussed in the next section.

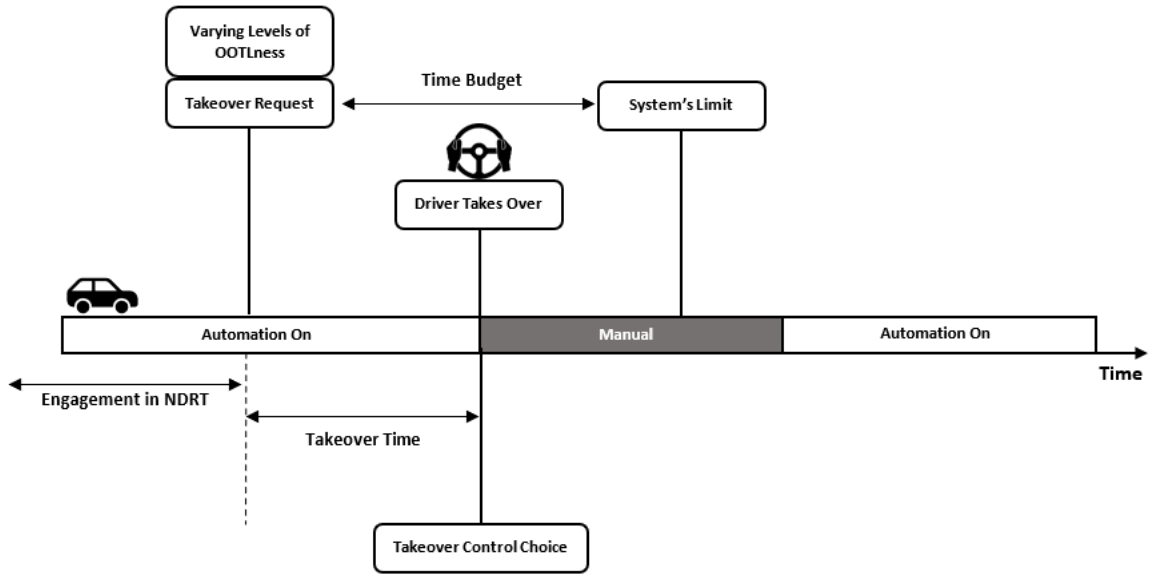


Figure 5. Understanding drivers' takeover behavior prior and during a takeover from conditional automation

2.5 Out of the Loop Behavior

As automated/computer controllers take over system functions, the operator will be removed from the control loop, limiting their interaction with the system, which could lead to reduced awareness about the system's states. With the operator no longer actively controlling the system and being out of the control loop, there is a higher probability of the operator having a slower response when the system malfunctions or breakdowns (Kaber & Endsley, 1997; Wickens, Christopher D Hollands et al., 2015). A lack of operator awareness and understanding of the automated system states can lead to human information processing errors which have contributed to catastrophic accidents such as the Three Mile Island in 1979 (Hall et al., 1981), and the crash of US Air B-737 on take-off at New York's LaGuardia Airport in 1989 killing two people (National Transportation Safety Board, 1990).

In the domain of automobile driving, increased levels of automation are commonly believed to reduce drivers' interaction with, and control of, certain driving tasks, undermining drivers' ability to intervene with a timely and appropriate response to safety-critical events. This phenomenon, relating to how road vehicle automation will influence driver performance and behavior, has been termed "Out of the Loop" (OOTL) (Merat et al., 2018).

2.5.1 Defining OOTL

The term OOTL has been used very liberally, and inconsistently in the academic literature, lacking a shared understanding among its users. The term requires a concrete definition as well as a methodological approach to highlighting its potential consequences, both negative and positive. The field of aviation has a long history of studying the effects of OOTL, which can provide insights into how humans interact with automated systems informing human-vehicle automation interaction. Research dating back to the 1970s and 1980s found that pilots who were left out of the control loop were delayed in detecting changes in the control dynamics and had a poor recovery in comparison to pilots who had manual control(Wickens & Kessel, 1979, 1981). Further examining how pilots interacted with varying levels of automation, Kaber and Endsley (1997), found that as more system functions are assigned to the automated system, the more limited the interaction between the human and the system becomes, leading to the operator's awareness of the system decreasing (Kaber & Endsley, 1997)

When discussing the OOTL concept defining the "Loop" itself is core to understanding the operator's performance. Traditionally, the term "loop" can be traced back to Control Theory in Systems Dynamics, describing "open-and-closed-loop" concepts. In these engineering contexts, loop usually refers to the control loop depicting elements of the system, and their connections (Merat et al., 2018). In psychology/behavioral sciences, the term control refers to controlled performances coming from higher cognitive functions like working memory, depending on attentional effort. Such behavior is usually concerned with novel situations or difficult tasks rather than effortless, more automatic performances that are established through repeated exposures creating mappings between stimuli and responses (Schneider & Shiffrin, 1977).

According to the Oxford dictionary, control has been defined as "The power to influence or direct people's behavior or the course of events." In the context of human-machine systems, control can be described as the controlling agent's means to influence the situation, so that it develops or stays in the desired way (Flemisch et al., 2016). Apart from achieving a goal state, the agent might also be looking to reduce uncertainty through control. Either end would involve the process of sensing and responding to changes in the environment, requiring some form of interaction to influence the state of a system (Merat et al., 2018). The definitions of control in different domains often distinguish between the cognitive and physical aspects of control. These distinctions are crucial when unifying the definition of OOTL and studying its consequences. In

OOTL, the loss of physical control mainly eludes to not managing the lateral or longitudinal control of the vehicle, while the loss of cognitive control generally refers to drivers removing their attention from the primary driving task (Louw, Kountouriotis, et al., 2015; Louw, Merat, et al., 2015). Another definition of OOTL is from the International Harmonized Research Activities (IHRA) Working Group on Intelligent Transport Systems (ITS), who support the activities of the United Nations Economic Commission for Europe (UNECE) Work Package 29 (World Forum for Harmonization of Vehicle Regulations). According to them, a driver is out of the loop when he/she is not actively monitoring the driving situation, making decisions regarding the driving task or manually controlling the vehicle (Kienle et al., 2009).

When discussing different driving tasks involved in vehicle control, applying a hierarchical control structure is common (Hollnagel & Woods, 1995; Michon, 1985). Vehicle control can be divided into three control loops, with driving subtasks being divided by different spatiotemporal scales. The innermost loop focuses on operational functions which are performed continuously or on a moment to moment basis (ms-s). Such operations involve lateral and longitudinal motion control tasks ranging from initiating them to maintaining stable vehicle control (Merat et al., 2018). The middle loop covers more intermittent actions (s-min), also known as tactical functions. This loop involves tasks such as event/object detection and planning and executing responses (e.g., lane changes and negotiating intersections). Strategic functions are in the outermost loop. In this loop, drivers perform infrequent (min-h) tasks such as navigation and selecting destinations. During manual driving, the subtasks performed at each level are strongly interdependent, resulting in a nested hierarchical structure. For example, a response to a detected object (tactical), could potentially lead to a path change requiring a new navigation task (strategic) to be performed.

Visual information is the main source of information to maintain vehicle control, through detecting cues in the environment and predicting potential changes in the roadway, causing driving to be a primarily visual task (Merat et al., 2018). The rate by which information during a driving task change, heavily influence the rate of visual sampling (Senders et al. 1967). For instance, increased information density which could be due to traffic, roadway curvature, lane width, and roadway layout or a combination of such factors (L. B. McDonald & Ellis, 1975; Tivesten & Dozza, 2014; Tsimhoni & Green, 2001) along with driving at higher speeds will lead to higher frequency of sampling the forward view by drivers to maintain their lateral control.

Situation awareness (SA), defined as “the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future” (Endsley, 1995, p. 36) can be used to best describe drivers’ monitoring behavior in terms of attention to dynamic changes in the environment (Merat et al., 2018). The three levels of SA, perception, comprehension, and projection are present in all three control loops (Ma & Kaber, 2005).

Combining the physical aspects of vehicle control and the monitoring of the driving situation by the driver will provide a more precise definition of “being in the loop.” As described by Merat et al. 2018, “when in the loop, the driver can be seen as dynamically “embedded” in driving, perceiving the past, comprehending the present and predicting the future at different levels of the driving task.” As a result, three states can be defined for the human driver concerning his/her interaction with the automated vehicle. These states are “In the Loop”, “On the Loop”, and “Out of the Loop”. These three states have been defined by Merat et al. 2018 as:

- In the loop: In physical control of the vehicle and monitoring the driving situation
- On the loop: Not in physical control of the vehicle, but monitoring the driving situation
- Out of the loop: Not in physical control of the vehicle, and not monitoring the driving situation, OR in physical control of the vehicle but not monitoring the driving situation

It is important to note that these states are not discrete but rather define the drivers’ level of engagement along a continuum (Merat et al., 2018). Given this continuum, as different aspects of vehicle control are transferred to automate driving, the potential for degraded physical vehicle control and monitoring increases, especially when drivers engage in non-driving related tasks (NDRTs) when automation is active (Norman, 1990).

2.5.2 Quantifying OOTL

As stated in the previous section, the goal of having a precise definition for OOTL is to be able to examine its effect on human-vehicle automation interaction and counter its negative consequences. So far, timing and the type of driver response have been the main measures to study changes in situation monitoring and physical vehicle control at and after a takeover from automation. Such measures include, time to feet on pedals and/or, hands on steering wheel, direction and force of steering, or ability to successfully avoid a collision (Eriksson & Stanton, 2017; C. Gold et al., 2018, 2013; Louw, Markkula, et al., 2017; Zeeb et al., 2015, 2016).

Therefore, a slower brake response time or failure to avoid an obstacle by proper steering, in comparison to the drivers' manual driving, would be an indicator of the driver being OOTL (Merat et al., 2018).

Measures of OOTL often rely on eye-tracking as an indicator of drivers' visual attention due to their ease of use (Merat et al., 2018). Using eye-tracking devices, eye gaze, and fixation patterns to specific elements in the environment or inside the vehicle have been used to quantify monitoring and the drivers' consecutive ability to detect and avoid real or impeding hazards while in automation or after a period of automated driving (Hergeth et al., 2016; Louw, Madigan, et al., 2017; Zeeb et al., 2015). Such studies have shown that with increased levels of automation, drivers display more dispersed eye movements. Moreover, drivers focus on the center of the road, and its surrounding environment tends to decrease, which could be due to factors such as increased focus towards non-driving related tasks (Carsten et al., 2012). It can be concluded that drivers' state regarding being "in", "on", or "out" of the loop is measured through two categories (Merat et al., 2018), with the first assessing the degree of drivers' physical control during or after automation, using vehicle-based sensors, and the second measuring the degree of monitoring of the driving situation through driver-based sensors and measures. Sensors for measuring drivers' monitoring levels include a wide range of options such as devices collecting drivers' physiological states (e.g., measuring heart rate, galvanic skin response) or using remote devices such as video cameras to record the drivers' eye and head position, hand location, and seating position and posture in the vehicle (Subit et al., 2017). On the other hand, questionnaire-based metrics offer the drivers' subjective evaluation of the consequences of being OOTL (Merat et al., 2018).

The importance of having a unified understanding of OOTL and its potential consequences becomes more crucial as the role of the driver is changing from that of a physical controller of the system, to a more supervisory role, monitoring the driving situation, to a role in which there is no need for the driver to monitor, control or supervise all together, but only respond to system limitations (Merat et al., 2018). Studying OOTL behavior and its consequences is central to understanding how interactions with automated systems in a vehicle or the driver engaging in Non-Driving Related Tasks (NDRTs), will affect drivers' trust and understanding of such systems, their level of complacency in interacting with these systems, and whether and how it

affects drivers ability to detect system failures and intervene and respond to such failures appropriately (skill decrement) due to the presence of automation (Merat et al., 2018).

When a takeover request is issued, the drivers' level of being out of the loop can translate into the drivers' situation awareness concerning the driving task and the surrounding environment. This could affect how drivers' sample and accumulate evidence during a takeover, subsequently influencing their takeover time and control decision. This will be particularly important when drivers have delayed takeovers where the vehicles' state evolves to a more extreme condition, increasing the probability of an evasive maneuver. Understanding the underlying processes that led to these substandard takeovers and the effect of the drivers' level of being out of the loop when the takeover request is issued is especially crucial to inform the design of safety systems in these vehicles and their many design choices.

2.6 Models of Human Behavior

To assure the safety and effectiveness of how automated vehicles handle a variety of traffic scenarios, design options need to be tested and validated. Given the infinite combinations of traffic situations and driver-related factors alone, virtual testing methods seem like a reasonable approach to assess the safety consequences of design choices (Markkula, Romano, et al., 2018; A. McDonald et al., 2019). Computer simulations of automated vehicles will integrate mathematical models of vehicles, sensors, and self-driving algorithms, but there is also a need to simulate human agents that interact with these systems (Markkula, Romano, et al., 2018). Integrating all these components along with different traffic situations, as shown in Figure 6, can produce safety-related predictions (Bärgman et al., 2017).

In the specific context of takeover scenarios which is the focus of this dissertation, virtual testing methods using computer simulations based on such models could assess and validate a variety of simulated takeover scenarios, while providing a more in-depth understanding into the interaction between the automated systems' design, the driver and the takeover situation (Chen et al., 2017; Kalra & Paddock, 2016; Markkula, Romano, et al., 2018). Having quantitative models of human behavior will allow us to simulate bounds on human physical and cognitive performance and calculate realistic predictions of human behavior such as takeover time. This will also allow designers to approximate the safety impact of design choices such as time budget for automated vehicles (A. McDonald et al., 2019). In this dissertation, two segments of the takeover timeline

were mathematically modeled, the perceptual decision-making process and drivers' lateral takeover control behavior. In this section, each model will be discussed in more detail.

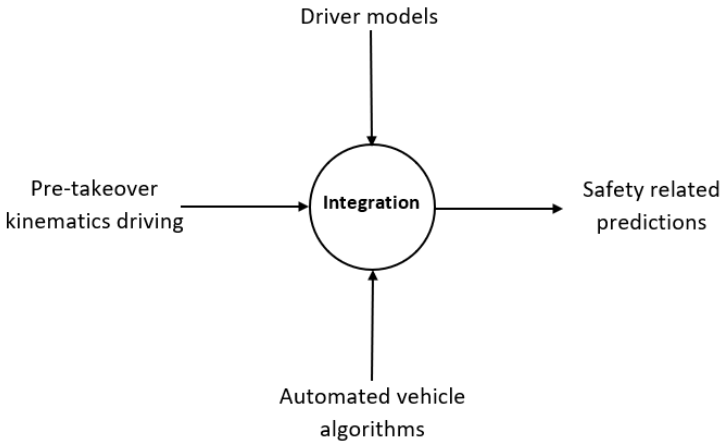


Figure 6. An example process of applying virtual simulations to improve safety, adapted from Bärgman et al. (2017).

2.6.1 Predictive Processing

According to the notion of predictive processing, the human brain is a statistical organ and embodied in it is a hierarchical generative model. Over time, this generative model has learned how our bodies, events, and states in the world generate sensory input allowing it to make predictions about its own sensory inputs continuously. If there is a deviation between our predictions and the actual online sensory signal, our brain will attempt to minimize this prediction error using two main principals. One of these is perception, which is mostly a top-down process (Helmholtz, 1876), allowing us to update our predictions based on the sensory input. Second through action, making the sensory input conform to our predictions by moving our eyes, head, and/or the whole body. Based on this notion, human cognition can be explained in terms of expectation-driven active engagement with the world instead of a set of sequenced information processing stages (Clark, 2015; Engström et al., 2018).

The hierarchical structure of the brain's generative model leads to sensory predictions at different spatiotemporal scales or levels of abstraction. The lower levels of the hierarchy cover basic sensorimotor control, capturing detailed, modality-specific features like the shape of an object and visual looming. Higher-level predictions are concerned with bodily or environmental regularities at larger scales, disambiguating, and contextualizing lower-level predictions (Engström et al., 2018; Pezzulo et al., 2015). These higher-level predictions are related to more

abstract and multimodal features that cover a wider range of spatiotemporal scales (e.g., negotiating an intersection, overtakes, and the more abstract example of arriving on time). When there is a prediction error at a certain level of the hierarchy, perception and action will work in tandem to cancel it with this process being labeled as active inference. The prediction error may not always be resolved at its current level of the generative model, causing it to be sent upwards in the hierarchy for a potential resolution. This leads to the updating of predictions at higher levels, generating new downward predictions (top-down) so that lower-level prediction errors can be canceled (Clark, 2015; Engström et al., 2018).

An important characteristic of these predictions is that they are probabilistic, illustrating the probability of sensory data given their causes. This translates to predictions at different levels of the hierarchy, having an estimation of the sensory input's expected precision. As a result, sensory prediction errors are scaled by this precision estimate so that prediction errors coming from certain (high-precision) predictions will have a higher weighting in comparison to deviations resulting from low-precision predictions. An example of such weighting from Engstrom et al. 2018 is on how drivers modulate their corrective steering actions in reduced visibility conditions (e.g., rain or fog). In such situations, drivers will typically select more reliable visual cues such as lane markings instead of visual aspects of the scene that are hard to perceive, like the curvature of the road ahead. This notion of precision-weighting of prediction error explains the selective enhancement of sensory input that can also be tied back to the concept of attention (Feldman & Friston, 2010). Precision weighting of prediction errors also helps explain how humans control their behavior by shifting control between lower and higher levels of their generative model. For example, a shift of control towards higher levels indicates an increased trust in our knowledge over the actual sensory stimulus, leading to behavior that is guided by top-down longer-term predictions (Miller & Cohen, 2001).

Lastly, the concept of precision provides a means to better discuss the arbitration between pragmatic (or extrinsic) and epistemic (knowledge-oriented) action (Clark, 2015; Friston et al., 2015). In this context, pragmatic actions can be defined as actions that directly cancel prediction error, whereas epistemic actions (e.g., explorative eye movements) are supposed to increase the precision of predictions related to pragmatic action, leading to an overall minimization of the prediction error over time. For instance, if a driver is confident in their predictions meaning that they have high precision, the predicted action is typically directly applied to cancel prediction

errors (i.e., pragmatic action). However, a prediction such as, “I will overtake successfully”, might benefit from an increase in its precision through epistemic actions such as the driver checking the mirrors for oncoming cars prior to an overtake (Engström et al., 2018).

So far, in this section, we have discussed perceptual inference, which focuses on the moment-to-moment update of predictions and their precision according to received sensory data. However, there is also a longer time scale component to prediction error minimization related to the gradual tuning of our generative model over time. The long-term modification of the generative model would result in the brain becoming attuned to statistical regularities in the environment, corresponding to the concept of learning. According to predictive processing, in the early stages of learning, initial attempts at predicting sensory inputs are crude, causing large prediction errors. Over time, the parameters of our generative model will adjust (e.g., at the neural level this can be explained by synaptic strength, (Hebb, 1949) improving predictions by attuning us to capture behaviorally relevant statistical regularities in the sensory input (Friston et al., 2015; Pezzulo et al., 2015). Repeated and frequent exposure to these regularities will eventually result in a strong model that has high-precision predictions with highly weighted prediction errors indicating skilled and fluent behavior (Engström et al., 2018).

Together, the three main components of active inference, precision, and tuning in the context of predictive processing can provide a new perspective on some of the current human factors challenges related to automated driving systems. For example, a drivers’ understanding of the automated systems’ functions and limitations has been explained by mental models. A mismatch between the drivers’ mental model and the actual state of the system can lead to safety-critical events (Seppelt & Lee, 2015). Using the predictive processing framework, mental models can be explained by the hierarchical generative model. For example, through repeated exposure to a reliable automated driving system, the agent’s generative model will become gradually attuned to how the automation controls the vehicle in response to environmental states (Engström et al., 2018).

Similarly, according to the predictive processing framework, the notion of over-reliance and complacency can be explained by an inappropriately tuned generative model that comes from the agent’s infrequent exposure to the automation reaching its functional limits. One way to ameliorate this issue is to provide the driver with transparent feedback on the state of the system

(Bennett & Flach, 2011; Flemisch et al., 2014; Seppelt & Lee, 2007), through ecological displays (Vicente & Rasmussen, 1992). Such an interface can support the development of a more accurate generative model allowing the driver to make correct predictions that properly account for the automated system's functional limits.

On the other hand, reduced monitoring is a natural side effect of highly trusted systems (J. D. Lee & See, 2004), which can be explained by the exploration vs. exploitation component of predictive processing. Actions such as visual scanning fall under the category of epistemic actions that drivers use to reduce uncertainty and increase the precision of the predictions associated with their pragmatic actions. As a result, drivers will assign a high precision to the prediction that the automated driving system can maintain the safety of the vehicle, deeming any monitoring required to minimize prediction errors as unnecessary. This becomes particularly important in emergency avoidance reactions in safety-critical situations (Engström et al., 2018).

For humans and other primates, detection, recognition, and classification of information in the world mainly come from vision. Over time, our visual system has evolved, allowing it to quickly identify features and objects even in complex and cluttered scenes (Summerfield & De Lange, 2014). For example, in rear-end collision avoidance scenarios, the kinematics of the situation are mainly dictated by the optical expansion (looming) of the lead vehicle. τ which is the ratio of θ the optical expansion angle in the drivers' retina, and its angular rate $\dot{\theta}$ provides an estimate of time-to-collision and has been considered as the main source of information that guides drivers' braking (D. Lee, 1976). On the contrary to the traditional assumption that the sensory signal itself regulates drivers' responses (e.g., looming), the predictive processing framework suggests that drivers act on sensory prediction error (e.g., unexpected looming). The drivers' generative model is continuously making predictions about expected looming or the lack of it. When there is a mismatch between the looming prediction and the actual looming in the driving scene, drivers will initiate avoidance actions such as steering and braking to cancel this discrepancy (Engström et al., 2018).

Relying on visual sensory information like looming and the notion that drivers use prediction error and not the error itself per se, the next section will go over perceptual decision making and how to model such processes. Applying models that incorporate the concepts discussed in this

section will allow us to estimate variables such as drivers' perception-response time (Engström et al., 2018).

2.6.2 Models of Perceptual Decision-Making

In general, many assume the term "decision-making" refers to decisions with an extended deliberation period, such as deciding on where to eat for dinner or what university to attend. The timescale of the decisions discussed in this dissertation is much shorter. Examples of such decisions include the decision to steer left or right to avoid a sudden obstacle, giving the driver a very limited time window to react while relying on lower-level cognitive processes (Ratcliff et al., 2016). These types of decisions are typically single-staged, on the contrary to multiple-stage decision processes that could occur in cases such as reasoning tasks, and decisions that are relatively fast two-choice decisions (i.e., having a mean RTs less than about 1000 to 15000 ms) (Ratcliff & McKoon, 2008).

Other features of the type of decisions considered in this dissertation include being naturalistic, dynamic, online, and probabilistic. Naturalistic refers to decisions that are made by agents who have some degree of task familiarity, in the environment with which they naturally encounter the decision (Orasanu & Connolly, 1993). This is an important factor considering that many studies of perceptual decision making are performed in laboratories. The dynamic aspect of such decisions means that they unfold over time. As a result, it is usually impossible to define a single point of decision since it is more of a deliberation course. Information during a dynamic decision is not gathered instantaneously but rather acquired over time. Apart from the decision being dynamic, the situation itself possesses external dynamics causing the situation to change over time. For example, during a takeover from automation, an open lane might no longer be available within seconds due to a vehicle approaching from behind, or a pedestrian suddenly entering the lane. Concerning decisions being online, some decisions need to be made while the situation is in motion, for instance, a player deciding to throw a ball to a teammate, or a driver initiating a brake response due to the lead vehicle suddenly slowing down. Such decisions are different from reflective decisions that are made using all available information in an offline fashion, like a driver deciding on which route is the most fuel-efficient for an upcoming trip. Lastly, such decisions are probabilistic. Assuming deterministic human behavior, aside from hard-wired mechanisms or reflexive responses, is invalid. In naturalistic dynamic decision-making scenarios, variability, whether from the agent or the environment, is a given. In other words,

deterministic models that take specific inputs to predict the same output(s) are not accurate depictions of how decisions are made in contexts such as sports and driving (Johnson, 2006).

The decision-making process after a takeover request falls under the category of dynamic decision making (DDM), which is a sequence of interdependent, real-time decisions that are made in an environment, and can change exogenously or as a function of the decision maker's previous choices. In DDM, decisions are sequentially linked together by their effects, resulting in an action influencing future actions directly or indirectly (Brehmer, 1992; Busemeyer, 2002; Edwards, 1962). For example, in the context of driving, during a lane change, the drivers' decision to check his side and rear-view mirrors can affect the safety of his lane change and the need to suddenly steer to avoid a missed vehicle approaching from behind. DDM can be conceptualized as a closed learning loop in which previous choices and their outcomes inform current decisions (Gonzalez et al., 2003, 2017).

This type of decision making is also the case during a takeover scenario, which is the focus of this dissertation. After drivers receive a takeover request, up until they resume manual control, the vehicle and the environment are evolving. When the driver takes over, the drivers' input will also be a contributing factor to an evolving situation, hence matching the description of DDM throughout the takeover process until vehicle stabilization or a collision. Decision making in complex dynamic systems has been shown to be challenging for humans (Gonzalez et al., 2017). Humans struggle with dynamically complex situations. In this context, complexity refers to decision tasks that involve many alternatives, have severe time constraints, and high levels of uncertainty. A given task can be structurally simple but still, be dynamically complex. Dynamic complexity arises from the relationship between decisions and their consequences that play out over time, due to the sequential nature of the interdependencies between these decisions, along with the lags between actions and their effect on the environment (Gonzalez et al., 2017). Instead of focusing on the poor strategies applied to these complex dynamic tasks and the human's suboptimal performance, the focus should be on the underlying processes involved in decision making and how humans actually make decisions (Gonzalez et al., 2003; Hotaling et al., 2015).

In this dissertation, the underlying cognitive processes during the driver's evidence accumulation after a takeover request, along with the driver's situation awareness, will be examined. Such a process has been referred to as perceptual decision making, which is the process of gathering

information through sensory systems to guide our behavior in the world (Heekeren et al., 2008). During a visual decision, retinal activation patterns are converted into a categorical proposition regarding the presence, location, or identity of the source(s) of those patterns (Joshua Gold & Stocker, 2017).

Advancement in current neuroimaging techniques and data analysis methods allow researchers to associate behavioral measures (e.g., perceptual decisions) to specific signals in the human brain on a trial-by-trial basis. For instance, recent neuroscientific findings have shown that contrary to traditional psychological theories that characterize decision-making as a hierarchical process, progressing from perception to action, some of these serial stages in the hierarchy happen in parallel (Heekeren et al., 2008). Moreover, it has been shown that apart from incoming sensory information that affects perceptual decision-making other factors such as task difficulty, attention, the prior probability of the occurrence of an event and the outcome of the decision could also influence the decision process (Ridderinkhof et al., 2004; Ullsperger et al., 2004). Another important aspect that should be considered when studying any kind of decision-making in the driving environment is that it is both dynamic and uncertain, with many potential sources for visual uncertainty. For example, consider driving and trying to locate a specific store. The task is to identify a specific visual object: the desired store. This might sound like a simple task, however, adding scenarios such as the relevant features being partially obstructed (many pedestrians in front of stores), ambiguous (all the stores in that block look similar), or unclear (it is a rainy day or the lighting of the store is poor) make it more difficult. In such cases, apart from the issues above, the features will have to be processed by noisy neurons in the brain, which will add more uncertainty which could change with attention (being distracted by a phone conversation), processing time (being in a hurry), and other factors.

Concerning uncertainty, Senders et al., (1967) quantifies uncertainty in driving using an entropy-based uncertainty model for the drivers' visual information. According to this model, when a driver looks away from the roadway, the drivers' memory of the roadway will decay, and uncertainty builds. The driver will act, in this context, look back at the road when the integrated uncertainty reaches the drivers' threshold. Therefore, the drivers' visual behavior (i.e., glance pattern) is influenced by the amount of information on the roadway during the period of eyes on-road and the evolving environment and vehicle dynamics (J. Y. Lee & Lee, 2017). In other words, the world itself, along with sources of external and internal uncertainty, may change at

any moment. Therefore, as described by Helmholtz, perceptual decisions are a form of inference, representing the best guess of what the correct decision would have been, based on currently available, uncertain evidence (Helmholtz, 1924). As stated by Gold & Stocker (2017), this guesswork is easily influenced by new evidence, context, predispositions, and other factors. If this incoming flow of information is interpreted correctly, it can help reduce uncertainty and secure the best possible outcome (Joshua Gold & Stocker, 2017).

On the other hand, the human brain is like a prediction machine, aiming to correct errors. As the definition of control in the OOTL section, apart from uncertainty, error cancelation is another source requiring decision making and control. Recent neuroscientific research has shown that humans often act on prediction errors rather than the error itself. When faced with a prediction error, people might respond in one of two ways; 1) update their perception with additional samples so that their prediction matches the newly perceived sensory input or 2) perform an action to make the actual state of the world match their predictions and cancel out the errors (Clark, 2013; Engström et al., 2018). To formalize this process and its influencing factors, the neural architecture for perceptual decision making can be considered as four distinct but interacting processing modules. The first module accumulates sensory evidence and compares them; the second aids in processing a task accurately by detecting difficulty or perceptual uncertainty and signaling the need for more attentional resources; the third module, represents decision variables and includes motor and premotor structures; and the fourth is responsible for performance monitoring, detecting errors and the need for decision strategy adjustment to maximize performance (Heekeren et al., 2008).

Given the underlying cognitive processes involved in dynamic decision making (DDM), the next section will discuss model alternatives to simulate drivers' decision making after receiving a takeover request.

2.6.3 Sequential Sampling Models

Processing information from the surroundings and integrating it into a coherent image that can guide safe behavior is a critical aspect of driving, specifically during a take-over situation. The basic assumption in sequential sampling models is that humans sample information from the environment over time and gather evidence to select between competing responses. An action is initiated when the accumulated evidence reaches a boundary/criterion (Smith & Ratcliff, 2004;

Townsend & Busemeyer, 1993; Usher & McClelland, 2001)Given a short time buffer, people can choose to increase the speed of their decision-making process, but this usually comes at the cost of lower precision (Dambacher & Hübner, 2014). Sequential sampling models have been applied to a wide range of perceptual tasks (S. Brown & Heathcote, 2005; Ratcliff & McKoon, 2008) and are a suitable method to implement speed-accuracy trade-off (Dambacher & Hübner, 2014).

In scenarios involving time pressure, the trade-off between speed and accuracy of the decision has been associated with lowering the decision boundaries. A lower threshold, reduces the amount of evidence required for a decision, decreasing decision time, coming at the expense of increased error rates due to noisy samples of evidence reaching the wrong boundary more frequently (Dambacher & Hübner, 2014; Ratcliff et al., 2003; Ratcliff & McKoon, 2008). A recent study modeling several datasets has shown that apart from the decision threshold being lowered, the emphasis on speed over accuracy can also reduce the quality of the perceptual processing during evidence accumulation (Rae et al., 2014). Therefore, other model components such as the rate of evidence accumulation and non-decision time, should also be examined along with the response boundary (Dambacher & Hübner, 2014).

Over the past 20 years, diffusion models for simple, two-choice decision processes have been receiving more widespread recognition. One of the driving factors for such an increase in attention to these models can be attributed to their success in accounting for an increased number of behavioral data in various experimental paradigms in the field of cognitive psychology (e.g., J. Gold & Shadlen, 2001; Ratcliff & McKoon, 2008; Townsend & Busemeyer, 1993). The diffusion model has proven to be one of the most promising models of choice reaction time (Wagenmakers, 2009). Concerning modeling the speed-accuracy tradeoff, Ratcliff's diffusion model for speeded binary decision processes allows for the statistical separation of the model's different components. In other words, each parameter represents specific components of the decision process (Voss et al., 2004). These parameters include the decision threshold, the drift rate, bias, and motor response, also referred to as non-decision time. The boundaries include zero and a point greater than zero, a, and the bias, z is a point between zero and a. The rate of information accumulation towards a boundary that prompts a response is the drift rate (v). The quality of the information extracted from the stimulus has been attributed to defining the drift rate, and as a result, different stimulus conditions that vary in difficulty will lead to different drift

rates (Ratcliff & McKoon, 2008). The diffusion model provides a quantitatively and qualitatively accurate account of data, while components of the information processing are represented by the parameters of the model. Using such a model, the effects of experimental manipulations on the components can be studied. For instance, Voss et al. found that by inducing the motivation for accuracy resulted in higher decision thresholds (i.e., conservatism), the presentation of stimuli that were hard to discriminate led to lower drift rates (Voss et al., 2004). Overall, the full response time distributions for correct and erroneous responses, the mean response times for correct responses and for erroneous responses, and accuracy are some of the aspects of the two-choice decision data that the diffusion model (Ratcliff, 1978) will account for when examining the effects of different experimental manipulations (Ratcliff & McKoon, 2008).

In the context of driving, such models have been able to explain driver reaction times in response to stimuli in traffic. The traffic stimuli cover both discrete stimuli like brake lights (Ratcliff & Strayer, 2014), and also, dynamic stimuli such as the visual looming of collision threats or approaching road users (Markkula et al., 2016; Svärd et al., 2017). To the best of our knowledge, the application of perceptual decision-making models to drivers' takeover behavior has not been explored in the literature. Variables of the evidence accumulation models (e.g., threshold, initial bias), could potentially simulate the effect of the deadline introduced by the takeover request and the level of drivers being out of the loop before the takeover, on drivers' takeover time and control choice across a variety of situations.

2.6.4 Models of Lateral Control

Lateral control or steering models have a long history, with the earliest mathematical model of human steering control dating back 50 years (Tustin, 1947). This early model described the drivers' steering profile as a jerky curve with flat segments that can be partially approximated using a linear transfer function. However, that model failed to account for non-linear behavior, which has increasingly become the focus of much research (Benderius, 2014). Among the many proposed driver lateral control models, such as the cross over model (McRuer & Krendel, 1959) and the two-level model of steering control (Donges, 1978) one of the most prominent and promising models is the two-point visual control model (Salvucci & Gray, 2004). The two-point visual control model is a linear transfer function—a Proportional-Integral controller—that uses psychologically plausible perceptual cues as the input to a continuous output steering control model (Markkula et al., 2014). Although recent research is shifting towards the notion that

human drivers' steering response is mainly the sum of instances of intermittent control based on motor programs and not continuous control like the two-point visual control model (Markkula, Boer, et al., 2018). , Such a model might be useful in estimating drivers' steering performance after a sudden transfer of control.

2.7 Gap Analysis

Based on this literature review, takeover time is the most frequent measure for assessing drivers' takeover behavior. However, the focus of most of the studies in the literature has been on mean takeover time while the tails of the distribution that can have a disproportionate effect on safety outcomes have been neglected (Horrey & Wickens, 2007). This raises the question of whether the mean takeover time is sufficient to represent drivers' takeover behavior. Chapter 3 address this gap by exploring the quantiles of takeover time distributions across a variety of takeover scenarios.

Another gap in the literature was the lack of validated models to estimate drivers' takeover time and control choice. Based on this literature review and to the best of our knowledge, current state of the art models of drivers' perceptual decision-making have been applied to either routine manual driving or safety-critical control maneuvers that lack a warning. In the context of a takeover, especially for SAE Level 3 automation, the effect of the takeover request needs to be considered in modeling drivers' takeover behavior. The takeover request introduces a deadline into the decision-making process, obligating drivers to resume manual control of the vehicle. This urgency may affect required caution levels, and one method to model such a phenomenon is to use a dynamically changing threshold (Cisek et al., 2009; Frazier & Yu, 2009; Katsimpokis et al., 2020). In addition, though the details of evidence accumulation models for multi-alternative choices in the domain of driving have been discussed in the literature, there are no models that have been validated with data. In Chapter 4, using empirical data collected for this dissertation, we validated an evidence accumulation model with a separate accumulator for each control choice alternative (i.e., braking and steering), while modeling the effect of the takeover warning using a linearly collapsing threshold.

Chapters 3 and 4 focused on gaps relevant to drivers' takeover time, such as the misplaced focus on the mean and the need to model takeover time distributions across a variety of takeover scenarios. Looking at drivers' takeover performance through the notion of a speed-accuracy

trade-off, addressing the gaps on the timeliness of takeovers will only cover half the equation being speed. To also contribute to the other half, which is accuracy, we identified some of the main gaps in the literature on the quality of drivers' takeover control maneuvers.

The evidence accumulation model from Chapter 4 will predict the drivers' initial control choice. Still, the success and safety of the takeover will depend on how drivers execute that response and its subsequent control maneuvers. In this literature review, we explored different lateral and longitudinal quality metrics. We found that there is a need for a metric that can reflect the stability of drivers' lateral control response. In Chapter 5, we introduce a new lateral quality metric, the number of chain corrections which is based on drivers' overshooting in their steering followed by excessive steering corrections.

Another gap in the takeover quality literature was the lack of diversity in the types of takeover events that have been studied so far. A potential solution to this gap is to examine the underlying dynamics of events instead of their specific details so that findings can be generalized across similar events. Another solution to this problem includes modeling drivers' takeover control maneuvers, which will then allow us to evaluate the quality of drivers' takeover control behavior across a variety of conditions. To this aim, Chapter 5 proposes a model of drivers' lateral control, simulating drivers' steering maneuvers after receiving a takeover request.

Overall, to ensure the safety of SAE Level 3 automated vehicle's design alternatives, they need to be tested and validated across a diverse range of scenarios (Markkula, Romano, et al., 2018). Using virtual simulation tools will allow us to predict how drivers' take over from these systems in a variety of traffic situations. In addition to exploring how different design choices and situational factors influence drivers' takeover performance, this dissertation explored two modeling efforts. The first focused on drivers' evidence accumulation after receiving a takeover request and the second on modeling drivers' lateral takeover control to address current gaps in the literature on drivers' takeover behavior.

3 Chapter 3: Drivers' Response Time to Take Back Control from Automation Using Bayesian Quantile Regression

3.1 Introduction

SAE J3016 has defined conditional automation for an automated driving system, SAE Level 3, as automation that performs all the dynamic driving tasks, which include lateral and longitudinal control along with event and object detection and response (SAE International, 2018). According to this definition, the driver is free to engage in non-driving tasks when automation is active, on the condition that the driver takes manual control when the automated system exceeds its operational design domain limits or some other performance-relevant system failure occurs (Bazilinskyy et al., 2017). In such cases, Level 3 automation should issue a takeover request (TOR) that provides the driver with sufficient time to take back vehicle control (SAE International, 2018). Therefore, the time between the takeover request and drivers' responses, as well as the quality of their responses are critical for the safe operation of the vehicle. Time buffer, lead time, and time budget (Gasser & Westhoff, 2012; SAE International, 2018; Zeeb et al., 2016) are some of the names for the time allowance given to the driver to regain manual control of the vehicle after the takeover request (Lu et al., 2017). Gold et al., have defined the time budget as the time available between a takeover request and the system reaching its limit, requiring driver intervention due to a critical event (C. Gold et al., 2018). During this period, drivers should relocate their hands and feet to the driving position, assess the situation, gain situation awareness, and formulate a response to take control and avoid a possible safety-critical event (C. Gold et al., 2013; Mok et al., 2015; Zeeb et al., 2015). The absence of a reasonable time budget could limit the drivers' ability to gain sufficient situation awareness to guide a response, resulting in a crash (Mok et al., 2015). In addition, several factors such as the intensity and modality of the takeover request (Naujoks et al., 2014), engagement in a non-driving task (Merat et al., 2012), and the criticality and complexity of the situation (Merat et al., 2012; Radlmayr et al., 2014) influence response time and quality (Zeeb et al., 2016). Given all the factors affecting the drivers' takeover behavior, the safety and smoothness of the takeover cannot always be guaranteed. This highlights the need for the design of fallback procedures based on an understanding of human performance to a takeover request (Bazilinskyy et al., 2017). This includes the effect of the time budget provided to the driver during a takeover (C. Gold et al., 2013; Zeeb et al., 2015), the quality of the takeover performance (Happee et al., 2017; Merat et

al., 2014; Zeeb et al., 2016), and the effect of different human-machine interface designs on the takeover (Petermeijer, Cieler, et al., 2017).

Time budget has been the focus of many studies and has been shown to affect drivers' information preferences, decision making (Eriksson et al., 2015), and performance during a takeover event (Van Den Beukel & Van Der Voort, 2013). However, drivers' response time to a takeover request should not be considered as a single value, but one that depends on factors such as traffic density, human-machine interface concepts, non-driving task type, and drivers' mental state (e.g., out of the loop distracted, or drowsy), as well as driver-specific variables such as experience and age (Zeeb et al., 2015). Zhang et al. (2019), performed a meta-analysis of 129 studies that measured the takeover time (TOT) following a critical event or a takeover request and found that the available time, the presence of hand-held devices and lack of experience with takeover requests substantially increased mean TOT, while the modality of the takeover request had a small effect on the mean TOT (Zhang et al., 2019). Another meta-analysis found that a time-budget of 5 seconds led to a mean response time of 2.1 s (SD = 0.41), while a 7 s time budget delayed driver intervention (2.9 s, SD = 0.65) (C. Gold et al., 2013). These studies provide a general understanding of driver behavior during a takeover and distill drivers' response time to a mean value. However, the mean is not always representative of the whole response time distribution and might not reflect how various factors affect different regions of the distribution. This is important because the tails of the distribution can have a disproportionate effect on safety outcomes (Horrey & Wickens, 2007).

The focus on the mean has a long history. General linear models (GLM), generalized additive models (GAMs), generalized linear models (GLZM), and analysis of variance (ANOVA) have been a staple in understanding human behavior, and all focus on the mean response. However, an important detail regarding the regression coefficient that tends to be forgotten is that this value does indicate the effect of x on y, but as stated by Porter, "a regression coefficient tells us the effect of x on the mean of y controlling for other x's, not just 'y'." (Porter, 2015). For example, we consider a hypothetical experiment examining the effect of a human-machine interface (HMI) on drivers' takeover time. In this example, drivers have a five-second time budget until the safety-critical event after the takeover request is issued. Figure 1 shows the control group's normally distributed takeover time with a mean of six seconds and a standard deviation of 0.43; with such a distribution, 99% of the takeover times are longer than the time budget of five

seconds (z = 2.33). Analyzing the hypothetical data for the HMI group, a regression model shows that drivers' takeover time is reduced by two seconds; however, the conclusion should be more precise and state that the HMI reduced the mean response time. Conclusions about other points of the distribution should not be made unless it is normally distributed, an assumption that is frequently violated in response time data (Whelan, 2008). In this example, if the takeover times were normally distributed, the mean would be four seconds and 99% of the takeover times would fall within the time budget. However, if takeover times are only reduced in the lower part of the distribution, then the upper part may remain vulnerable to negative consequences such as crashes. Figure 7 shows how this may happen when the distributions are skewed, which is common in response time data. In this example, approximately 75% of responses are within the time budget while the other 25% result in collisions with the revealed vehicle. Such results could arise if the factors influencing the tails are different from the means, such as driving skill, age, or other individual differences.

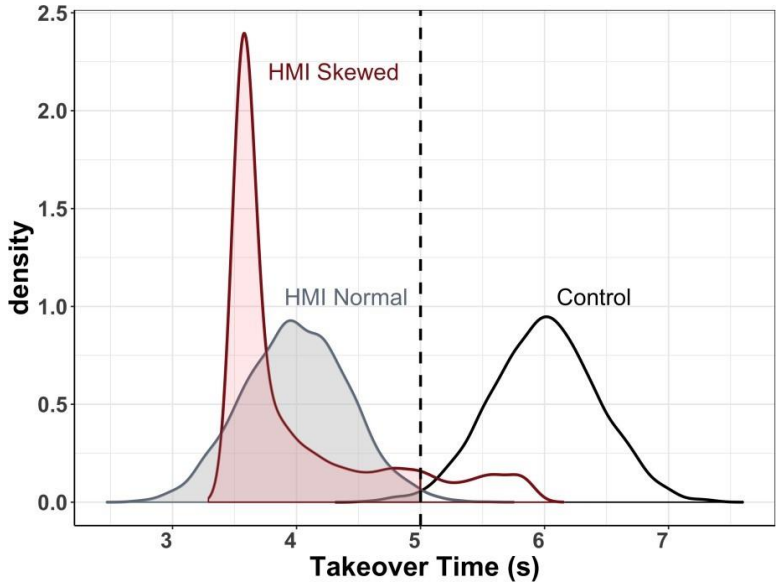


Figure 7. Hypothetical example comparing the effect of an HMI on drivers' mean takeover time across different distributions.

An obvious advantage of traditional models that rely on the mean is that they are easy to interpret and estimate, but they assume the response distribution responds uniformly to the independent variables. For research questions that focus on quantifying risk, considering only the central tendency might fail to properly represent the data (Umlauf & Kneib, 2018). For instance, in the hypothetical example discussed above, the upper tail of the distribution is often most indicative of safety outcomes, while focusing on only the mean value might overstate the benefit

of the new takeover request modality. A variety of scientific domains ranging from studies in material science (Farris et al., 1990) to educational research (Feingold, 1992) to studies on human's short-term memory (Luce, 1986a) have cautioned against focusing on the mean and overlooking the response distribution. Luce argues that by studying distributions, more information about the underlying mental processes can be obtained which will be missed by using summary statistics such as the mean (Luce, 1986b).

Townsend's hierarchy of stochastic dominance relationships also advocates using more powerful distributional characteristics to assess experimental and societal effects. He states that such measures are non-parametric and even distribution-free, allowing them to offer stronger statements about the effect of different treatments compared to conclusions made only on estimates of central tendencies, such as the mean or median (Townsend, 1990). Quantile regression is a potential solution because it can estimate how independent variables affect the entire distribution of the response variable instead of only the mean, shifting the focus of discussion to the entire distribution. It will estimate the effect of the independent variables on different components of the distribution, such as the 10^{th}, 25^{th}, or 95^{th} percentiles (Porter, 2015).

In the context of driver behavior, studying the tail of the distribution using quantile regression could encourage safer designs by considering a wider range of driver behaviors. However, Liu et al., performed an ISI Web of Science search on the application of quantile regression in the field of Human Factors, finding only six related research papers and only one published in Human Factors, demonstrating that this method is rarely used (Liu et al., 2018). The routine emphasis on mean response times could have a profound negative effect on the design of safety-critical systems, where more extreme parts of the distribution have an outsized influence on risk (Horrey & Wickens, 2007; Porter, 2015). For example, the upper tail of off-road glance distribution strongly influences crash risk (Horrey & Wickens, 2007; Liang et al., 2014). Other studies have found that longer-than-average responses are associated with greater safety implications for unexpected events (i.e., the left side door of a parked car suddenly opening, requiring drivers' intervention) (Summala, 1981). Another study used quantile regression analysis to show that text length, system delay, and secondary task type, affected the tail of the glance distribution differently than the mean of the glance distribution (Liu et al., 2018).

Given the importance of studying the tails of the distribution, the present study considers the consequence of relying on mean TOT as a safety-relevant metric by comparing the effect of experimental conditions on the quantiles of the TOT. Specifically, we examined the effect of takeover request timing, visual demand of the environment, and event type (e.g., lead vehicle, pedestrian, lane departure) on TOT. A smaller time budget has been shown to reduce drivers' TOT (Zhang et al., 2019) while the complexity of the situation (e.g., varying levels of traffic), could lead to slower responses as the complexity of the situation increases (Eriksson et al., 2015). We expect the smaller time budget, and less complex situation to reduce drivers' response time. Different takeover scenarios in combination with the other factors have not been studied extensively (Zhang et al., 2019), but we expect that the event type will have a strong but indeterminant effect.

Drivers' TOT in response to these independent variables was measured in an advanced driving simulator with acceleration motion cues. The effect of these variables on drivers' 15^{th}, 50^{th} and 85^{th} percentile response time was evaluated using quantile regression. Contrary to the traditional focus on the mean, summarized in the meta-analyses on driver behavior during a takeover (e.g., Eriksson & Stanton, 2017; Zhang et al., 2019), we expect that the 50^{th} and 85^{th} percentiles will show considerable differences in both the patterns and magnitudes of effects.

3.2 Methods

3.2.1 Participants

The initial study design required the recruitment of 72 participants evenly divided by sex and age (18-40 and 41-61 years old). However, four subjects were replaced due to lack of engagement with the secondary task (n = 3) and simulator issues (n = 1), bringing the total number of participants to 76. Driver responses were removed as needed on a drive-by-drive basis for specific experimental conditions, leaving each participant with at least one good combination of conditions.

3.2.2 Apparatus and Secondary Task

The experiment was conducted at the National Advanced Driving Simulator (NADS) at the University of Iowa using the NADS-1 high-fidelity ground vehicle driving simulator. NADS-1 houses an actual vehicle cab inside a dome with its interior wall projecting the scenery 360 degrees around the driver. The combination of motion, audio, graphics, software systems, and

control feel response on the NADS-1 provides the closest experience to driving an actual vehicle. Data were sampled between 60 and 240 Hz. The speed limit throughout all drives was 55 mph. During the events, to distract the participants and get their eyes off the road, they were instructed to perform a trivia task where they should complete as many trivia questions as possible. The trivia task included a variety of topics that participants could select based on their interests, providing the potential for continuous engagement. Participants performed the trivia task on a tablet while the vehicle was in the automated mode. Although self-paced, the trivia task provided extended engagement where participants felt compelled to perform the task. Drivers' scores for the trivia task were recorded but not included in this analysis.

3.2.3 Experimental Design

A 3 (takeover request timing) x 2 (visual demand) x 5 (event type) mixed factorial design was used. takeover request timing varied between subjects with three levels of short (3 s), medium (6 s), and long (9 s). Visual demand and event type were within subject variables. The scenarios each included ten events, five in a low-demand environment and five in a high-demand environment. Given the need to resume lateral and longitudinal control of the vehicle after a takeover request, different hazards in the environment could bias drivers' control decision towards steering or braking. The five events targeted control responses for either lateral or longitudinal control, to demand a variety of control responses. These events included a revealed stopped car, a lane depart failure, a work zone, a pedestrian crossing in a work zone, and a slow lead vehicle. The ordering of events was varied between demand levels, event type and timing. The takeover request modality across all events was a combination of an auditory warning (repeating tone) with a visual takeover request on the dashboard. Figure 8 shows the visual takeover request, which was a steering wheel displayed on the dashboard. The steering wheel graphic was always present, even when the automation was turned off.

(a) (b) (c) (d)

Figure 8. Dashboard graphics for automation status. (a) On, (b) Off but available, (c) Takeover request, and (d) Off and unavailable.

The solid blue steering wheel indicates active automation (Figure 8a), gray indicates off but available automation (Figure 8b), the blue steering wheel with hands indicates a takeover request (Figure 8c), and the dotted wheel indicates off and unavailable automation (Figure 8d).

3.2.4 Procedure

The NADS participant registry was used for participant recruitment. Participants were screened by phone for eligibility and possible health conditions. The eligibility criteria included having a license without restriction (other than corrective lenses), being able to drive without the aid of special equipment and having driven at least 2,000 miles per year. More information about the screening process can be found in Dinparastdjadid et al. (2018). Each test session ranged between 1.3 hours and 2.0 hours and participants were compensated for their time. The University of Iowa Social and Behavioral Institutional Review Board approved all procedures.

3.3 Results

Drivers' takeover time was defined as the difference between the time of the takeover request being issued and the driver initiating a steering or brake response. Specifically, any steering wheel angle greater than 3 degrees that also had a steering rate of 10 degrees per second or a brake pedal press greater than 3 lbf was considered as a response. In this experiment, some drivers noticed the critical event and resumed manual control before the takeover request, resulting in negative response times due. These negative response times along with responses that were larger than 12 seconds were removed from the dataset. In addition, given studies on minimum reaction time and processing of visual information (e.g., Thorpe et al., 1996), takeover times smaller than 0.15 seconds were excluded from this analysis. These considerations resulted in the removal of 116 out of 764 observations. The remaining 648 response times to the takeover requests ranged from 0.17 to 6.47 seconds.

Figure 9 shows the distributions of drivers' takeover time across the experimental conditions (visual demand, time budget, and event type). The solid black line in each distribution is the mean, the inner light area is one standard deviation from the mean. The outer solid lines depict the 95% credible interval, showing the 95% most credible values for drivers' response time in each condition (J. K. Kruschke & Liddell, 2018). By focusing on central tendency or even considering the standard deviation of drivers' takeover time, delayed takeover times such as the 85^{th} percentile may be neglected. The blue point in each distribution in Figure 9 is the 85^{th}

percentile associated with that condition. Considering a normal distribution, one standard deviation away from the mean is the 84.1th percentile, while in many cases in Figure 9, especially the revealed stopped car event, the 85th percentile falls outside of the standard deviation zone. This emphasizes the need to focus on the entire distribution and its credible interval.

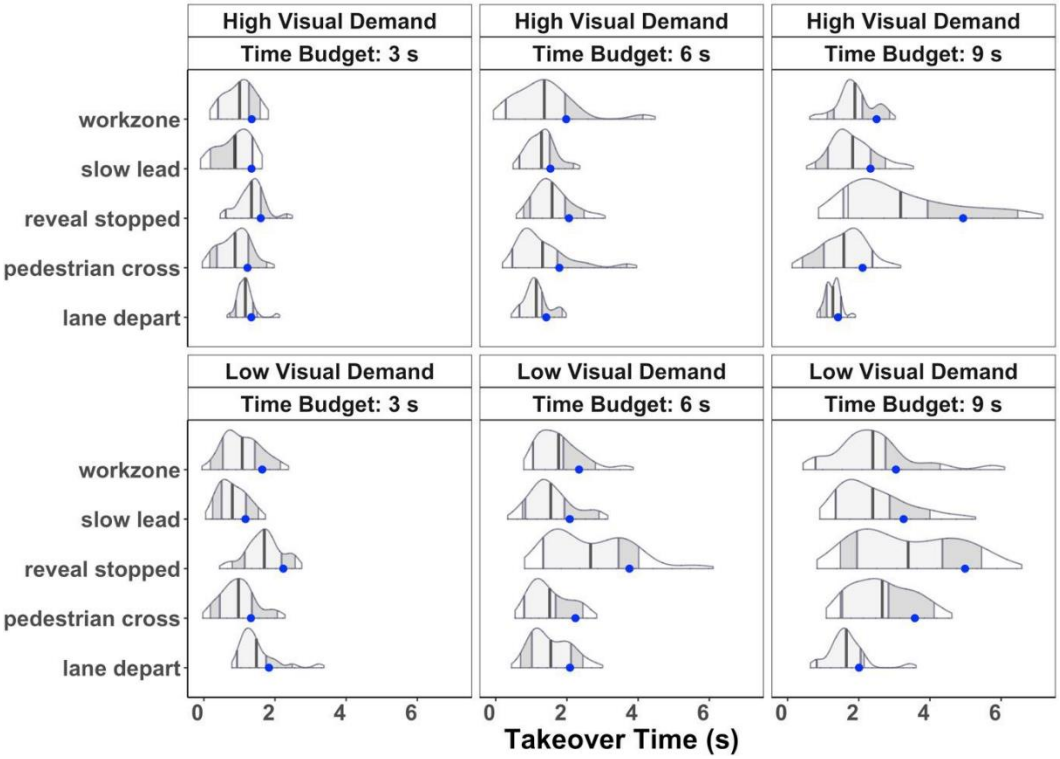


Figure 9. Takeover time distributions across different experimental conditions; Each distribution contains the mean, standard deviation and 95% credible interval with the blue dot being the 85th percentile takeover time for that condition.

Figure 10 complements Figure 9 by showing the difference between the mean (gray point) and the 85th percentile value (black point) across each condition, with values ranging between 0.14 to 1.76 seconds. Inside each panel, the vertical solid and dashed lines are the overall mean and 85th percentile for that specific timing and visual demand combination. The difference between the mean (solid vertical line) and 85th percentile (dashed vertical line) for a given time budget and visual demand, excluding event type was labeled QD (quantile difference), and is shown in the panel above each box. These differences, ranging between 0.32 to 1.24 seconds, are higher for the lower visual demand and greater time budgets.

Examining the differences between the mean and the 85th percentile across different conditions, larger differences suggest that relying on mean takeover times for safety-relevant systems, such as vehicle automation, may fail to identify the most safety-critical conditions, generating

conclusions that lead to designs that have higher crash risk. In Figure 10, the revealed stopped vehicle event, which has an inherent delay in drivers noticing the hazard, has a greater mean than the overall mean (solid vertical line in each panel) while its 85th percentile is even larger. With the tail of drivers' takeover times being disproportionately delayed compared to the mean value, and the dynamic nature of a takeover scenario in which other vehicles and road users are also changing their behavior, such delays could compromise the takeover. This is in line with previous studies showing that collisions and collision velocities could be significantly reduced by decreasing delays in inattentive drivers' response time by values as small as 300 milliseconds (T. Brown et al., 2001).

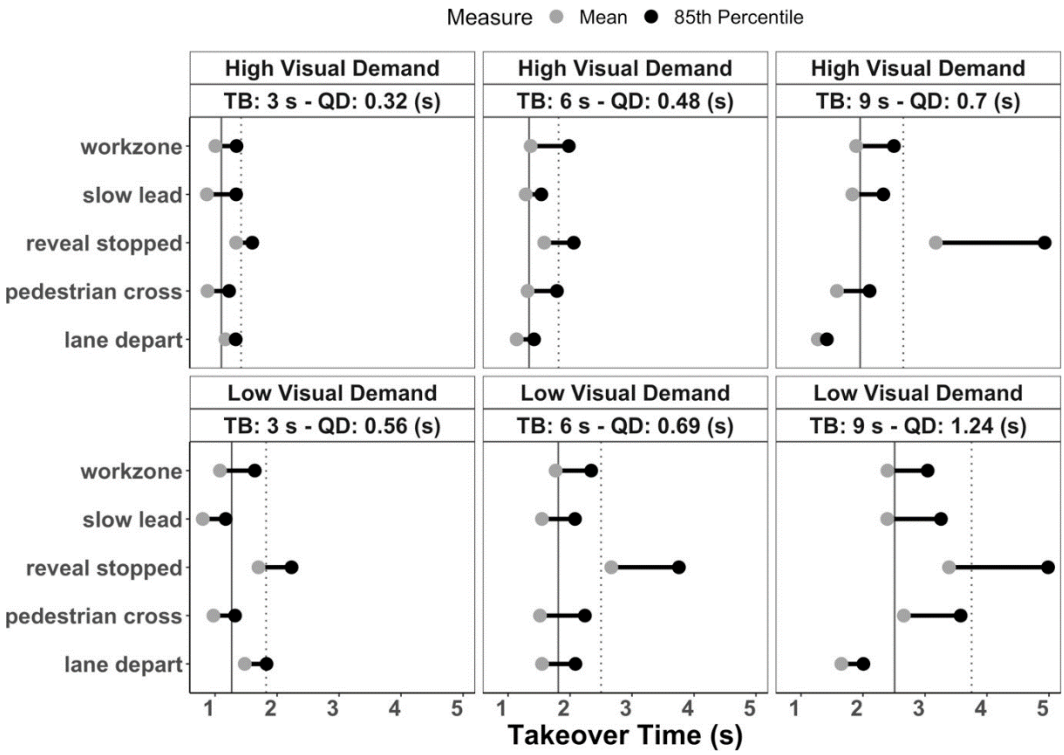


Figure 10. Effect of experimental conditions on drivers' mean and 85th percentile takeover time; Solid and dashed lines in each panel are the mean and 85th percentile takeover time for that visual demand and time budget level.

The shape of the distributions in Figure 9, shows a skewed distribution of drivers' response time across different conditions, with Table 2 showing the skewness value for each condition (Komsta & Novomestky, 2015). A normal distribution has a value of zero and the further the value deviates from zero, the more skewed the data. A negative value indicates a negatively skewed dataset, while a positive value indicates positively skewed. To further explore the effect of the

independent variables under these departures from normality and homogeneity of variance, a Bayesian approach to quantile regression was used.

Table 2. Measures of skewness based on timing, visual demand and event type

	High Visual Demand			**Low Visual Demand**		
	3 s	6 s	9 s	3 s	6 s	9s
Work zone	-0.14	1.28	0.04	0.37	1.20	1.13
Slow lead vehicle	-0.22	0.43	0.64	0.25	0.71	0.99
Reveal stopped	-0.48	0.71	0.96	-0.09	0.69	0.25
Pedestrian crossing	0.04	1.45	-0.11	0.47	0.56	0.27
Lane departure	1.67	0.55	0.47	1.90	0.48	1.50

First introduced by Koenker and Bassett (1978), quantile regression estimates conditional quantile functions. It supplements the notion of minimizing sums of squared residuals in classical linear regression methods where the focus is on estimating models for conditional mean functions. Quantile regression minimizes asymmetrically weighted absolute residuals to estimate conditional median functions in addition to a full range of other conditional quantile functions (Buhai, 2005). Using quantile regression, the effect of changes in the independent variable on the entire distribution of the response variable can be studied rather than just focusing on the mean. Also, traditional regression is less robust and more sensitive to outliers than conditional median regression (Porter, 2015; Yu & Moyeed, 2001).

The R package brms package was used to implement the Bayesian quantile regression analysis. brms supports the development of Bayesian generalized linear and nonlinear multivariate multilevel models using the probabilistic programming language Stan (Bürkner, 2017, 2018; B. Carpenter et al., 2017). Packages such as brms have made Bayesian computational methods more accessible, increasing the use of Bayesian statistics in many fields such as social and behavioral sciences and psychology. Bayesian statistics allows us to update our understanding of the parameters of interest by combining our prior knowledge of those parameters weighted by the evidence provided in the current data (Van de Schoot et al., 2014). The brms package enables the

user to specify prior distributions, encouraging users to use distributions that reflect existing knowledge (Bürkner, 2017, 2018). However, in this analysis, uninformative priors were used.

To investigate the influence of the experimental conditions on the different quantiles of drivers' takeover time, models with all the main and interaction effects were fit to the 15^{th}, 50^{th}, and 85^{th} percentiles. For all three models, participant was included as a random effect. The same models were created using event as a random effect, given that they represent a sample of possible events (Baayen et al., 2008). The results showed a minimal difference and given our interest in how response time was influenced by specific events, it was considered as a fixed in the analysis. The purpose of this analysis is inferential and descriptive. The intention is not to create a model for predicting drivers' takeover time based on visual demand, time budget, and event type, but to assess how potential design factors and scenario-specific variables affect the distribution of drivers' takeover time. Had the focus been on creating a predictive model, cross validation would have been used to guard against overfitting.

In Figure 11, the beta weights for the 15^{th} and 50^{th} percentiles can be seen in gray while the 85^{th} percentile is in black. If the data from this experiment met the general assumptions of standard linear models—normality and heterogeneity of variance—then the effects of the independent variables would be uniform across the distribution of the quantiles—lines in Figure 11 connecting the three points (i.e., 15^{th}, 50^{th}, and 85^{th}) would be vertical. However, because the independent variables affect the quantiles of the response time distribution differently the lines are not vertical. The magnitude of the coefficients for the 85^{th} percentiles in Figure 11 are typically larger than the values for the median (50^{th} percentile), suggesting that the independent variables had a stronger effect on the tail of the distribution than on the central tendency (i.e., the median in this case). This is especially evident in the revealed stopped vehicle event with high visual demand across all three timing conditions (short, medium, and long). In these conditions, the coefficients for the 50^{th} and 85^{th} percentiles are very different, hence forming a non-vertical line, resulting in disproportionately longer response times in comparison to other events with the same timing and visual demand. In contrast, the short time budget with the lane departure event and high visual demand condition is relatively vertical, indicating that levels of the independent variables in this condition had a relatively uniform effect across the takeover time distribution.

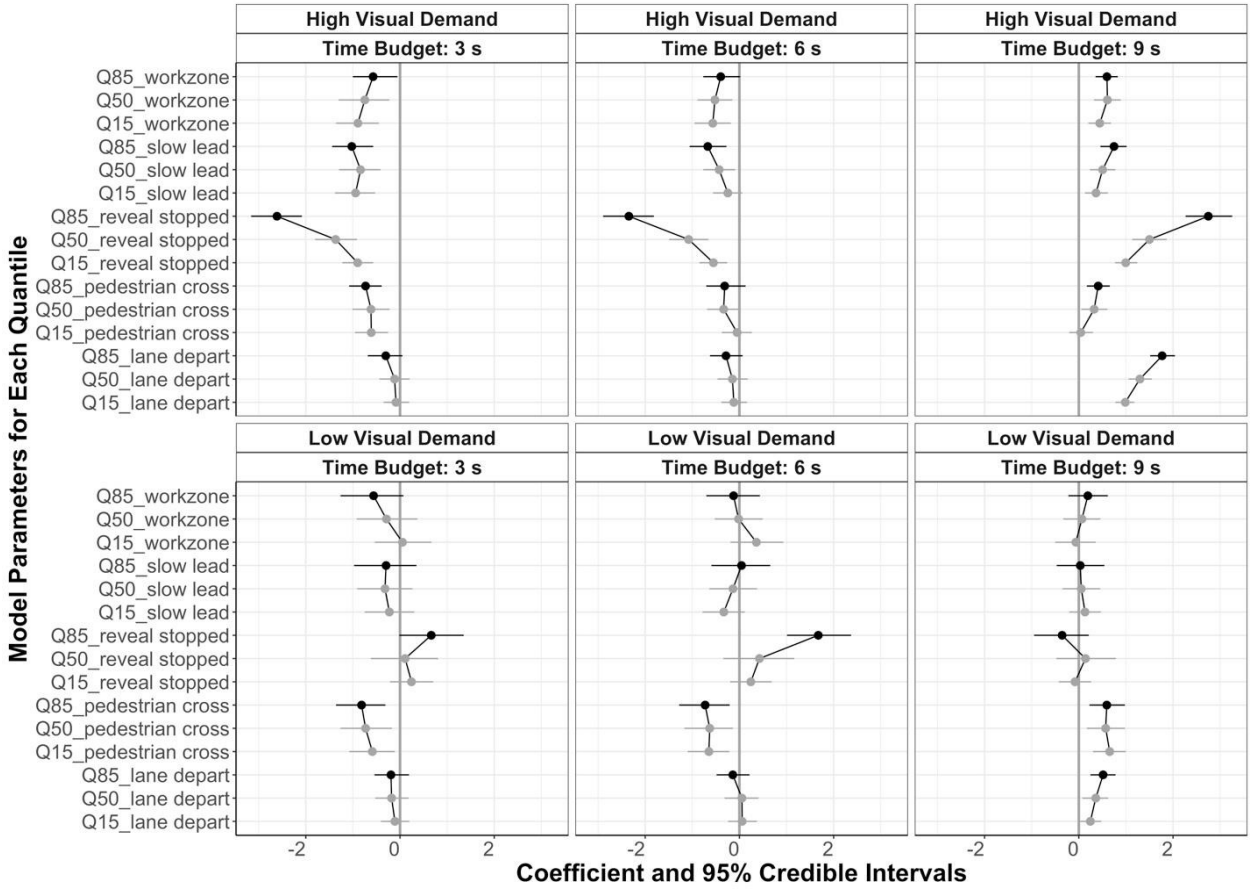


Figure 11. Forest plot of the parameter values showing the effect of independent variables on takeover time for each quantile, including the 15th, 50th, and 85th percentile.

3.4 Discussion

Among the many metrics used to study drivers' takeover behavior, takeover time is the most common (Eriksson & Stanton, 2017). Consistent with expectations, the three independent variables of takeover request timing, the type of critical event, and the level of visual demand influenced drivers' response time. Concerning the effect of visual demand, even though scenarios with less visual complexity might be easier to process and evaluate (Eriksson et al., 2015), this study found that events with a higher visual demand level had a shorter mean response time, 1.52 s (SD = 0.85) in comparison to the lower visual demand conditions (1.88 s, SD = 1.02). This could potentially be explained by drivers associating greater urgency with high visual demand and scene complexity, leading to shorter response times. Apart from visual demand and timing, event type also had a strong effect on drivers' response time. The mean TOT for the revealed stopped vehicle event was the highest (2.34 s, SD = 1.27), in comparison to other events. This could be due to the delay with seeing the revealed vehicle after the takeover

request, in comparison to events such as the slowing vehicle and pedestrian which are more salient. The coefficients associated with the 85th percentile for this event visibly deviated from the coefficients of the 50th percentile. Given the criticality related to such events, the 85^{th} percentile (e.g., 3.72 s for the revealed stopped vehicle) might merit more attention.

The meta-analysis by Zhang et al., showed that the mean and standard deviation of TOT were highly correlated ($r = .82$; $\rho = .74$), indicating that one could infer information regarding the tail of the distribution from the mean (Zhang et al., 2019). This finding is consistent with our results—the factors affecting the median value affected the upper tail of the distribution more strongly. These results suggest the tail of response distribution merits attention using techniques, such as quantile regression because a focus on the mean response might underestimate the safety consequence of conditions that produce very long response times.

Quantifying the effect of variables such as time budget, event type, and visual complexity on TOT using conventional methods that focus on the mean, fails to address potential safety-critical events that stem from the upper tails of the response time distribution. Applying Bayesian quantile regression to the results of this study further affirms this statement by showing that changes in design specifications, such as the takeover request timing and situational variables of visual demand and event type, influence the quantiles of the distribution differently.

The interpretation of the effect of independent variables on the tails of drivers' response time distributions should be tempered by the fact that the experiments were performed in a driving simulator. A possible side effect of studying driver takeover behavior in simulators is that it could potentially accentuate longer response times due to the minimal consequences in comparison to the real world. Therefore, in generalizing the results from any simulator study to the roadway, it should be noted that the drivers' response distributions might not be as skewed. Regardless, knowing that the tails could lead to extreme consequences, quantile regression provides a tool to assess the effect of different variables on the distribution of driver response time to ensure that vehicle automation provides the driver with sufficient time during a takeover. In addition, small takeover times in the experiment (e.g., 0.17 seconds) may be due to the driver initiating the takeover process before the takeover request; specifically, the drivers may have noticed the hazard before the takeover request. This may be indicative of two different response mechanisms in the distribution, where drivers who began responding before the takeover request

are combined with drivers responding to the takeover request. We treated these responses as arising from a single distribution to simplify the modeling process. However, future studies could apply more complex models, such as a mixture model, to address this limitation. Non-responses after a takeover request could also be added to the analysis of the continuous response distribution using models such as the two-part model that is used to study discrete-continuous data (Belotti et al., 2015; J. D. Lee et al., 2019). This study focused on the need to consider the tails of the distribution in safety-relevant systems, such as vehicle automation takeover requests, where more delayed responses occur. While knowing the drivers' takeover time is important, takeover time alone is not the only measure to reflect the drivers' understanding of the situation and readiness to take over (Louw, Kountouriotis, et al., 2015). Even though the timing of a takeover is critical, simply resuming manual control does not guarantee that the driver will successfully respond to the situation in a safe manner (Louw, Markkula, et al., 2017). Assessing the quality of drivers' vehicle control response in combination with the takeover time can provide a more comprehensive measure of the drivers' takeover performance. The quality of the drivers' takeover responses has been examined through measures such as minimum time headway to an obstacle, minimum time-to collision (TTC), (C. Gold et al., 2013; Louw, Kountouriotis, et al., 2015), and maximum accelerations during vehicle control in the transition (C. Gold et al., 2013; Hergeth et al., 2016; Zeeb et al., 2015). Another consideration for future research is applying the assessment function, A(t), a generalized version of the reaction time-based workload capacity function C(t), which measures the effect of increases in workload on human operator efficiency (Townsend & Altieri, 2012; Townsend & Nozawa, 1995). Using such measures, the interaction between the accuracy and speed of drivers' takeover performance can be studied, providing a more comprehensive assessment of drivers' takeover behavior.

3.5 Conclusion

Focusing on traditional statistical models of mean values can lead us to design for the average user and the average situation. In the context of takeover time for vehicle automation, neglecting the tails of the distribution can underestimate safety challenges. This is analogous to anthropometry, where designing for the mean of the population is often inappropriate and designing for the 85^{th} or 15^{th} percentile is needed to create designs that fit the task (J. D. Lee et al., 2017). In driving, the 85^{th} percentile of the response time may be a more relevant safety metric because it directly estimates the part of the distribution that is most directly related to

safety. This study demonstrates that designing for these extremes using the mean and standard deviation to estimate the 85^{th} percentile can be misleading. Quantile regression provides a more precise estimate of how design parameters influence the response distribution.

The ability to simulate drivers' takeover time using validated computational models will allow us to replicate hours of driving with alternative designs for SAE Level 3 automated driving systems in a variety of traffic conditions. Such a tool would be instrumental in exploring how different takeover scenarios affect the quantiles of drivers' takeover time distributions while enhancing the safety of such systems. Chapter 4 will explore models of perceptual decision making to predict drivers' takeover time and control choice.

4 Chapter 4: Modeling Drivers' Takeover Time and Control Choice

4.1 Introduction

Among the many temporal measures that have been used to evaluate take-over performance, takeover time is the most widely applied metric. As mentioned in Chapter 3, takeover time is the time between when a takeover request is issued, or an event becomes visible for silent failures, and the first instance of when the drivers' braking, or steering input exceeds the control thresholds (Dinparastdjadid et al., 2018; A. McDonald et al., 2019). Given the variability of drivers' takeover time across different conditions and the different quantiles of driver takeover time within a condition (DinparastDjadid et al., 2019), understanding how drivers process information from the surroundings and integrate it into a coherent image that can guide safe behavior is a critical aspect of driving, specifically during a take-over situation. Having quantitative models of human behavior will allow us to simulate bounds on human physical and cognitive performance and calculate realistic predictions of human behavior such as takeover time. This will also allow designers to approximate the safety impact of different design choices, such as time budget for automated vehicles (A. McDonald et al., 2019). The underlying process of perceptual decision-making has been confirmed in recent neuroscientific studies in typical laboratory tasks where noisy neural evidence accumulation leading to a decision threshold initiates a specific response (Purcell et al., 2010). Likewise, in the context of driving, such models have been able to explain driver reaction times in response to stimuli in traffic. The traffic stimuli cover both discrete stimuli like brake lights (Ratcliff & Strayer, 2014), and also, dynamic stimuli such as the visual looming of collision threats or approaching road users (Markkula et al., 2016; Svärd et al., 2017).

Among the many choice response time models, also known as response time and accuracy models, the evidence accumulation (or sequential sampling) models have had the most success (Donkin & Brown, 2018). The basic assumption in evidence accumulation models is that humans sample information from the environment to gather evidence towards one of several competing responses at some rate (known as the drift rate). Once the evidence for one alternative surpasses some level of evidence (known as the decision threshold), a decision is triggered (Donkin & Brown, 2018; Evans & Wagenmakers, 2019). Evidence accumulation models include several

different variants such as the diffusion model (Ratcliff, 1978); the Poisson accumulator model (Pike, 1966; Smith & Vickers, 1988; Van Zandt et al., 2000); the EZ diffusion model (Wagenmakers et al., 2007); the leaky competing accumulator model (Usher & McClelland, 2001); the urgency gating model (Cisek et al., 2009); the Ising decision model (Verdonck & Tuerlinckx, 2014); and the ballistic accumulator models (S. D. Brown & Heathcote, 2008; R. Carpenter & Reddi, 2001).

Using evidence accumulation models, researchers have qualitatively captured a range of different choice and response time benchmarks (S. D. Brown & Heathcote, 2008; Ratcliff, 1978; Usher & McClelland, 2001; Verdonck & Tuerlinckx, 2014). Another desirable feature of using evidence accumulation models is that they represent the underlying latent variables of the decision-making process. Two of these latent variables, drift rate, and the decision thresholds are consistent across the different variations of evidence accumulation models. Drift rate is the rate of evidence accumulation for each alternative, and it reflects both people's task ability and the task's difficulty level. The decision threshold is the amount of evidence needed to trigger a decision alternative and is indicative of people's level of cautiousness in their decision strategy. Such latent variables can be used to assess the effect of different experimental conditions on people's choice response time distributions (Donkin & Brown, 2018; Evans & Wagenmakers, 2019; Ratcliff et al., 2016).

The decision threshold, which is associated with a person's level of caution, has typically been assumed to be constant over time. Researchers have recently begun to reconsider the psychological assumptions associated with thresholds being fixed, and new studies are proposing that response thresholds change (e.g., collapse or decrease) over time. This points to a revised assumption that urgency can lead to caution decreasing over time (Cisek et al., 2009; Drugowitsch et al., 2012) so that as more time is spent on a decision, the amount of evidence required to trigger a decision alternative will decrease (Ditterich, 2006; Drugowitsch et al., 2012). This becomes especially relevant in explaining the underlying cognitive processes in decision-making when faced with a deadline. A deadline can be imposed internally or externally, prompting the decision-maker to respond prior to the deadline (Katsimpokis et al., 2020). In the context of a takeover scenario, the deadline is the takeover request or the presence of a hazard that can potentially be modeled using a collapsing threshold.

In this chapter, we will apply a linearly collapsing threshold to model the effect of the deadline introduced by the takeover request. We hypothesize that with larger time budgets, there is minimal perceptual evidence in the scene requiring a takeover response. Hence short takeover times should be explained by the warning. For example, if the takeover request is issued for a vehicle blocking the lane 9 s ahead, the hazard will not be visibly detectable when the takeover request is issued. Using a collapsing threshold to model the warning, the threshold will go towards the negligible amount of evidence, triggering a control decision. In addition, we hypothesize that drivers will execute steering and braking control responses in close temporal proximity during their takeover response, pointing to the need to apply dual accumulation over upper and lower threshold models. The general hypothesis examined in this chapter is that an evidence accumulation model with a separate accumulator for each decision alternative and a collapsing threshold will simulate drivers takeover time distributions and control choice (brake vs. steer) across different time budgets, levels of visual demand, and event types.

4.2 Methods

4.2.1 Evidence Accumulation Models

The standard Weiner diffusion model is a continuous-time stochastic process providing a basic model of human evidence accumulation. The four parameters of the standard Wiener diffusion model include the boundary separation *a*, the non-decision time τ, the bias parameter *z*, and a drift rate parameter δ. Figure 12 provides a schematic view of the evidence accumulation process that can lead to either decision A or B when their corresponding threshold is reached. The parameter, *a*, the boundary separation, reflects the boundaries which, when reached, the evidence accumulation process will be completed, triggering a decision. The distance between the two boundaries is *a*, with the first boundary being at 0 and the second being at *a*. This parameter has been associated with speed-accuracy trade-offs in decision making, with high values of *a*, indicating higher accuracies.

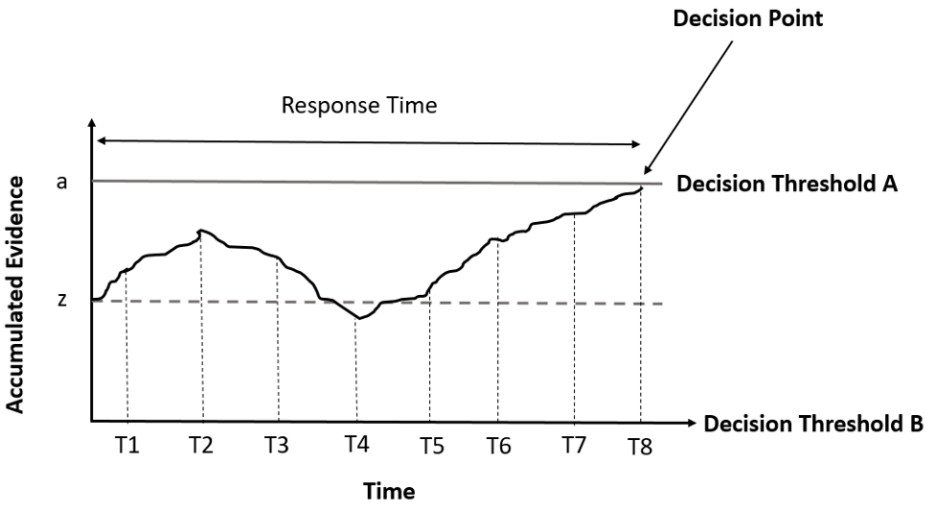


Figure 12. Schematic view of the drift-diffusion process.

Figure 13 shows an example of the potential effect of lowering the decision threshold. In this example scenario, the upper boundary represents the correct choice while crossing the lower boundary results in an erroneous response. As seen in Figure 13, considering identical evidence accumulation processes, a lowered decision threshold leads to a faster response, at the cost of decreased accuracy.

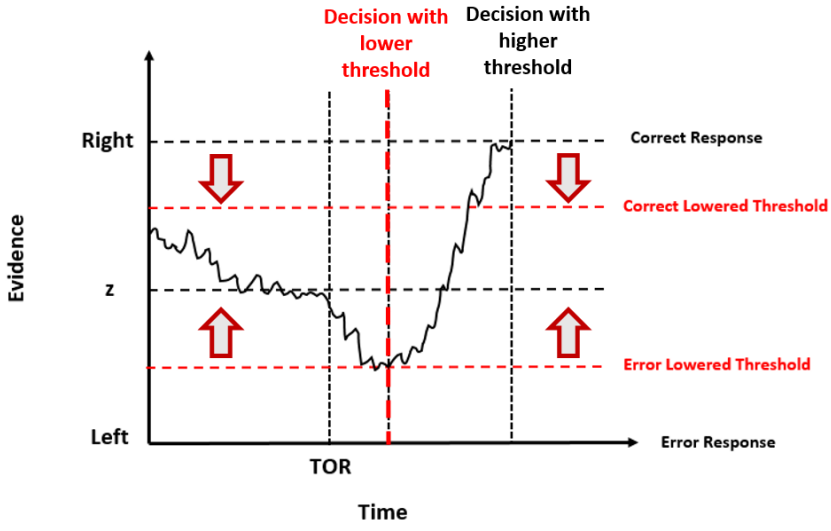


Figure 13. Effect of the boundary parameter on the evidence accumulation process.

The second parameter, the non-decision time τ is time with no diffusion process, representing the time required to encode a stimulus and execute a motor response. High values of τ, reflect slow encoding and execution. The bias parameter *z* is the relative starting point of the diffusion process between the two boundaries. Any value greater than 0.5 indicates a bias towards the

"upper" response among the two choices. In this dissertation, we are proposing that the bias point can be reflective of drivers' initial situation awareness when they receive a takeover request. The final and fourth parameter, the drift rate, δ, captures the tendency of the diffusion process to drift towards the upper boundary. This parameter reflects the quality of the stimulus, with values close to zero being indicative of an ambiguous stimulus (Wabersich & Vandekerckhove, 2014; Wagenmakers, 2009). Traditionally, the upper bound has been associated with correct trials, while the lower boundary corresponds to error trials. In the context of driving, qualitatively different responses can be mapped to each boundary (e.g., steering and braking choice alternatives).

Drivers are continuously receiving information from their surroundings, which is dynamic and constantly evolving. In the particular case of avoiding a collision with a lead vehicle, one source of information indicating the lead vehicle is slowing down would be the brake lights. This cue, however, lacks critical information such as the lead vehicle's deceleration profile and distance to the lead vehicle, causing drivers to rely on other sources of information such as visual looming (D. Lee, 1976). When an object moves towards the subject, looming is produced, and as its value increases, it could indicate an impending collision (Terry et al., 2008). Looming can be estimated using either θ, the angular projection of an object on the subject's retina or $\dot{\theta}$ being the angular expansion rate (D. Lee, 1976). Figure 14 shows a simplified depiction of the angle θ.

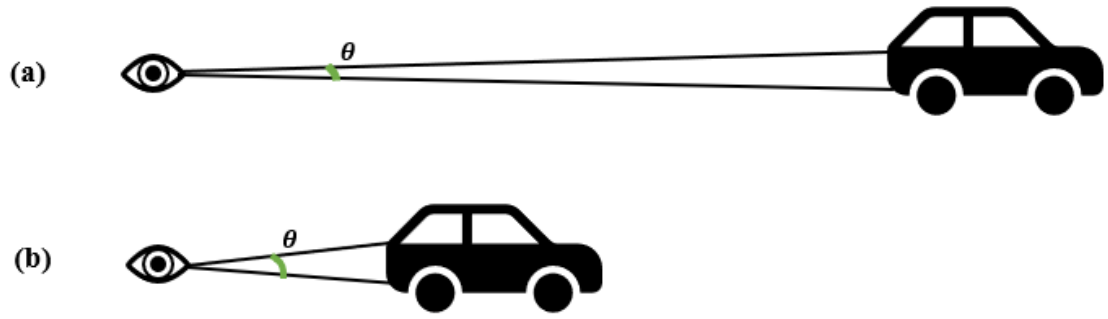


Figure 14. Depiction of the looming angle in two examples with the lead vehicle being near and far.

In Figure 14 (a), as the vehicle is further away from the subject, hence θ is smaller, but as the distance decreases, the angle will grow on the subjects' retina as in Figure 14 (b). Another alternative for looming would be the optical parameter τ which is the ratio of θ and $\dot{\theta}$ or its derivative $\dot{\tau}$. The parameter τ can be considered as an approximation of time-to-contact and has units of time. Lastly, the inverse of τ, $\tau^{-1}$is another alternative that has been considered as a cue

in near accident control with larger values being indicative of a more critical situation. Based on a study by Xue et al. (2018), that explored mechanistic models predicting brake onset, τ^{-1} was a better measure of looming in comparison to $\dot{\theta}$. They reported that τ^{-1} is a better representative of what visual cues drivers use during a rear-end collision avoidance maneuver (Xue et al., 2018). In this study, we also use looming as evidence that influences drivers' response to a takeover request.

Incorporating the underlying concepts that were just discussed on evidence accumulation models and looming, a revised version of such a model that better applies to the context of driving was considered. This model, which is taken from Svard et al. (2020), uses looming prediction error as the perceptual sensory input being accumulated.

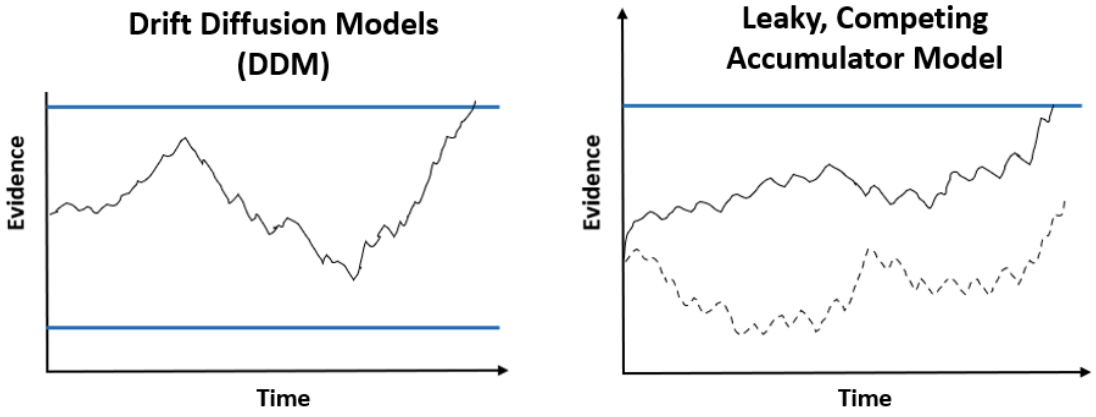
$$\frac{dA(t)}{dt} = K * \varepsilon(t) - M - C * A + \nu(t) \qquad \text{Equation 1}$$

Equation 1 shows the details of the model used to estimate drivers' takeover time with K, *M*, and *C* being the free parameters gain, gating, and leakage, respectively. The function $\nu(t)$ is a Gaussian zero-mean white noise at time *t* with a standard deviation σ. The gain parameter *K* is a proportional constant reflecting the impact of the looming prediction error on the activity level; parameter *M,* gating is the sum of all non-looming evidence for or against braking, and *C* is the leakage term concerned with the decay in the accumulated evidence over time (Svärd et al., 2020).

Moving beyond a single decision alternative like braking, another factor to consider when modeling the accumulation process is whether to have separate accumulators for each decision alternative or to have a single signal that accumulates towards different thresholds with each threshold representing a different decision alternative. Drift Diffusion models fall into the second group, while Leaky competing accumulator models shown in Figure 15.b have a separate accumulator for each decision alternative (Evans et al., 2020; Usher & McClelland, 2001).

In the context of driving, specifically urgent situations like takeover from automation, we hypothesize that drivers will execute steering and braking control responses back to back with little time between them. This is inherently different from cases in which the driver brakes and is then accumulating evidence to assess whether the initial brake response resolved the situation or if more braking or even a lane change is needed (Markkula, Romano, et al., 2018). We

hypothesize that these two control actions (brake and steer), will often occur in such close temporal proximity that the most suitable model would be to apply two separate streams of information that accumulate somewhat independently. Therefore, using Equation 1, we will be modeling two accumulators like those in Figure 15.b.



(a) (b)

Figure 15. Different evidence accumulation models. In figure a, there are two thresholds and one accumulator, while figure b has a single threshold with the solid and dashed lines representing accumulators for each decision alternative.

4.2.2 Collapsing Threshold Models

To the best of our knowledge, perceptual decision-making models in the context of driving have always used a fixed threshold that was held at a constant. These models were applied to either routine manual driving or safety-critical control maneuvers that lack a warning. In the context of a takeover scenario, especially for SAE Level 3, the effect of the takeover request needs to be considered in modeling drivers' takeover behavior. The takeover request introduces a deadline into the decision-making process, obligating drivers to resume manual control of the vehicle. This urgency has been suggested to affect required cautions levels, and one method to model such a phenomenon is to use a dynamically changing threshold (Cisek et al., 2009; Frazier & Yu, 2009; Katsimpokis et al., 2020). With a takeover request warning, regardless of how the evidence is developing in the scene, there is a sense of urgency building in the driver signaling to an increasing probability that as time passes, the automated system will cede control of the vehicle.

Current evidence accumulation models in the driving literature apply a constant threshold like Figure 16.a, in which as time progresses, dynamic evidence from the scene accumulates towards

the threshold in a noisy fashion. However, there are cases in which an obvious threat requiring a reaction from the driver is not present, leading to a small amount of evidence accumulation like in Figure 16.b, shown as the noisy blue line. Even in such situations, drivers' will still initiate a control response and resume manual control due to the nature of a takeover scenario with the vehicle ceding control after the time budget is exhausted. We propose a linearly decreasing threshold, as shown in Figure 16.b. to model the effect of the deadline introduced by the takeover warning. In both plots of Figure 16, time zero is when the takeover request was issued. In Figure 16.b, similar to the evidence being dynamic, the threshold is now also changing over time and linearly decreasing.

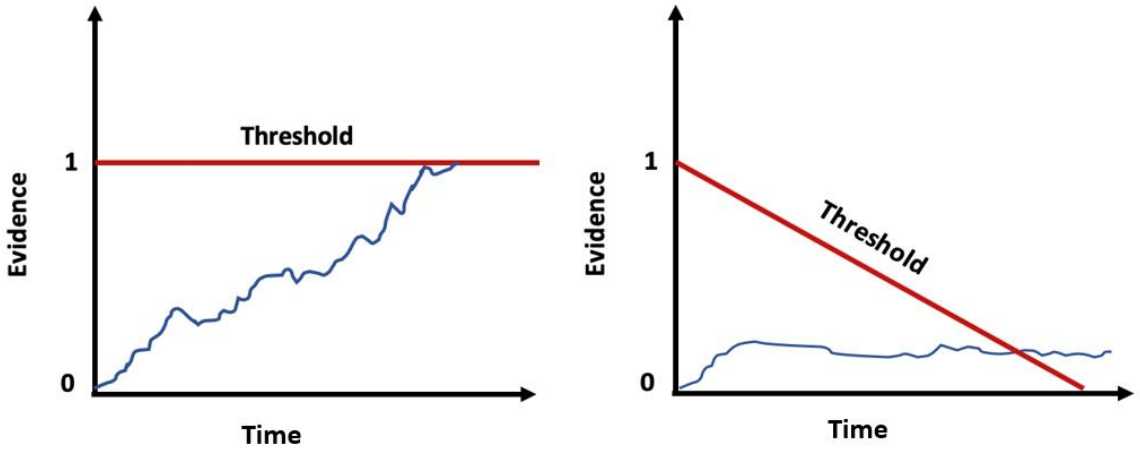


Figure 16. Constant versus linearly decreasing threshold.

The linearly collapsing threshold can be modeled using Equation 2, with the threshold starting at one and linearly collapsing while the evidence is accumulating. The parameter *slope* in Equation 2 defines how fast the threshold collapses with larger values leading to a quicker collapse.

$$threshold = 1 - slope * time \qquad \text{Equation 2}$$

This will allow the model to cover cases where the scene involves no looming prediction error or an imminent threat, but there is still a takeover maneuver due to the warning being issued. At each moment, the output of Equation 1 will be compared with the threshold value from Equation 2. When the evidence crosses the threshold, the driver will initiate a control response with the elapsed time being the drivers' takeover time.

4.2.3 Bayesian Parameter Estimation

Parameter estimation is central to fitting a model to a dataset (Turner & Van Zandt, 2014). Also, when studying the effect of different experimental conditions, the model parameters provide a systematic method to study the effect of different independent variables on model predictions. Bayesian data analytic methods are gaining widespread popularity in cognitive sciences due to their many desirable properties (J. Kruschke, 2014; M. Lee & Wagenmakers, 2014). One potential reason is their ability to go beyond finding the most likely value of each parameter, by providing the full posterior distribution of each parameter makes it possible to precisely quantify the uncertainty in their estimation (Wiecki et al., 2013). Bayesian methods provide a probability distribution, called the posterior distribution of model parameters, given the observed data, while also incorporating prior knowledge about the parameter values (Turner & Van Zandt, 2014). However, the likelihood function, which is an essential part of Bayesian estimation, can sometimes be difficult or even impossible to specify mathematically, resulting in researchers resorting an approximation of least-squares estimation when fitting models to simulation-based and intractable models (e.g., Ratcliff & Starns, 2009; Tsetsos et al., 2011).

Approximate Bayesian Computation (ABC) is a likelihood-free method that has gained popularity in estimating parameters of dynamic models in environmental and biological sciences (Beaumont, 2010; Pritchard et al., 1999; Toni et al., 2009). With ABC, the model is simulated using different combinations of parameter values. The simulated data are then compared to the observed data, and if they are close, it can be assumed that the parameter subset has some density in the posterior distribution, as shown in Figure 17. This allows the estimation of the posterior distribution without requiring the likelihood function (Turner & Van Zandt, 2014). For high-dimensional systems, then it becomes necessary to decrease the dimensionality by using summary statistics which are a set of mappings from a high dimension to a low dimension (Beaumont, 2010). Summary statistics capture the essential characteristics of the observed behavior and are central to the quality of the approximation.

Using parameter estimation methods, such as ABC, for evidence accumulation models, we are bound to have imprecisions in our findings, which can be explained by factors such as noise in the data, the nature of Bayesian methods, and in general, the approximate nature of MCMC. This can, in addition to the previously discussed reasons, be explained through the intrinsic “sloppiness” or “mimicry” of such models (Apgar et al., 2010; Evans & Wagenmakers, 2019;

Gutenkunst et al., 2007; Holmes & Trueblood, 2018). Sloppiness refers to when a model that has more than a few parameters can account for equal observed data using a wide range of parameter combinations. Using methods such as ABC to estimate the parameters of an evidence accumulation model, we are not able to observe the process itself and must rely on observable inputs and outputs to infer the latent accumulation process. In this analysis, the input includes information about the stimulus (e.g., looming prediction error), and the outputs are the summary statistics (e.g., takeover time and control choice).

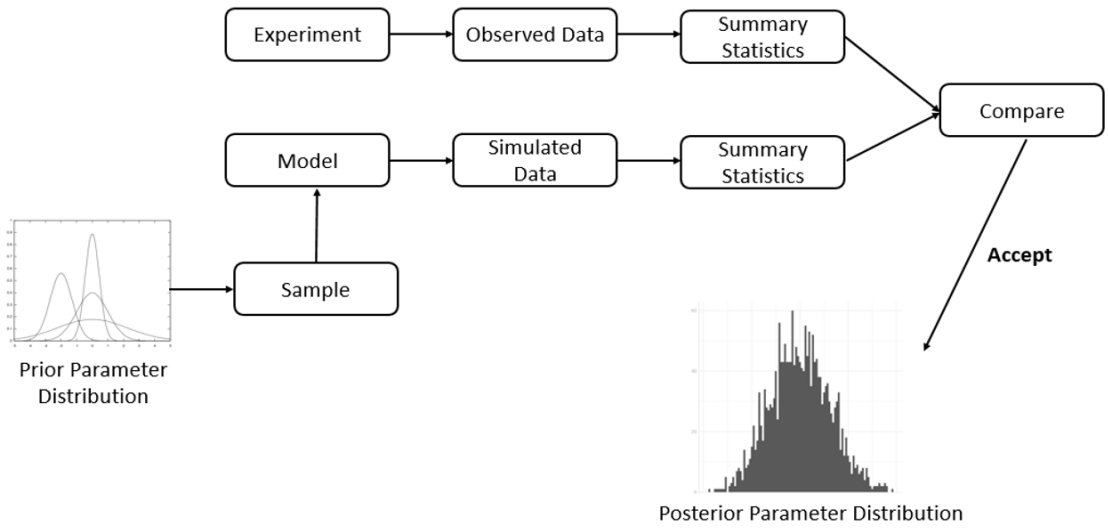


Figure 17. Schematic overview of Approximate Bayesian Computation (ABC).

4.3 Results

After a takeover request was issued, drivers' takeover time was defined as the time between the takeover request and when the driver initiated a control response. A control response consisted of either steering or braking. A response was categorized as steering if the steering wheel angle were greater than 3 degrees and had a steering rate of 10 degrees per second. A brake response was recorded if the brake pedal press was greater than 3 lbf (DinparastDjadid et al., 2019). The takeover control response type was whichever control action (steering or braking) occurred first. For this analysis, only takeover times that were between 0.2 and 9 seconds were considered. In addition, to focus the scope of the analysis, we selected two events from the experimental design: the slow lead vehicle or revealed stopped vehicle. This led to 235 event combinations across the

three different time budgets (3, 6, and 9 s) and two levels of visual demand (low and high). Before discussing the results from the modeling and parameter estimation, this section will first explore the data to evaluate the hypotheses, which could lead to model revisions.

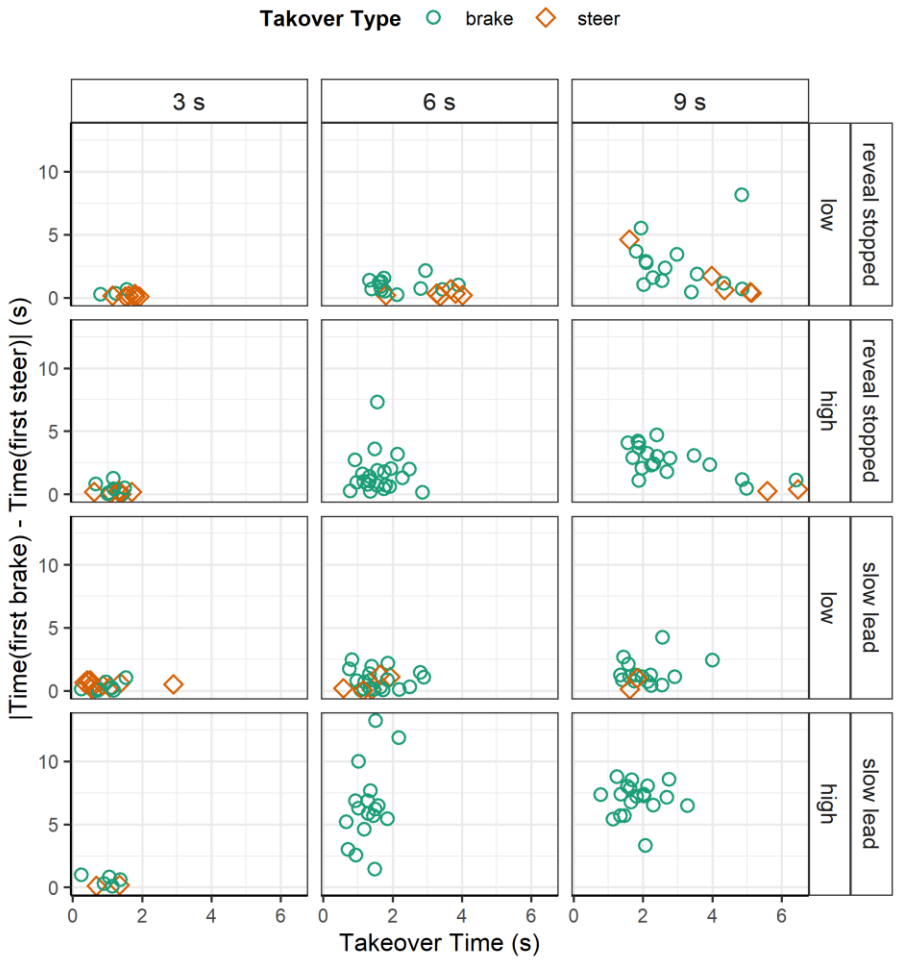


Figure 18. Time difference between the first braking and steering control responses across different conditions. Time Budgets: 3, 6, and 9 s. Visual demand: low and high.

Figure 18 was created to assess the temporal proximity of the drivers' first steer and brake responses. The y-axis is the time difference between the first braking and steering response actions while the a-axis is the drivers' takeover time. Each cell of the grid represents one combination of the experimental conditions, and the shape and color of the points shows which control action was chosen first. Time differences that were more than 15 seconds were excluded from this plot. As hypothesized, in some instances, especially in the shorter time budget-revealed stopped event condition, steering and brake responses were close in time, endorsing our decision to model these two choice alternatives as two separate accumulators.

4.3.1 Takeover Control Response

Figure 19 shows the takeover time distributions for these two selected events (slow lead vehicle and reveal stopped vehicle events) across different time budgets and visual demand levels. The color for each distribution indicates the type of control response that was first initiated after the driver resumed manual control. In the 3 s time budget-low visual demand revealed stopped vehicle event of Figure 19, the steering responses tend to be delayed in comparison to the brake responses.

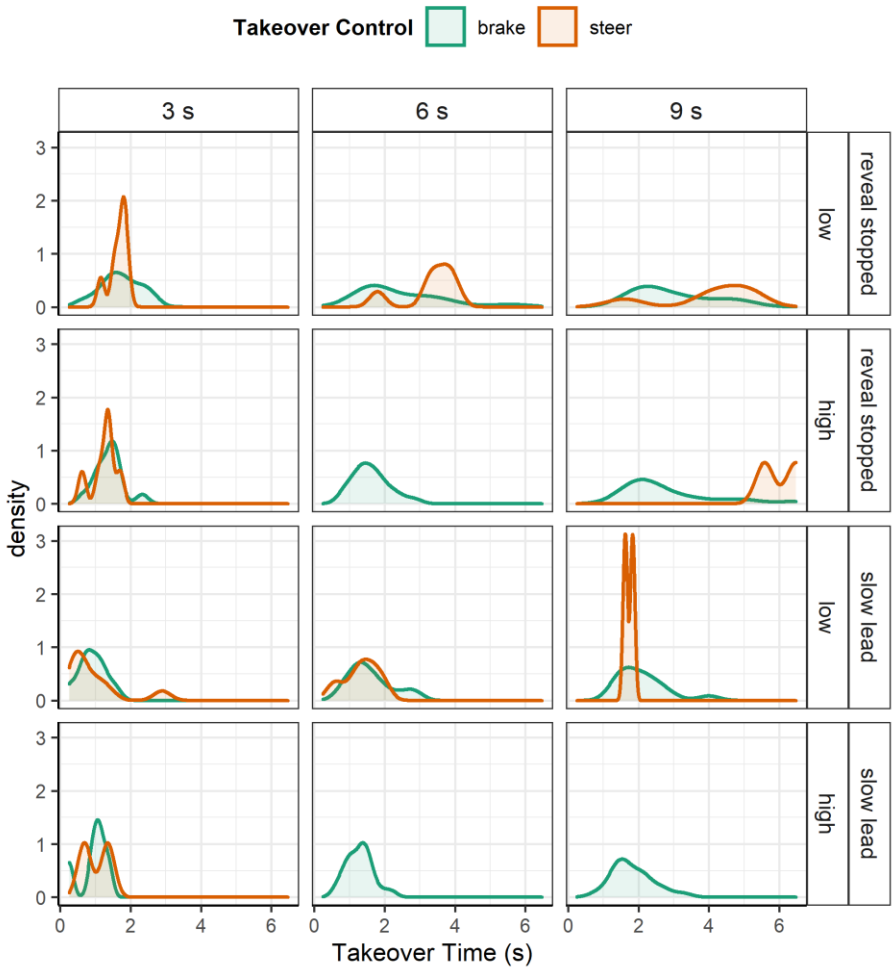


Figure 19. Distribution of takeover times across high and low visual demand and slow and reveal stopped lead vehicle for the 3, 6, and 9-second time budgets.

If a grid in Figure 19 only has one color distribution, it means that for that specific condition, all initial takeover control responses were entirely either steering or braking. According to Figure 19, in some groupings of the 6 and 9 s time budgets, drivers' initial control response was only to brake, and it seems like brake responses tend to have earlier takeover times.

Further looking into the frequency of drivers braking vs. steering as their initial takeover control response, Figure 20, provides a breakdown of these percentages. Given that both events involve a vehicle blocking the road ahead, but with different dynamics, braking was expected to be the initial response, which is in correspondence with Figure 20. In general, it seems like most drivers started by braking when they took over. Examining Figure 19 and Figure 20 together further affirms this statement that brake responses were more frequent than steering. At the same time, brake responses also tend to have takeover time distributions that are mostly skewed to the left, which are shorter takeover times.

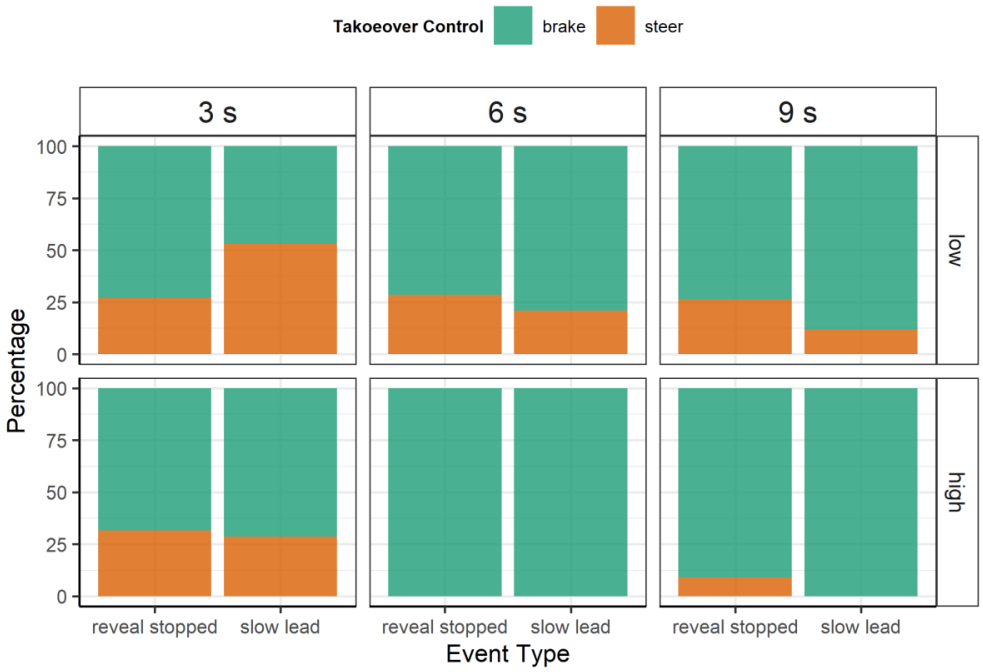


Figure 20. Percentage of braking vs. steering as drivers' initial takeover response across conditions. Time Budgets: 3, 6, and 9 s - Visual demand: low and high.

Based on Figure 19 and Figure 20, we hypothesized that drivers' control choice would depend on the magnitude of looming and how it evolves. This would mean that high looming values (very close proximity to the lead vehicle) might not be resolved by braking, and the driver will have to steer. Because both the braking and steering accumulators use the looming prediction error, this idea can be operationalized through the gain parameter so that, as the looming prediction error increases, the gain parameter for steering increases, while its counterpart gain for braking decreases. To model this phenomenon, we set the gain parameter to be a function of inverse tau, which is also a function of time because as time progresses between when the takeover request is

issued and the driver resuming manual control, the situation's criticality also increases. Equations 3 and 4 below depict this relationship and how each gain is estimated over time.

$$k_{brake} = e^{-|invTau+M|} \quad \text{Equation 3}$$

$$k_{steer} = 1 - k_{brake} \quad \text{Equation 4}$$

Assuming the M parameter is zero, Figure 21 shows the relationship between the two gains and how their sum will always equal one. Like Equation 1, the M parameter reflects evidence beyond looming that is in favor of steering over braking. For example, even with very high looming values, the adjacent lanes might be blocked prohibiting the driver from a lane change, which makes a brake response more favorable. Such context dependencies beyond looming were incorporated into the gains from Equations 3 and 4 using the parameter "M".

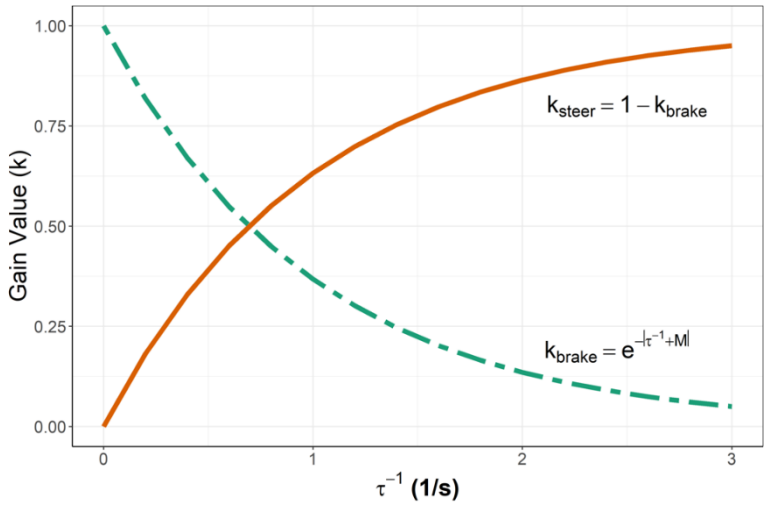


Figure 21. A simple version of brake and steering gain parameters with M = 0.

Figure 22 shows the effect of different values of parameter M for the braking accumulator's looming gain. Based on Figure 20, we know that not all drivers steer with larger looming values, and braking is sometimes the selected control response in these cases. On the other hand, sometimes drivers steer even in the presence of small looming values. Parameter M accommodates such instances to reflect non-looming related evidence when drivers make a control decision.

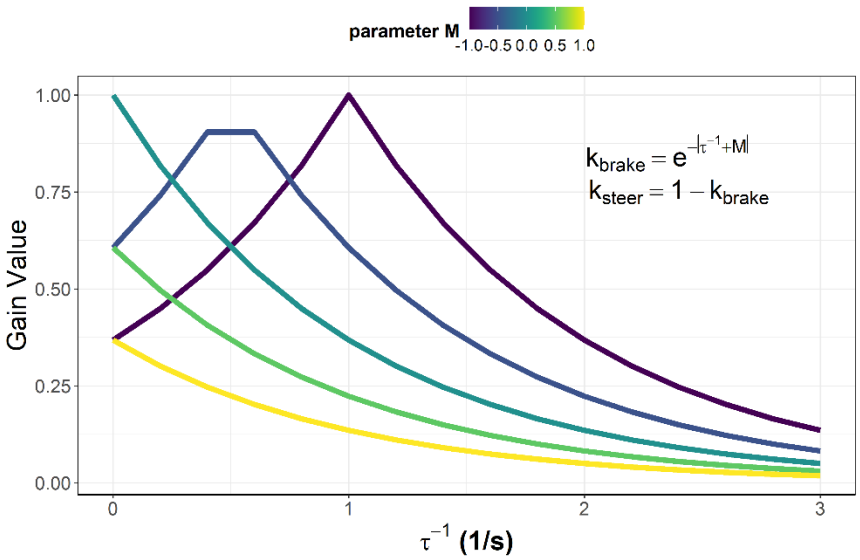


Figure 22. Effect of parameter z on the braking accumulator's gain k.

Based on the proposed gain functions, Equations 5 and 6 show the accumulator functions for each control response. Before using these equations to simulate takeover time and control choice, the next section will justify a collapsing threshold based on the underlying characteristics of the experimental data.

$$\frac{dA(t)_{brake}}{dt} = k_{brake} * \varepsilon(t) - C * A + \nu(t) \qquad \text{Equation 5}$$

$$\frac{dA(t)_{steer}}{dt} = k_{steer} * \varepsilon(t) - C * A + \nu(t) \qquad \text{Equation 6}$$

4.3.2 Effect of The Takeover Request Warning

As discussed in the introduction, there is growing evidence that an individual's level of caution and belief of urgency can change over time while deliberating a decision. As a result, as time goes by in the presence of a collapsing threshold, less evidence will be required to trigger a decision.

Figure 23 shows a few examples of the time series profiles of $\dot{\theta}$ which is one of the looming cue variations. As expected, the longer a driver waits to take over, the more the situation evolves and becomes critical (grid 50 in Figure 23). Based on the experimental conditions and when drivers resumed manual control, looming could be at different values and criticality levels at takeover. In

Figure 23, the dashed horizontal red line at $\dot{\theta}$ = 0.0036 rad/s, is where Morando, Victor, & Dozza (2016) suggested to be the threshold on human detection of looming based on studies of visual perception thresholds (Lamble et al., 1999; Summala et al., 1998). The first red horizontal solid line at 0.02 rad/s is the recommended looming threshold from which drivers' usually initiate a control response after a second while the top red solid line at 0.06 rad/s is the looming threshold where drivers are typically considered to begin their control response (Xue et al., 2018). In grids 1 and 200 of Figure 23, the looming barely evolved beyond the first threshold at 0.0036 rad/s, making it hardly perceivable when the drivers took over.

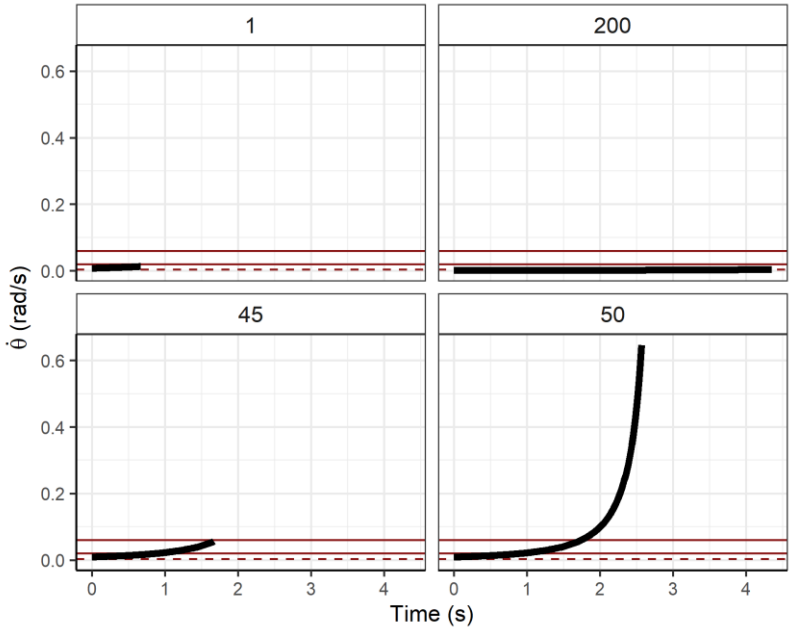


Figure 23. Examples of $\dot{\theta}$ over time prior to drivers taking over. The horizontal lines are different looming threshold.

Figure 24 provides a more detailed view of $\dot{\theta}$ when drivers resumed manual control across different conditions. The grey horizontal lines are the looming thresholds, like those explained in Figure 23. As seen in Figure 24, the shortest time budget did not leave much time before the situation became critical, as indicated by the higher looming values. The revealed stopped vehicle event with its surprising reveal of the stopped car also led to delayed takeovers causing more critical looming values across different time budgets. On the contrary, for the longer time budgets, the looming values are typically small, making these takeover maneuvers different from traditional studies on drivers' manual control behavior that model driver reactions to an imminent collision or routine manual driving.

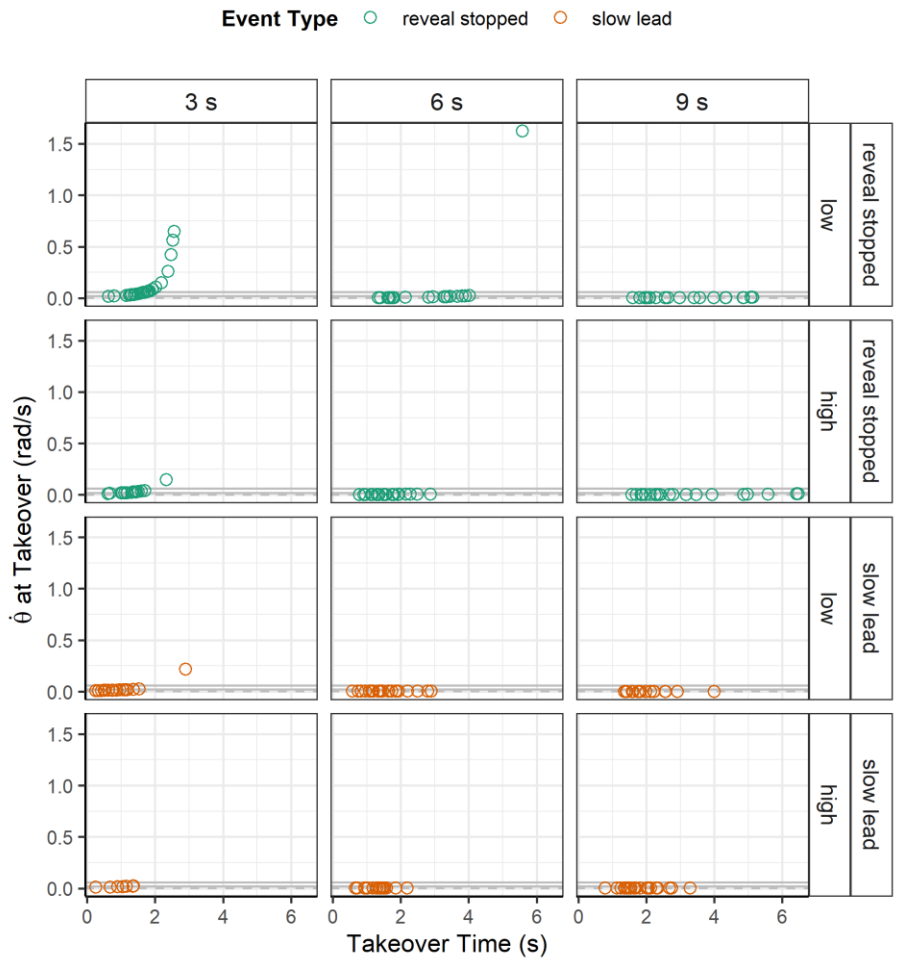


Figure 24. $\dot{\theta}$ values when drivers resumed manual control. Time Budgets: 3, 6, and 9 s - Visual demand: low and high. Grey horizontal lines are looming thresholds.

In takeover situations, regardless of the presence of the growing looming prediction error, drivers are compelled to respond because they know that the automated system will cede control soon. As seen in Figure 24, the revealed stopped vehicle event tends to have delayed takeover times and higher looming values at the moment of the takeover. We know that with the slow lead vehicle event, the hazard is visually salient, while with the revealed stopped vehicle, there is an absence of an immediately visible threat. Potentially, when there is no apparent visual hazard, drivers might opt to delay their takeover responses to gain more situation awareness, but as shown in Figure 23, grid 50, after the surprising reveal, they are faced with a steep rise in the looming signal. The findings from this section suggest that the warning signal by itself can prompt drivers to take over control, requiring it to be considered in the model. Using equations 2,

5, and 6, the next section focuses on estimating parameters of the model using Approximate Bayesian Computation (ABC).

4.3.3 Parameter Estimation and Takeover Time and Control Choice Simulation

This analysis was done in R using the EasyABC package, selecting the Marjoram ABC-MCMC algorithm. ABC-MCMC algorithms proposed by Marjoram et al. (2003) apply a Metropolis-Hastings algorithm to explore the parameter space and replace the likelihood ratio computation step with simulations of the model. The selected method Marjoram includes some improvements to the original algorithm including the addition of a calibration step so that the algorithm automatically determines the tolerance threshold, the scaling of the jumps in the parameter space during the MCMC, and the scaling of the summary statistics (Jabot et al., 2013, 2015). The takeover time and control choice of each observation served as the summary statistics. The leakage parameter was considered as a constant value of 0.25 taken from a recent study on drivers' pre-crash brake behavior (Svärd et al., 2020). The noise variable comes from a normal distribution with mean zero, leaving the standard deviation as a free parameter. Early simulations showed that this parameter's posterior distribution was uniform, and so the standard deviation was held constant at 0.5.

There was a total of 235 observations to simulate, with 3000 iterations for the ABC parameter estimation process of each observation. The three parameters that were estimated were a_0, M, and the slope of the linearly collapsing threshold. The priors for these parameters were all uniform distributions bound between (0, 1), (-1, 1), and (-8, 0), respectively. With the slope parameters, since it is collapsing, it had to be negative and larger values indicate a threshold that collapses faster. The single input to the model was the looming prediction error based on the variable τ^{-1}, which is used both as the evidence itself and to modulate the gains of each accumulator. To accommodate takeover times that were longer than the observed takeover time in the simulation, we extended the τ^{-1} based on a linear function for one extra second. This was done since in the actual data, once the drivers resume manual control, they influence the course of the vehicle which affects τ^{-1}, therefore, we had to simulate the τ^{-1} extension.

The outputs of the model, which were also the summary statistics of the ABC process, were takeover time and the control choice (brake vs. steer). Simulating the takeover times using the accepted parameters, a second round of rejection was done, only keeping parameters that

resulted in a takeover time difference less than 0.5 s. Figure 25 shows three examples of the simulated evidence accumulation process using the accepted parameters for that observation.

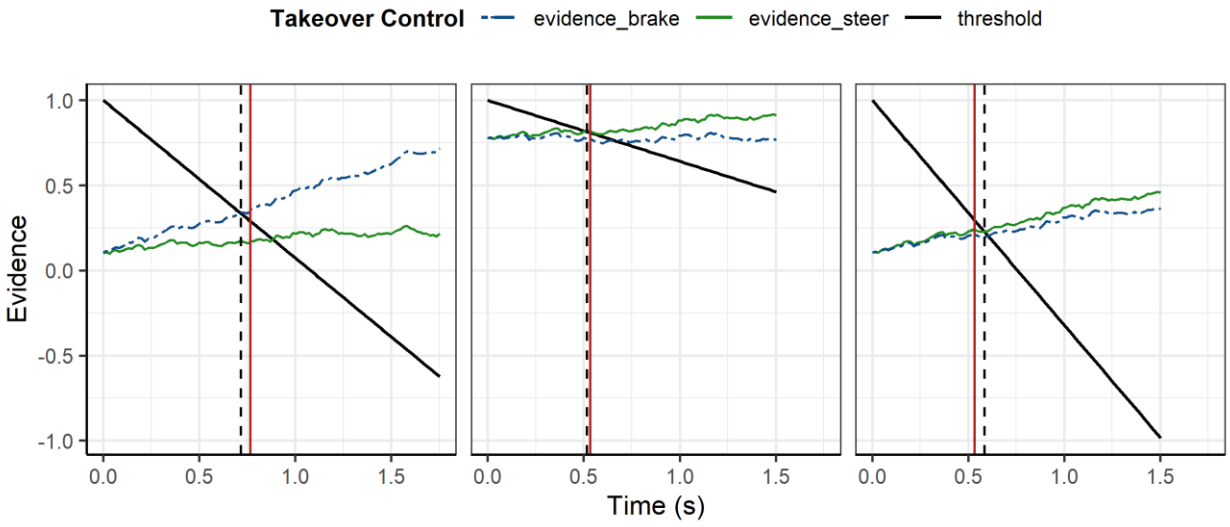


Figure 25. Example simulations of the evidence accumulation process.

In Figure 25, the solid green noisy accumulation is for steering while the dashed blue noisy accumulation is for a braking control response. The solid black line starting from one and linearly decreasing is the collapsing threshold. The solid red vertical line is the observed takeover time from the data, while the dashed blue line is the simulated takeover time, which reflects when one of the streams of accumulation surpasses the collapsing threshold. We simulated the two streams of accumulation for the time window between zero and the takeover time plus one. We then extracted the first moment at which one of the accumulators passed the threshold, giving us the simulated takeover time and the control choice type associated with that accumulator as the takeover control choice.

Figure 26 shows the scatterplot matrix of the parameter's posterior distributions based on the accepted parameter values along with the takeover time distribution from all conditions. In this figure, we have bivariate scatter plots below the diagonal with linear regression fits for both y by x and x by y, histograms on the diagonal, and the Pearson correlation values above the diagonal. The M parameter's posterior distribution seems to be bimodal, and the slope parameter has the highest correlation with takeover time.

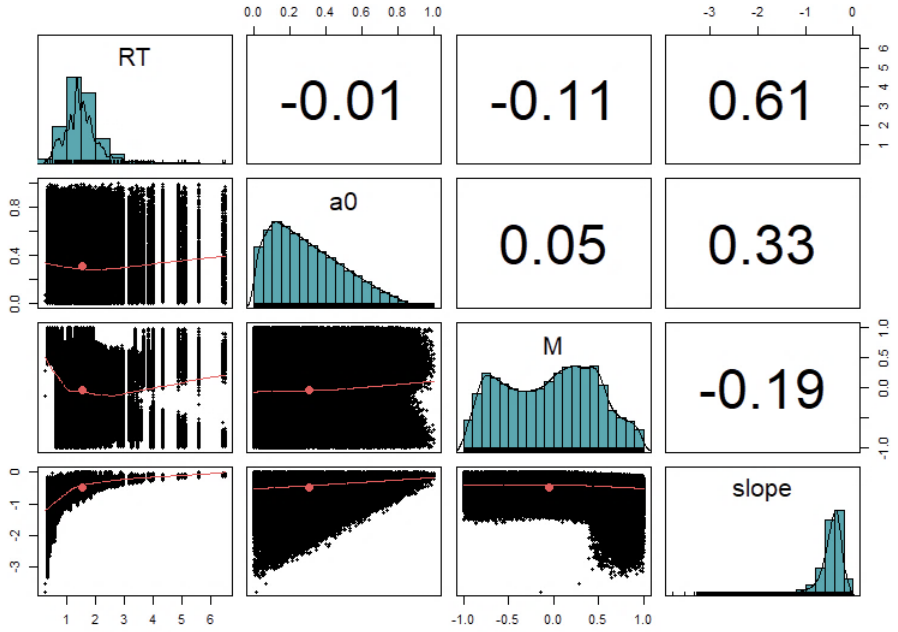


Figure 26. Scatter plot matrix of takeover time and the parameter's posterior distributions.

Drawing from the posterior distribution of the parameters, we simulated the takeover time for each observation, and Figure 27 shows the observed (solid green) and the simulated (dashed orange) takeover time distributions for all the different conditions of time budget, visual demand and event type.

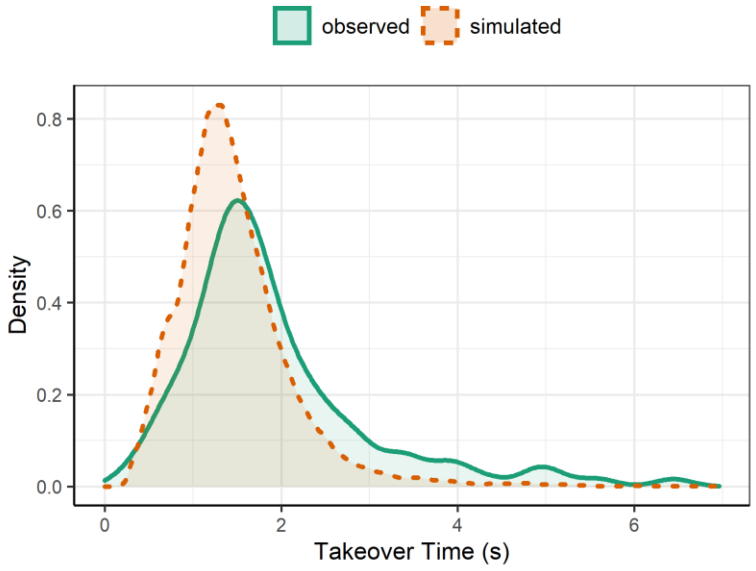


Figure 27. Observed vs. Simulated takeover time distributions for all conditions.

Using the simulated distributions, in the next step, we Further examined the fit of the simulated takeover time distributions for each individual condition. Each grid in Figure 28 displays the observed (solid green) vs. the simulated (dashed orange) for a single condition (i.e., a combination of time budget, visual demand, and event type). The slow lead vehicle event tends to have a better fit in comparison to the revealed stopped event. In addition, it seems like the simulated takeover time distributions for the revealed stopped event is more skewed to the left (shorter takeover times) in comparison to the observed data.

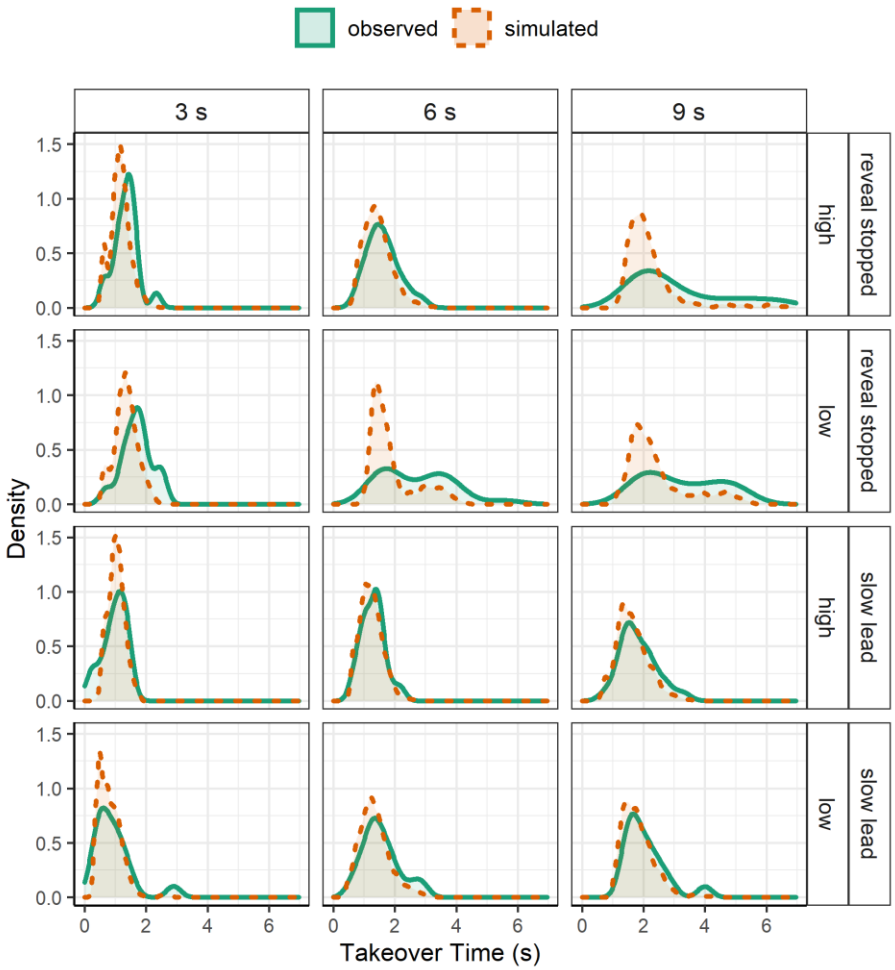


Figure 28. Observed vs. Simulated takeover time distributions for each condition combination. Time Budgets: 3, 6, and 9 s. Visual demand: low and high.

This might be explained by the sudden change of stimulus in the reveal stopped vehicle event. Some studies had suggested that when the stimulus changes during a single decision, there is a lag between when the stimulus change was introduced and the subject encoding and using the new evidence (Holmes et al., 2016; Holmes & Trueblood, 2018), increasing reaction times. The

surprise associated with the lead vehicle changing lanes and revealing a stopped vehicle could produce a lag that is missing from our current model. This missing lag could explain the shorter simulated takeover times relative to the observed data for the reveal stopped vehicle event while the slow lead vehicle event has a better fit.

In addition to takeover times, control choice (brake versus steer) was another summary statistic used to fit the model's parameters. Examining the 466,644 accepted parameter combinations across all conditions, the model predicted control choice with 96% accuracy.

Figure 29 shows the distributions of the accepted parameters across different experimental conditions and takeover control types (brake versus steer), which was one of the outputs of the model. With an ideal model, we would expect the parameters to be invariant across conditions allowing us to generalize across them. But, as discussed in the Methods section on parameter estimation, we are aware that such models and using approximate methods for parameter fitting lead to sloppiness, so caution will be taken when making inferences about Figure 29.

According to Figure 20, the 6 and 9 s time budgets with high visual demand levels showed none or close to none of the drivers selecting steering as their initial control response. Looking at Figure 29, the M parameter for these events also stands out. The bi-modal posterior distributions in these conditions led to the brake accumulator's gain being strengthened across different inverse tau values avoiding a steering response. The a_0 parameter did not show much difference across conditions while, in general, the slow lead vehicle has larger slope values. Larger slopes indicate a threshold that collapsed quickly, which will prompt a faster takeover response. The takeover time distributions in Figure 19 had shown that the slow lead vehicle events were skewed towards shorter takeover times, which is in accordance with the slope parameter's distribution. This makes sense since the initial looming evidence in the scene and even when drivers took over (especially in larger time budgets) were typically smaller in comparison to the reveal stopped vehicle event.

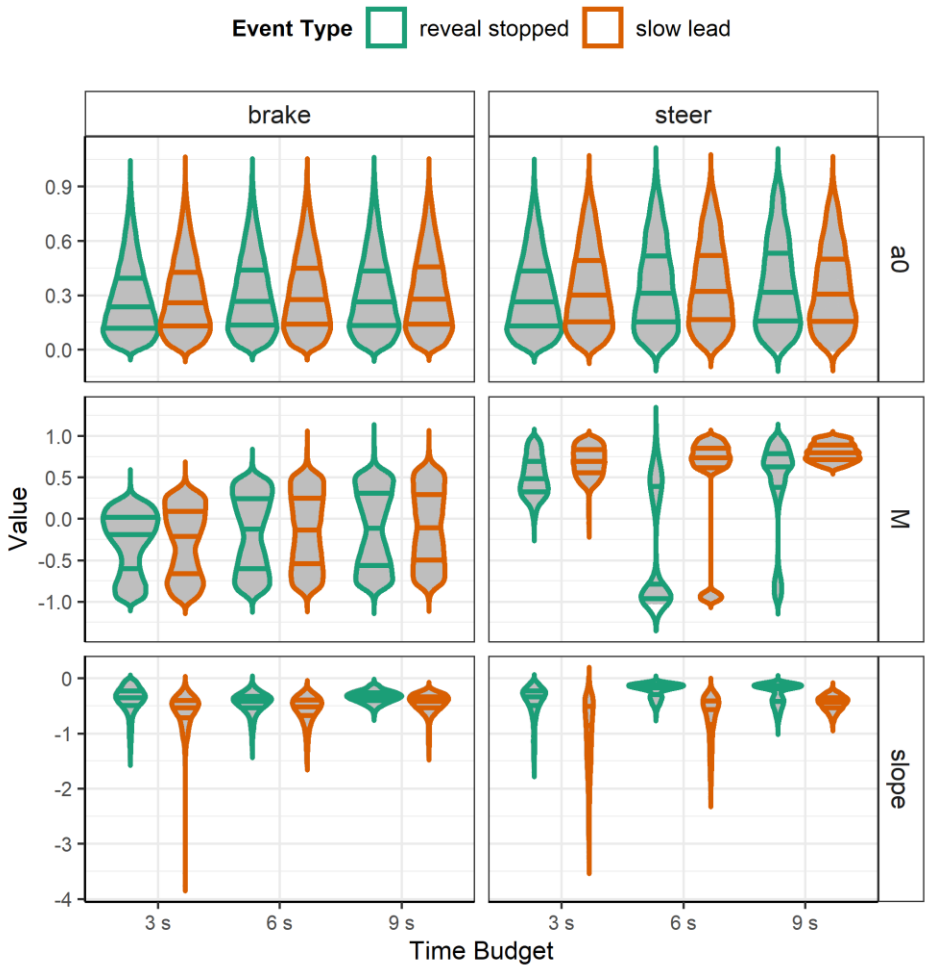


Figure 29. Violin plots of the posterior parameter distributions across conditions and takeover control types which was one of the model's outputs.

Figure 30. shows the potential effect of parameter a_0, on the evidence accumulation process while the other two parameters M and slope, are held constant at zero. If we consider a_0 to reflect drivers' initial situation awareness when the takeover request is issued, we would have expected higher levels of situation awareness to lead to faster takeovers. As anticipated, with a_0 increasing the takeover times decreases. However, the interaction between the three parameters, along with the sloppiness, makes any interpretation of how the experimental conditions affect the parameters and accumulation process difficult.

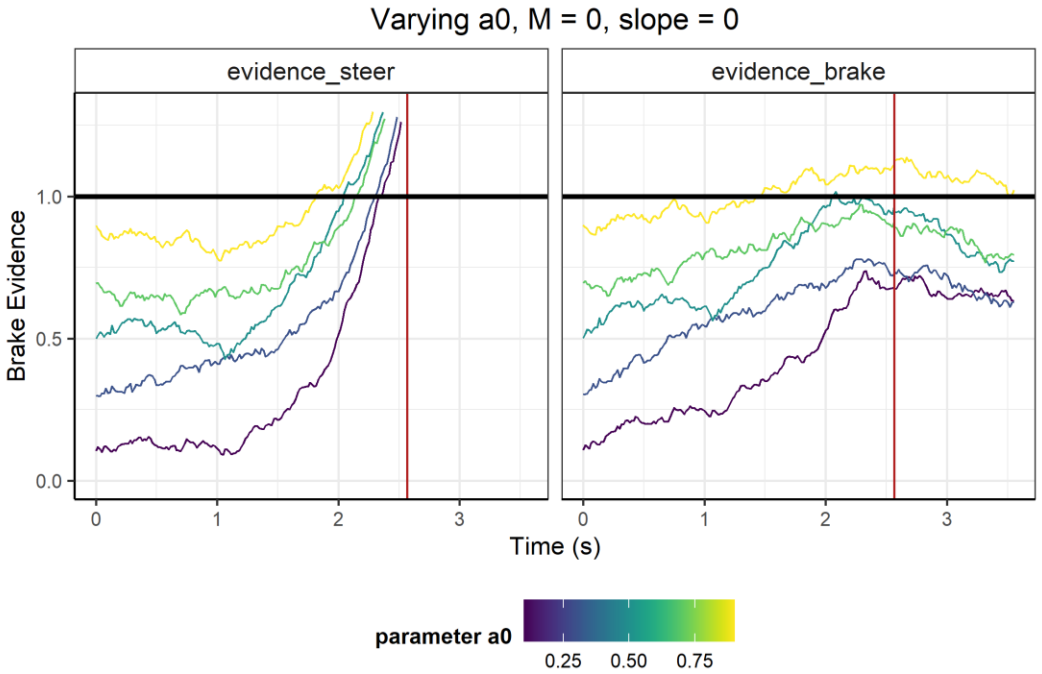


Figure 30. Exploring the effect of varying a0 parameter values on the evidence accumulation process. The red vertical line is this observations' actual takeover time.

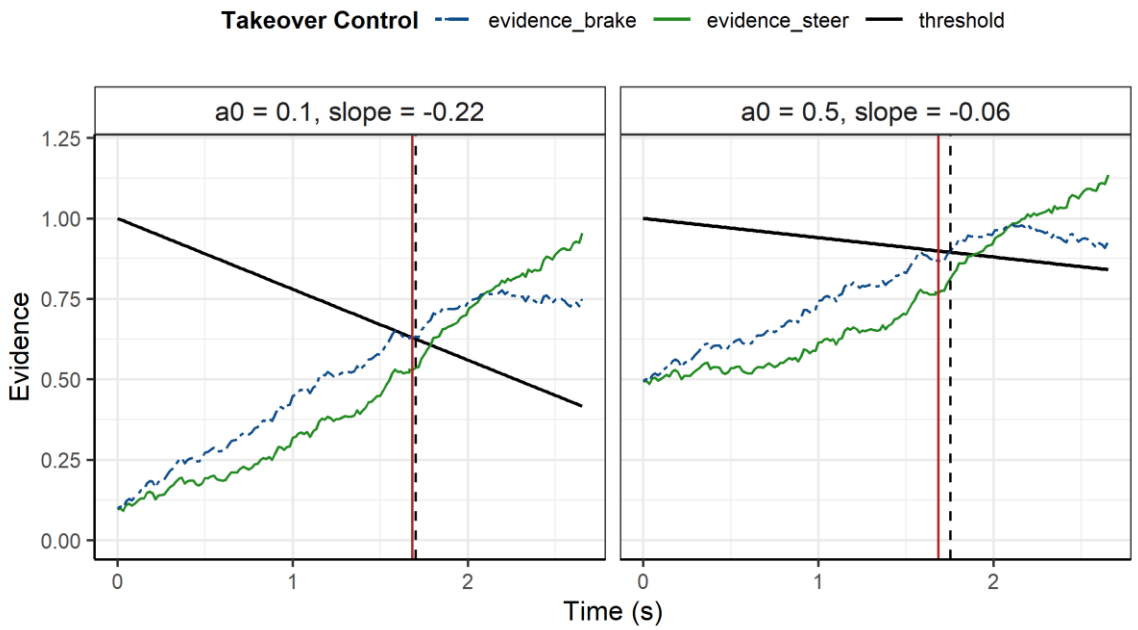


Figure 31. Example of how different parameter combinations produce similar summary statistics (takeover time, control choice).

Figure 31 further illustrates the issue of sloppiness with the parameter estimation process. In Figure 31, a single observation (same summary statistics; takeover time and control choice) was

simulated using two different sets of parameters. In these simulations, parameter M was held constant while a_0 and slope varied. If we were to consider a_0 as a proxy for situation awareness at the start of the event then fitting a model using only takeover time and control choice as summary statistics, we could have two different conclusions regarding initial situation awareness that are consistent with the data. This can be explained by the greater slope for the left plot of Figure 31 compensating for the smaller a_0 value, while the right plot shows the opposite.

4.4 Discussion

To ensure the safety of SAE Level 3 automated vehicles on the road, they need to be tested and validated extensively. Virtual simulations that include validated models of human behavior will allow us to explore the interaction between different design choices on drivers' takeover behavior across a variety of traffic situations (Markkula, Romano, et al., 2018). Given that takeover time is the most frequently used measure of drivers' takeover performance (Zhang et al., 2019), being able to estimate drivers' takeover time in different takeover scenarios can be very beneficial in evaluating design choices such as the time budget given to drivers.

To estimate drivers' takeover time, we must model drivers' perceptual decision making after they receive a takeover request. During this process, drivers need sufficient time to assess the situation (Mok et al., 2015), gain situation awareness (SA) and formulate a response to have a successful take over control and avoid a collision. Perceptual decision making can fall under the category of decisions traditionally known as "sequential sampling" or "bounded integrator models" in which sensory stimuli are sequentially sampled, and evidence is temporally integrated for different choice alternatives until a threshold (bound) is reached, marking the moment a decision is triggered (Cisek et al., 2009; Evans & Wagenmakers, 2019). Exploring the past 50 years of research on evidence accumulation models, the threshold has traditionally been held constant, reflecting a fixed level of caution during the decision process. However, more recent studies are pointing to the need to role of temporal modulation of caution or a sense of urgency during decision-making (Evans et al., 2020). In this chapter, we successfully implemented an evidence accumulation model with two separate accumulators for each decision alternative. Using a linearly collapsing threshold with dynamic evidence changing over time (looming prediction error based on inverse tau), we were able to simulate drivers' takeover time distributions and control choice across different experimental conditions.

Exploring the data, we realized that the effect of an impending deadline after receiving a warning becomes even more relevant in shorter takeover times that have negligible looming. The drift rate is related to people's task ability and the task's difficulty level (Evans & Wagenmakers, 2019). Therefore, simply increasing the drift rate to compensate for small looming evidence values would not be theoretically plausible. On the other hand, with minimal looming evidence accumulating and a fixed threshold, especially in the longer time budget conditions, we would expect to have longer takeover times because the looming evidence would have to grow over time. The data contradict this statement, and in some cases in the longer time budget condition, drivers resumed manual control even before the looming signal surpassed the threshold of when looming becomes detectable by humans at 0.0036 rad/s, which is (Lamble et al., 1999; Morando et al., 2016; Summala et al., 1998). This points to the need to model the effect of the increasing urgency in the scenario due to the deadline associated with the automated system ceding control after the time budget is exhausted.

Examining the parameter's posterior distributions, we did not find obvious differences across conditions. Approaches like the ABC parameter estimation method applied in this chapter rely on a sparse account of the latent process since the evidence accumulation is not directly observable. We had to constrain the properties of those intermediaries of the evidence accumulation process using input/output data alone (Holmes & Trueblood, 2018). In addition, using approximate methods, such as ABC, can exacerbate the sloppiness. Therefore, it is recommended not to use the posterior parameter distributions to make inferences about the effect of different experimental conditions since, due to the lack of proper constraints, a wide range of parameters would simulate similar takeover times due to sloppiness. Bayesian parameter estimation results are most suitable for comparing models.

Exploring the fit of the model by comparing the simulated versus observed takeover time distributions across different experimental conditions, we realized that the simulated takeover time distributions for the reveal stopped vehicle event tends to be skewed towards shorter takeover times in comparison to the observed distribution. The slow lead vehicle event showed a much better fit relative to the revealed stopped vehicle event, which might be explained by the details involved in these two events. From a high-level perspective, these two events are similar, with both requiring the driver to avoid a rear-end collision with a lead vehicle. However, in the slow lead vehicle event, upon receiving the takeover request, the hazard in the environment is

either visually salient or becomes salient gradually while in the other event category, the stopped vehicle is suddenly revealed, surprising the driver. It could be hypothesized that in the reveal stopped vehicle event, upon receiving the warning and looking back on the road, drivers are not sure about the situation or have a false sense of safety because they expect the lead vehicle to maintain its speed. When the lead vehicle changes lanes and the stopped car becomes visible, this change of stimulus is not considered in the current model setup except through the steep rise in looming. Future work could explore an additional parameter in the model, reflecting the delay in drivers' cognitive processes for encoding and incorporating the new stimulus after the surprising change happens. This delay could improve the model fit for the reveal stopped vehicle event, which was skewed towards shorter takeover times (Holmes et al., 2016). In addition, with a perfect model, we would have no variation in parameters across conditions since any dependence undermines the generalizability of the model. As a continuation of this work, we can explore whether the lack of change in the model parameters like a_0 is actually from issues such as sloppiness and the need for an improved model with additional parameters like the stimulus delay, or if we can use a constant set of parameters to replicate takeover time and control choice across a variety of conditions.

4.5 Conclusion

Processing information from the surroundings and integrating it into a coherent image that can guide safe behavior is a critical aspect of driving, specifically during a takeover situation. Understanding the underlying cognitive process of the drivers' decision making during a takeover can reveal how drivers balance the tradeoff between speed and accuracy. Given a short time buffer, humans can increase the speed of their decision-making process, but this usually comes at the cost of lower precision (Dambacher & Hübner, 2014).

In this chapter, we modeled the speed component (i.e., takeover time) of this speed-accuracy tradeoff that happens during a takeover. We applied an evidence accumulation model to simulate drivers' takeover time and control choice. The evidence accumulation model consisted of a noisy accumulator for each control choice alternative with looming prediction error based on inverse tau being incorporated into the model as a dynamic source of evidence. The model also included a linearly collapsing threshold to simulate the effect of the takeover request warning. To the best of our knowledge, this model introduces two main additions to the current state of the literature

on modeling driver behavior. First, it validated a model of choice-reaction time with separate accumulators for each control choice using empirical data, and second, it modeled drivers' response to takeover requests and the threat of an impending deadline through a collapsing threshold.

The following chapter will explore the second component of the speed-accuracy tradeoff, which is the quality of drivers' takeover control maneuvers and assess whether the tails of drivers' takeover time distributions lead to a specific trend in the quality of their control response.

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5 Chapter 5: Measuring and Modeling the Quality of Drivers' Takeover Performance

5.1 Introduction

The previous two chapters were focused on exploring drivers' takeover time across different time budgets, levels of visual demand, and event types while also modeling the perceptual decision-making process that led to drivers' takeover time and control choice. Given the dynamic aspect of a takeover scenario, we know that delayed takeover times are equal to the situation becoming more critical. Time pressure has always been a critical component in different decision-making contexts; specifically, one of its most established outcomes is the speed-accuracy trade-off (SAT) (Katsimpokis et al., 2020). According to SAT, increased accuracy comes at the expense of delayed response times, while quick decisions are more likely to be erroneous (Schouten & Bekker, 1967; Wickelgren, 1977). This introduces a different side to the argument on takeover time; while delayed takeover times can result in critical situations, speedy takeover times have the risk of inaccurate control that could also lead to critical situations.

Of the different measures that could assess drivers' takeover response, a meta-analysis of 93 studies of takeover behavior with SAE Level 2 automation or higher, by Zhang et al., stated that "takeover time (TOT), defined as the time that drivers take to resume control from automated driving after a critical event in the environment or after having received a TOR, appears to be the most frequently used measure in the literature" (Zhang et al., 2019, p. 3). Having an estimate of drivers' takeover time is beneficial in assessing drivers' response capacity and in evaluating warning design considerations such as time budget (Favarò et al., 2019). However, takeover time should not be the only measure of drivers' understanding of the situation and their readiness to take over (Louw, Kountouriotis, et al., 2015). Even though the timing of a takeover is crucial, simply resuming manual control does not guarantee that the driver will have a safe and successful takeover (Louw, Markkula, et al., 2017).

With conventional vehicles, fast control responses to dangerous situations can be risky, such as overcompensating to a lane departure resulting in a rollover or quickly responding to a deer in the road by swerving off the road (Sullivan, 2011). This can also be extended to takeover situations leading to risky and unsafe takeover behaviors including, erratic steering or brake input, abrupt lane changes, and colliding with surrounding traffic (Favarò et al., 2019).

After a driver resumes manual control, follow up questions can be raised, such as did the driver have to resort to erratic braking/steering/throttle usage? Was the driver able to avoid surrounding traffic or an abrupt lane change? Such questions suggest the importance of studying the quality of drivers' takeover performance (Favarò et al., 2019). Assessing the quality of drivers' vehicle control response, in combination with the takeover time, can provide a more comprehensive measure of the drivers' takeover performance.

The quality of the drivers' takeover responses has been examined through measures such as minimum time headway to an obstacle, minimum Time to Collision (TTC), (C. Gold et al., 2013; Louw, Kountouriotis, et al., 2015), which Hayward (1972) defined as "the time required for two vehicles to collide if they continue at their present speed and on the same path" (Hayward, 1972, p. 27), occurred collisions (Radlmayr et al., 2014), and maximum accelerations during vehicle control in the transition (C. Gold et al., 2013; Hergeth et al., 2016; Zeeb et al., 2015). Other measures that have been used to evaluate the quality of drivers' lateral and longitudinal vehicle control include the maximum and minimum accelerations, lateral deviations, lane departures, and steering wheel reversals (Louw et al., 2019). The quality of drivers' takeover behavior can also be judged in terms of drivers' evasive maneuvers (i.e., a fast and effective maneuver to avoid colliding with an obstacle). Takeover studies have shown that, similar to evasive control actions in manual driving, which could lead to an overshoot of the target lane, evasive maneuvers after automation use can also result in an overshoot, followed by poorly damped or oscillating stabilization (Happee et al., 2017). A measure such as TTC, though intuitive in critical takeover scenarios requiring braking and capturing the braking performance, is poorly suited to more complicated evasive maneuvers where steering inputs constantly change the projected path of the vehicle (Happee et al., 2017). TTC cannot provide sufficient information on steering behavior, so other measures such as Time to Line Crossing (TLC) or Standard Deviation of Lateral Position (SDLP) have been introduced. The downside of such metrics is that they are more appropriate for gradual lane and road departures, rather than rapid evasive maneuvers in which TLC and SDLP change quickly (Happee et al., 2017). The speed of the vehicle during the takeover process is another potential contributing factor to the take-over quality. A study by Favaro et al. (2019) suggests that establishing operational thresholds for speed could reduce the maximum drift and subsequent unintentional lane departures ensuring a more controlled takeover (Favarò et al., 2019).

A limitation with current measures for evaluating the quality of a takeover response is that they are often constrained to specific takeover events. For instance, in takeover scenarios involving a lane departure, the vehicle is already at an extreme lane deviation, making maximum lane deviation an inappropriate measure. In situations that do not involve a potential collision with an obstacle, lane departures might be more useful than minimum time to collision (Louw et al., 2019). In addition, how these events interact with different design and situational factors such as time budget or traffic density has not been fully understood. For example, in scenarios that have higher traffic density, drivers might face more uncertainty leading to increased caution. Gold et al. (2018), assessed the effect of situational and driver-related factors including, traffic density, time-budget, repetition, the current driving lane, non-driving-related task, and driver's age on drivers' takeover time, time to collision, brake application, and crash probability in a takeover scenario involving two vehicles blocking the vehicle's current lane. They found that traffic density, time budget, and repetition had a strong influence on drivers' takeover performance (C. Gold et al., 2018), but they were limited to a specific event type.

In this study, we will be exploring the interaction between takeover time and takeover performance metrics. Specifically, we are expanding our notion of quality to encompass not only safety but also the experience of the takeover. For example, if the driver were to suddenly brake and stop the vehicle in response to a takeover request, even though it was with the intention to avoid a collision, abruptly braking could make the driver and other passengers uncomfortable. This could decrease the passenger's confidence in the system to provide the driver with an effective warning through its interface, negatively impacting their trust and future adoption of such technology (Ghazizadeh et al., 2012). Therefore, we are proposing to evaluate the safety and comfort of the takeover in tandem.

As in Chapter 4, we will focus on two events, the slow lead vehicle and reveal stopped vehicle for this analysis. From a high-level perspective, these two events are similar (a vehicle blocking the road), but the details of how each event evolves will differ, with one becoming visible suddenly and surprisingly. As mentioned, studies of takeover performance have lacked event type diversity, and our intention for this analysis was to assess some of the underlying features in specific events that lead to different takeover qualities that can be extended to various event types. In addition, like Chapter 4 that was focused on creating models of driver behavior, we will attempt to model drivers' post takeover lateral control maneuvers. Using these simulated

profiles, summary statistics that capture the quality of drivers' lateral control responses can be extracted across a variety of takeover scenarios. With validated models of drivers' takeover control responses, we can simulate the safety outcomes of different design choices beyond the limited number of event types that can be explored using naturalistic or simulator studies.

5.2 Methods

5.2.1 Experimental Design

Data were collected using the NADS-1 high-fidelity ground vehicle driving simulator at the National Advanced Driving Simulator (NADS) at the University of Iowa. The experiment was a 3 (time budget) x 2 (visual demand) x 5 (event type) mixed factorial design and involved driving in a simulated conditionally automated vehicle (SAE Level 3). Time budget had three levels, including short (3 s), medium (6 s), and long (9 s). Visual demand, which referred to traffic congestion in the scenario had two levels, low and high. The five events included a lane departure failure, reveal stopped vehicle, slow lead vehicle, a pedestrian crossing in a work zone, and work zone. Visual demand and event type were varied as within-subject variables, while time budget was a between-subject variable.

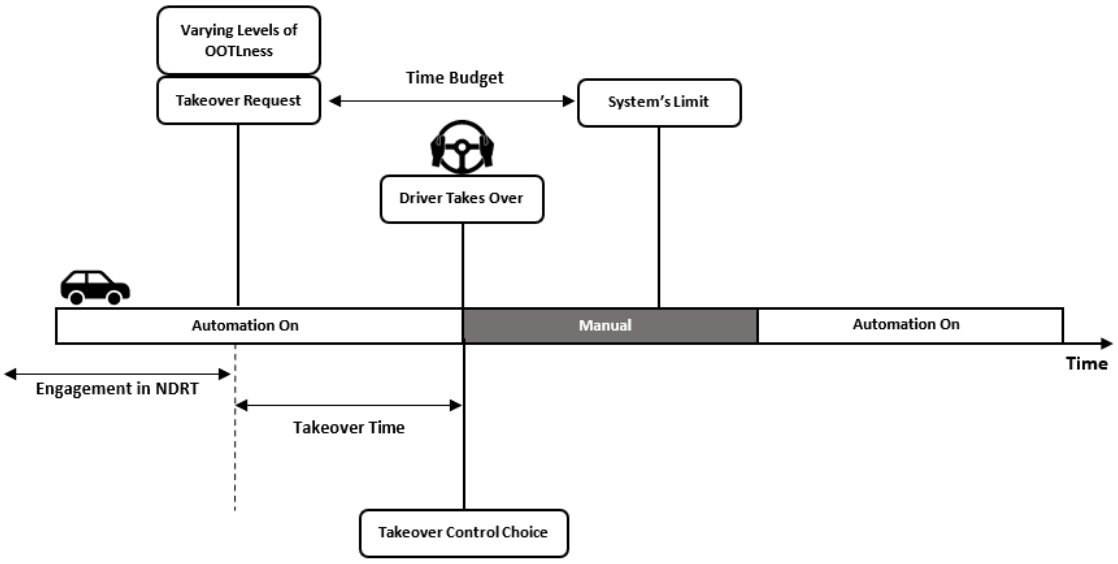

Figure 32. Timeline of the takeover process.

For this analysis, like Chapter 4, we will only focus on two of the five events: the slow lead vehicle and reveal stopped vehicle events. These two events are similar; however, the dynamics of how they evolve are different, providing an opportunity to explore the effect of the surprise

coming from when the hazard which was initially obscured after the takeover request suddenly becomes visible. The findings from this analysis could be extended to other event types that have a similar structure like a pedestrian suddenly entering the road from behind a parked vehicle.

Figure 32 shows the timeline of the takeover process and segments before and after the takeover request. As seen in Figure 32, drivers were asked to engage in non-driving tasks (NDRT) to remove their eyes from the road while the vehicle was in automated mode. The task was a trivia game, including different topics, which allowed participants to select a topic based on their interests. The trivia task was performed on a tablet.

The modality of the takeover request was consistent across all events and was a combination of an auditory warning with a visual TOR on the dashboard. Drivers would activate automation and reengage in the trivia task after each takeover event.

Seventy-two participants, evenly divided by age (18–40 and 41–61 years old) and sex were initially recruited. Four subjects were replaced due to simulator issues (n = 1), and lack of engagement with the secondary task (n = 3), increasing the total number of participants to 76. A more detailed explanation of the experiment can be found in (DinparastDjadid et al., 2019).

5.2.2 Models of Lateral Control

The two-point visual control model of steering developed by Salvucci and Gray (2004) predicts steering control based on drivers' perceptual orientation using two salient visual reference points on the roadway: a near point and a far point. The near point is used to monitor the position of the vehicle within the lane boundaries, and to maintain lateral position and stability. On the other hand, the far point term adds stability to the model by adding a predictive steering element to compensate for the roadway ahead (Salvucci & Gray, 2004). The near point angle is defined using a fixed distance ahead, and the visual angle from the driver to this point indicates the distance of the vehicle from the center of the lane. The far point is defined by one of three options: 1) a vanishing point on a straight road, usually calculated based on a time headway, 2) the tangent point of an approaching curve, and 3) a lead vehicle or a specific target on the roadway. This model uses the rate of change of the steering angle instead of the steering angle (Salvucci & Gray, 2004), with Equation 7 being the discrete form of the two-point visual control model.

$$\Delta\varphi = k_f \Delta\theta_f + k_n \Delta\theta_n + k_l \theta_n \Delta t \qquad \text{Equation 7}$$

In Equation 7, $\Delta\varphi$, is the change in steering wheel angle, θ_f the far point angle, θ_n, the near point angle, with k_f and k_n being the proportional gains while k_l is the integral gain of the near point angle. Moreover, Δt, can either be a constant for periodic updates of the steering output or it could a varying to account for intermittent updates to the steering wheel angle output (Salvucci & Gray, 2004). In this study, Equation 7 has been adjusted to include an additional parameter α, as reflected in Equation 8. This parameter reflects the neuromuscular lag and the physics of the human arm movement, which limits the frequency of steering corrections and extreme movements since the current steering wheel position depends on its previous value.

$$\Delta\varphi_{t_i} = -(k_f \Delta\theta_{f_{t_i}} + k_n \Delta\theta_{n_{t_i}} + k_l \theta_{n_{t_i}} \Delta t) + \alpha\varphi_{(t_{i-1})} \qquad \text{Equation 8}$$

According to Equation 8, drivers' steering behavior is a weighted combination of the near and far point angles along with the previous steering wheel angle. $\Delta\varphi_{t_i}$ is the current steering input, $\Delta\theta_{f_{t_i}}$ and $\Delta\theta_{n_{t_i}}$ are the change in the far and near point angles. $\theta_{n_{t_i}}$ is the current near point and $\varphi_{(t_{i-1})}$ is the steering wheel angle of the previous time step. k_f, k_n, k_l and α are the weights that need to be adjusted to replicate the human drivers' steering behavior.

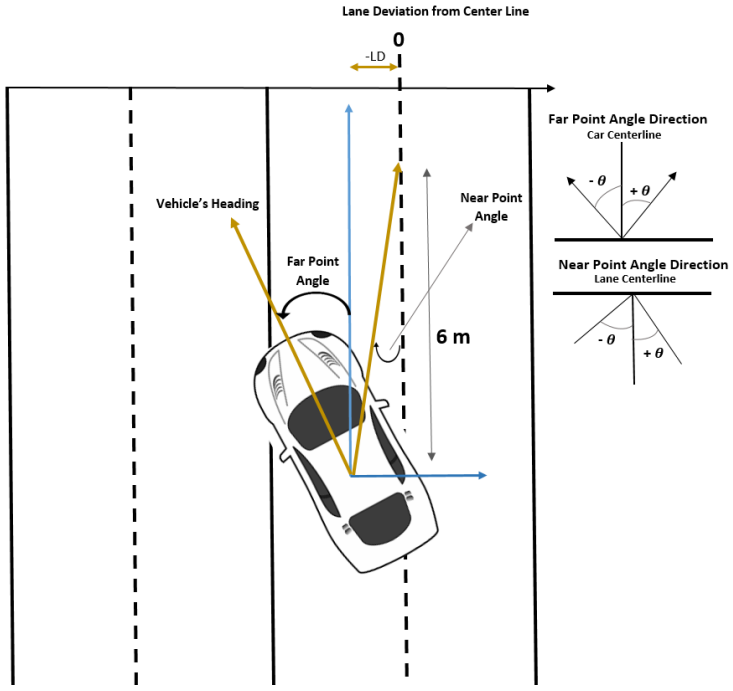

Figure 33. Depiction of the perceptual cues used to guide drivers' steering; near and far point angles.

In this modified model, shown in Figure 33, the near point angle is the angle between the vehicles' lane deviation from the center of the roadway and an offset six meters ahead of the vehicle on the centerline. The far point angle is the angle between the vehicles heading and the center of the roadway.

5.3 Results

Drivers' takeover time was defined as the time between the takeover request and when the driver initiated a control response. In this analysis, a control response consisted of either steering or braking. A response was categorized as steering if the steering wheel angle was greater than 3 degrees, and the steering rate was greater than 10 degrees per second. A brake response was recorded if the brake pedal press was greater than 3 lbf (DinparastDjadid et al., 2019). The takeover control response type was defined by the control action (steering or braking) that occurred first. It should be noted that there are alternatives beyond just steering and braking for the drivers' initial takeover control choice. For example, in some cases, braking and steering are performed in such close temporal proximity that their combination can be considered as one. At the same time, in some instances, drivers might accelerate to distance themselves from a potential threat. Following the analysis of Chapter 4 and to focus the modeling scope, we have limited the types of takeover control responses to either steering or braking especially since no one accelerated during their initial takeover response. Of the five takeover events in the original experimental design discussed in Chapter 3, we selected the slow lead vehicle, and the revealed stopped vehicle events, which led to 235 event combinations across the three different time budgets (3, 6, and 9 s) and two levels of visual demand (low, and high).

To analyze lateral post takeover behavior, we defined a time window. This time window had to extend an equal number of seconds after the time budget was exhausted to capture the interaction between the driver and the hazard in the environment (slow lead, reveal stopped vehicle) across a diverse range of takeover times. We considered 3 s after the time budget as the extended time window, so for example, if in a 6 s time budget, the driver had a 2 s takeover time, they still had 4 s left to the end of time budget, and we added an additional 3 s after the time budget was exhausted, leading to an analysis time window of 7 s. This will cause varying time windows, but capturing how drivers interacted with the hazard and the effect of longer takeover times on this interaction was the focus of this analysis. Prior to analyzing and modeling drivers' takeover

control behavior, examining the time series of drivers' speed, steering, and lane deviation profiles in each condition could provide useful insights and guide the subsequent sections.

Figure 34 shows the longitudinal component of drivers' takeover maneuvers using their speed profiles. The shorter time budgets seem to have had the largest drops in speed, with it reaching zero in some cases. This becomes more prevalent in the reveled stopped events in which both the amount and steepness of the speed drop tend to be more extreme compared to the slowing lead vehicle events.

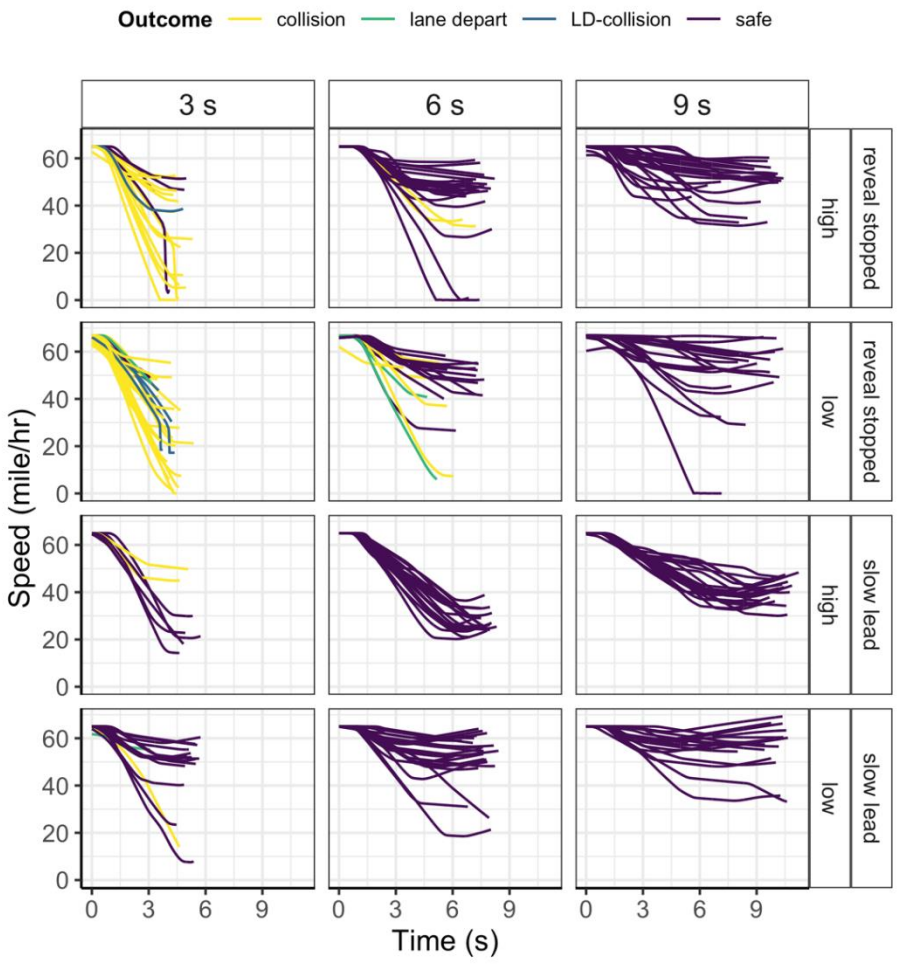

Figure 34. The vehicle's speed profile post takeover across different conditions. Time Budgets: 3, 6, and 9 s. Visual demand: low and high.

Assuming that drivers were distracted with the secondary task and out of the driving loop to a good degree, facing a driving scenario that is more congested because of the higher traffic density after the takeover request could cause higher uncertainty about possible control actions

(e.g., are the adjacent lanes open? is there a pedestrian crossing?). As a result, drivers might prefer to slow down to have more control over the vehicle and situation while buying more time to accumulate enough situation awareness. This is especially evident in comparing the high and low visual demand speed profiles for the 6 s time budget-slow lead vehicle event in Figure 34.

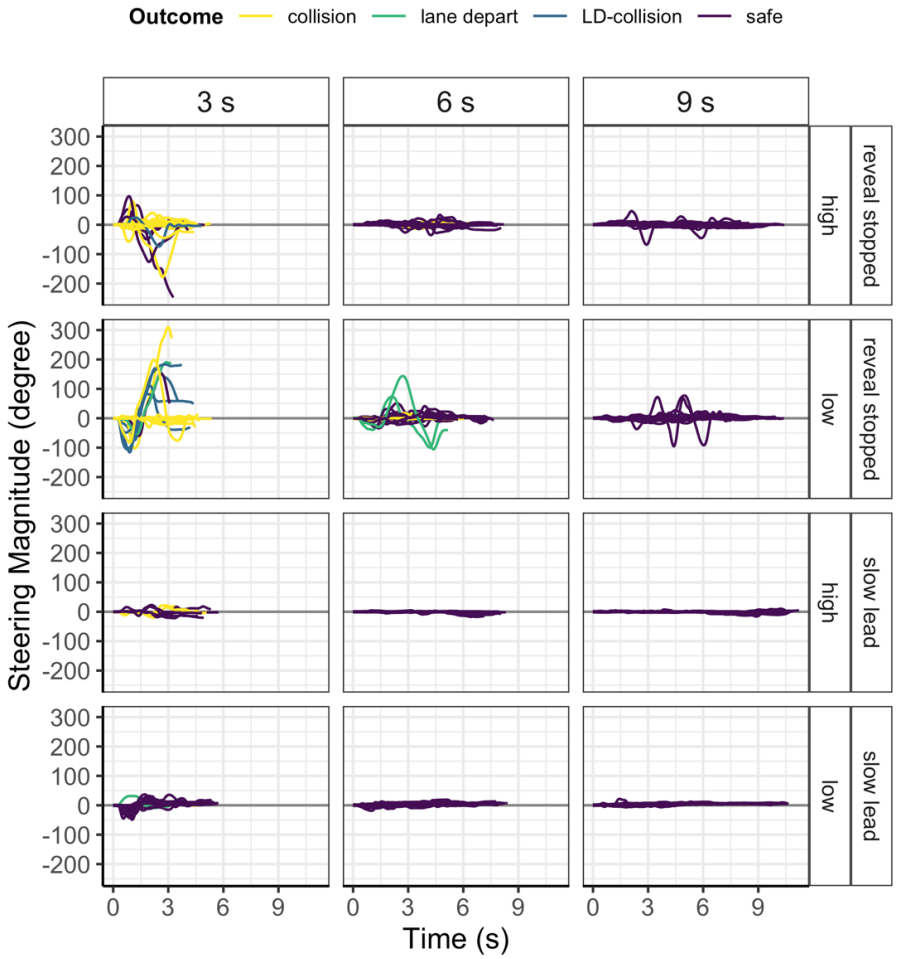

Figure 35. Drivers' steering wheel control input post takeover across different conditions. Time Budgets: 3, 6, and 9 s - Visual demand: low and high.

Figure 35 shows the steering wheel angle over time after drivers resumed manual control. Each cell shows the steering profiles for the participants in that experimental condition. This figure shows the temporal distribution of factors that could have led to the failed takeovers. On first notice, it seems like most failed takeovers occurred in the smallest time budget for the revealed stopped vehicle event. The steering peaks and valleys for the shorter time budgets are much larger in magnitude and for the revealed stopped event in comparison to the slowing lead vehicle event. With the sudden appearance of the revealed stopped car, drivers will have to suddenly

incorporate this new stream of information (i.e., looming prediction error) into their evidence accumulation process. Given the steep increase in time to collision after the reveal of the stopped vehicle, drivers might either delay their takeover response or have low-quality takeovers.

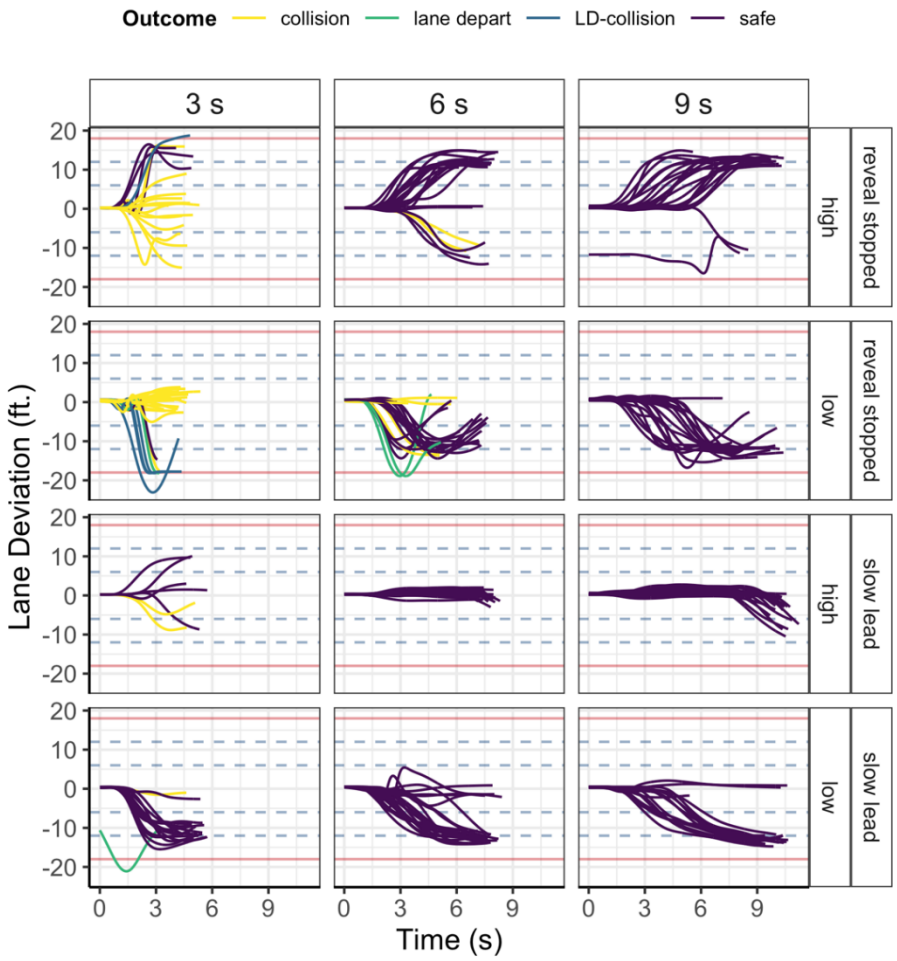

Figure 36. The vehicle's lane deviation profile post takeover across different conditions. Time Budgets: 3, 6, and 9 s. Visual demand: low and high.

Larger steering inputs alone are not always indicative of a hasty and poor-quality takeover because the driver might need to perform a lane change suddenly. Linking the steering input to the lane position of the vehicle and assessing whether it led to extreme lane deviation or even a road departure provides a more comprehensive view of the drivers' takeover behavior. The horizontal lines in Figure 36 are marked at 0, ±6, ±12, and ±18 with 0 and ±12 being the center of the middle, left and right lanes, and ±6 and ±18 the boundaries of those lanes. Given that ±18 is also the road's boundary, it has been depicted with solid red, differentiating it from the other

landmark positions. Based on Figure 36, most drivers changed lanes in response to the hazard after resuming manual control. After a lane change from the middle lane, it is expected that drivers' settle their vehicle somewhere around ±12, which is what Figure 36 shows with the dark purple color indicating safe takeovers. Figure 36 also shows that many of the unsafe takeovers can be traced back to the left grids representing the 3 s time budget, which required drivers to act quickly. The unsuccessful takeovers, which are none purple colored lines, seem to be more prevalent in the reveal-stopped event than the slow lead vehicle event. Specifically, in the 3 s time budget, low visual demand, reveal stopped vehicle event panel it seems that all the collisions (yellow lines), happened because of the driver not being able to perform a timely lane change to avoid the stopped vehicle.

Figure 37 further confirms the notion that most drivers performed a lane change to avoid the hazard. It should be mentioned that Figure 37 is only reporting on safe takeovers that did not lead to a collision, road departure, or a combination of these. In addition, Figure 37 only includes the analysis window between the takeover time and three seconds after surpassing the time budget. Hence if a lane change happened after the extra three seconds, it is not covered in this analysis.

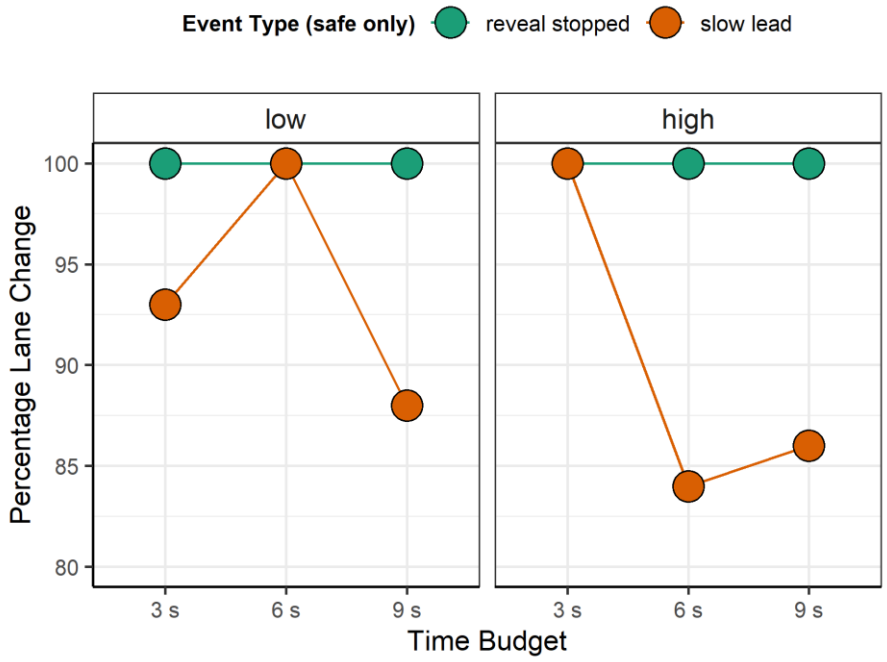

Figure 37. Percentage of lane change responses to a slowing or revealed stopped lead vehicle.

Knowing that most drivers resorted to a lane change to avoid the obstacle in their lane (slow lead or stopped vehicle), raises the question of when the steering maneuver responsible for the lane change was initiated. In Figure 38, the steering response in many cases is negligible and close to zero as the drivers' first takeover control choice. This is also visible in Figure 36, for which the lane deviations are centered around zero for the first few seconds. However, Figure 36 shows that later after the initial takeover response, some drivers executed a lane change to avoid the hazard in their lane. Figure 38 further affirms this theory by showing that braking was the most frequent initial takeover response for the two events in this analysis, explaining the initial tail in some of the steering responses in Figure 35.

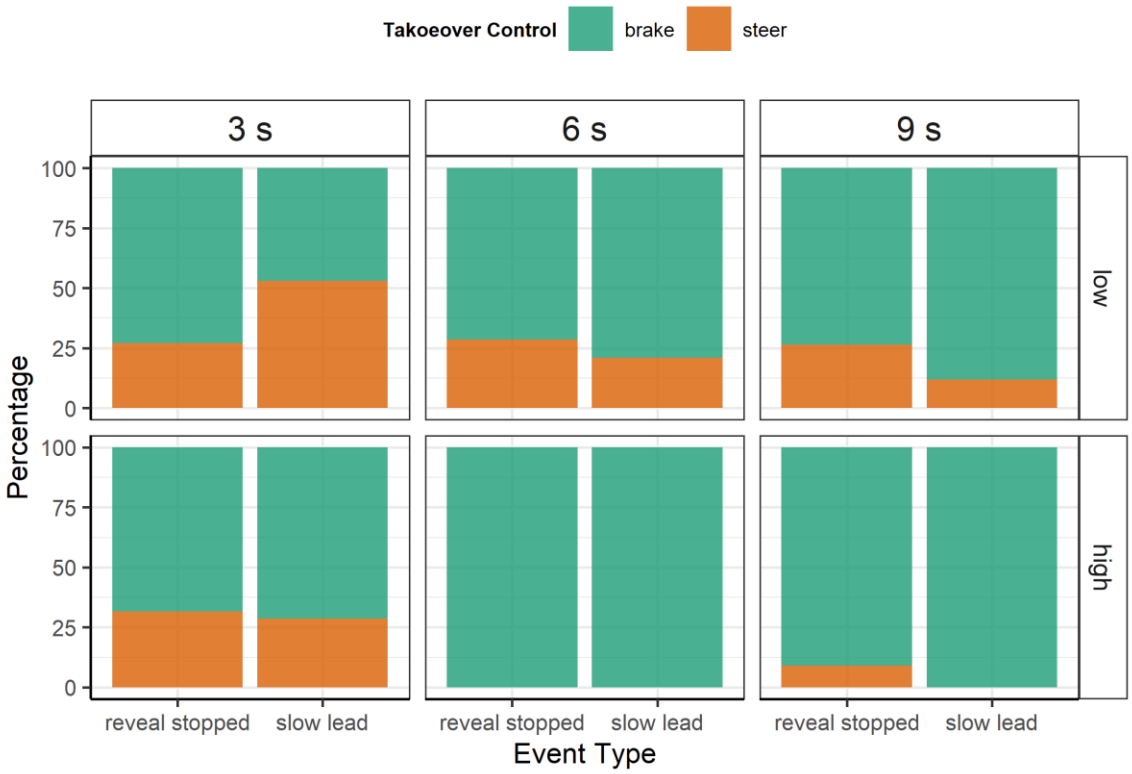

Figure 38. Frequency of braking versus steering as drivers' initial takeover response across different conditions. Time Budgets: 3, 6, and 9 s. Visual demand: low and high.

Based on the results from this section, it can be assumed that most drivers braked first, but later performed a lane change. This is particularly important for modeling drivers' lateral takeover behavior. Figure 39 provides an example of a drivers' steering profile after resuming manual control. Critical moments of the maneuver, such as when the lane change response was initiated or when the driver crossed the lane boundaries shown as red dashed horizontal lines, have been

indicated in Figure 39. It can be reasoned that drivers who have a tail of inactive steering at the beginning of their steering profile, were sampling information about the driving scene after their initial brake response. When the evidence in favor of a steering response crossed a threshold, a lateral control response was then triggered. In these situations, the initial takeover response might have heavily resulted from the takeover request warning. Afterward, drivers faced a steep rise in looming prediction error as they got closer to the end of the time budget, especially with the reveal stopped vehicle event. This sudden increase in time to collision could lead to poorly executed steering responses to avoid colliding with the stopped vehicle by performing a fast lane change.

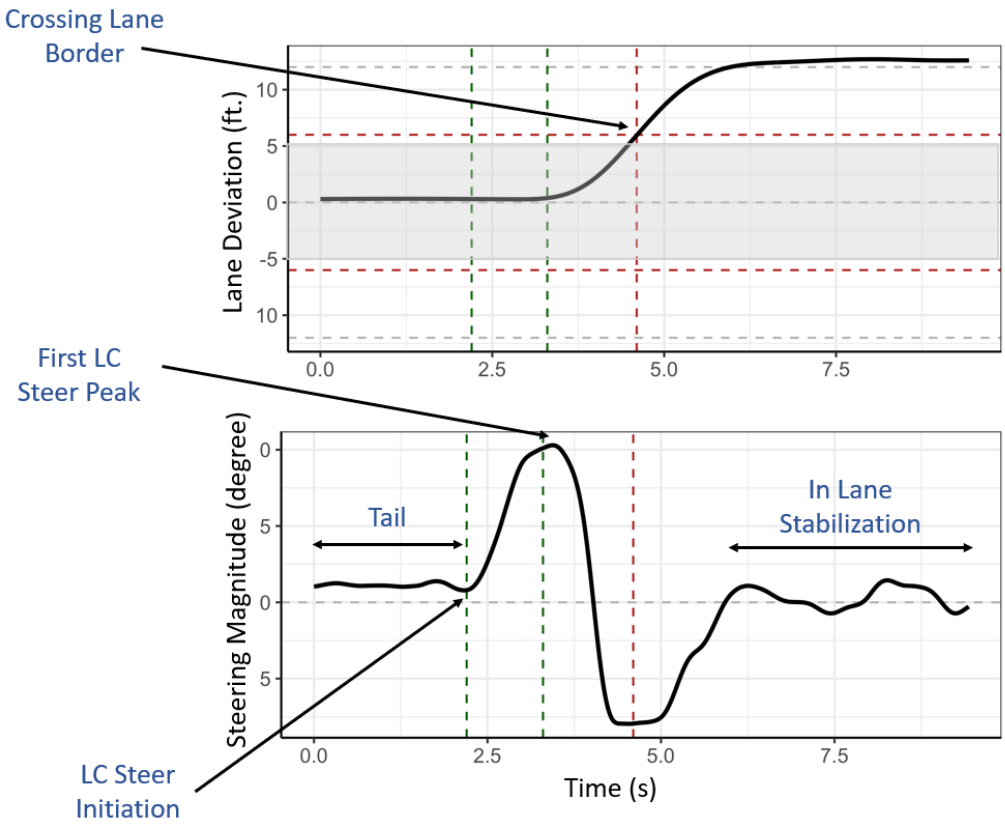

Figure 39. Example of drivers' steering profile post takeover.

Figure 40 shows the relationship between drivers' takeover time and the duration of their lane change (i.e., the time between when drivers' initiate a lane change steering response and them crossing their initial lane's boundary). According to Figure 40, with delayed takeover times, which involve more critical situations, drivers tend to execute faster lane changes. This seems to especially be the case for the reveal stopped vehicle event with the cluster of green dots in the

top left corner of each panel in Figure 40. Understanding such features of drivers 'steering responses could aid the modeling of drivers' lateral control responses.

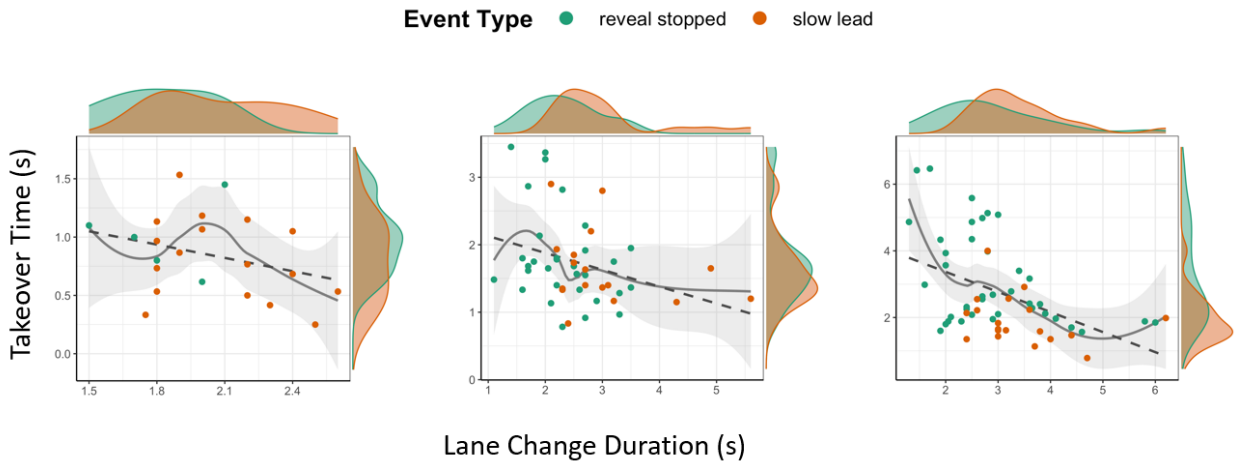

Figure 40. Drivers' takeover time vs. lane change duration for safe events that included a lane change in the window of analysis. From left to right is the 3, 6, and 9 s time budget.

5.3.1 Modeling Drivers' Lateral Takeover Control

In traditional models of drivers' lateral control like Equations 7 and 8 in the Methods section, the main inputs to the model are perceptual cues that are tied to lane deviation and heading angle. For example, Dinparastdjadid et al. (2018), who proposed Equation 8, validated their model against a dataset in which drivers were drifted to varying lane deviations and heading angles that required a steering correction. However, in the case of the slow lead vehicle and reveal stopped vehicle events, by design, when drivers resumed manual control, there was no lane or heading offset. This is further affirmed by Figure 36 in which there is close to zero lane deviation when drivers initiated a steering response, regardless of whether it was at the moment of the takeover or sometime after.

Figure 41 allows us to focus on two specific examples in which lane deviation is non-existent when drivers took over. The top row in Figure 41, is the drivers' steering control input, with the first two green dashed vertical lines showing when the lane change response was initiated and the subsequent first peak in steering. The left-side example is a case in which the steering response was initiated right after the driver resumed manual control while the right-side example has a gap of about 2.15 s between the takeover request (time zero) and when the steering maneuver was initiated (first green dashed vertical line in the right-side plot). It should be mentioned that an evidence accumulation process should model this gap and the triggering of the

steering response. The middle row in Figure 41, is the vehicle's lane deviation with the dashed horizontal red lines showing the lane boundaries for the current lane of the vehicle when the takeover request was issued. The dashed grey dashed horizontal lines at ± 12 are the center of the adjacent left and right lanes. The bottom row in Figure 41 is inverse tau over time, and the dashed red horizontal line is at 0.57 $s^{-1,}$ which is the suggested threshold for when drivers' initiate a control response (Xue et al., 2018).

Based on Figure 41, it can be concluded that the lane deviation in its current format is not guiding the initial steering response since it is close to zero but, it seems that looming prediction error can explain the steering response. To address the lack of far or near point angle errors, one explanation would be to somehow incorporate the looming prediction error into Equation 8. Initial attempts at exploring this option were unsuccessful but led to a promising explanation for modeling drivers' steering profile.

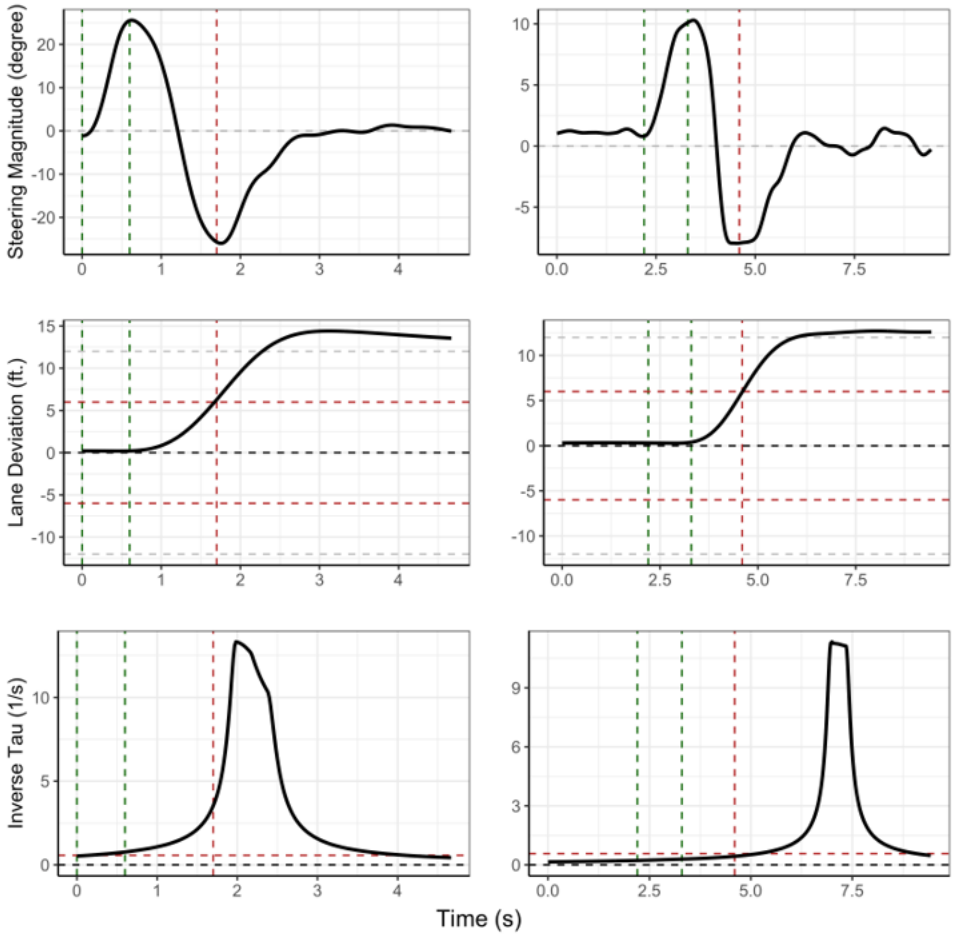

Figure 41. Examples of steering maneuvers and the corresponding kinematics of the vehicle.

In Figure 42 (a), we have a scenario in which the driver has both a non-zero far and near point angle error requiring corrective steering. The lane deviation is measured from the center of the vehicle's original lane and shown with a red two-sided arrow. The driver could cancel these errors by steering, centering the vehicle at the center of its current lane, with this location shown as a grey vehicle with the yellow "x". In Figure 42 (b), which is similar to the case of the takeover scenarios explored in this chapter, the black vehicle does not have any lane deviation from the center of its current lane, and its heading angle is zero. However, because of the growing looming prediction error, the driver decides to change lanes to avoid the lead vehicle. In this case, the lane deviation should be measured from the goal lane shown with a yellow "x". By doing so, now the vehicle has a large lane deviation that the driver must cancel in a limited amount of time before colliding with the lead vehicle. Applying this logic, the steering model in Equation 8 is still applicable, and the effect of the looming can be framed as triggering a switch in the reference lane center. The timing of when a steering response is triggered should be based on an evidence accumulation model, but the steering response's magnitude and profile can be modeled using the same cues as in Equation 8 (near point angle and far point angle), but with the appropriate reference lane center.

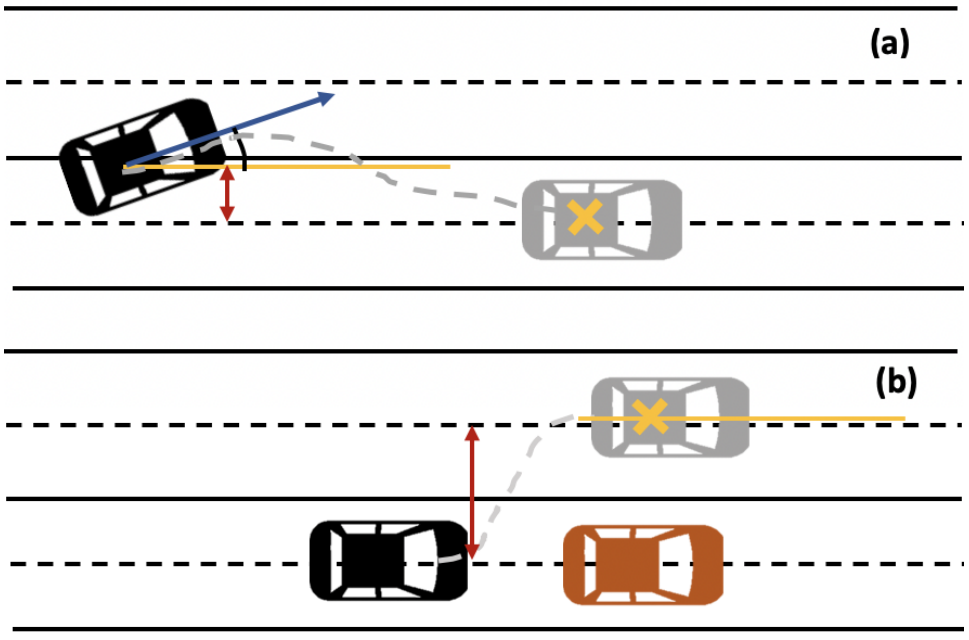

Figure 42. Two example scenarios prompting a steering response.

Following this logic, we revised the lane deviation from its original recording to a version that switches when a lane change response is triggered. In Figure 42, the top two rows are identical to the top two rows of Figure 41. In Figure 42's bottom row, however, we show the revised lane deviation signal in blue. Comparing the bottom left panel to the middle left panel, we can see how lane deviation changed from zero to about -11 ft., better aligning it with the high magnitude steering peak. The bottom right panel provides a clearer view of the switch in reference lane center. Initially, when there is no steering response, and the center of the original lane is the reference for calculating lane deviation. When a lane change decision is triggered, the corresponding switch in reference lane reflects the need to steer through the sudden jump in the lane deviation's magnitude going from zero to about -11 ft., shown in blue.

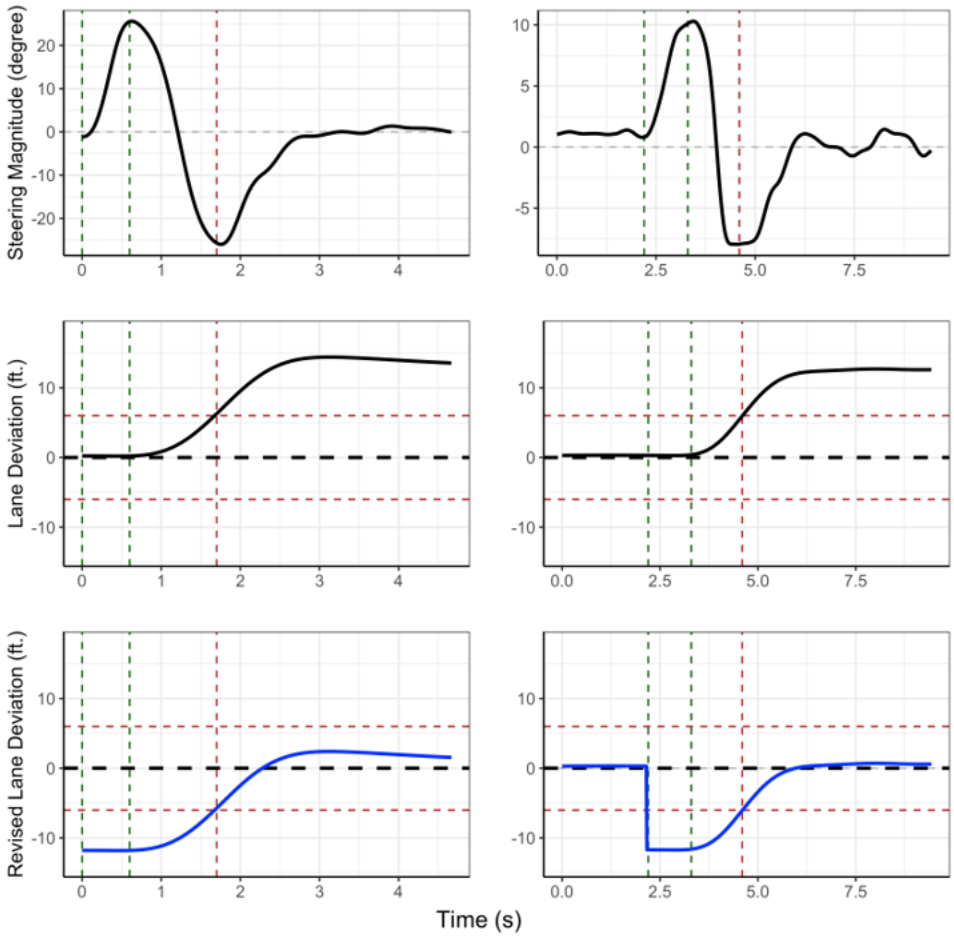

Figure 43. Examples of steering maneuvers and the revised lane deviation signal.

Using Equation 8 but with the switch in reference lane center for a lane change, we calculated the revised near point angles. We used the classical 2-D bicycle model as a simplified model for

vehicle dynamics. Using Approximate Bayesian Computation (ABC), we estimated the parameters of the model using the minimum, maximum steering values, the timing of the minimum, maximum steering values, and the mean and standard deviation of the steering profiles as the summary statistics. Figure 44 shows the results of the simulation for the two examples used throughout this section. It should be mentioned that for the right panel in Figure 44, we only model the steering maneuver and not the flat gap preceding it. As mentioned, that part should be simulated using an evidence accumulation model.

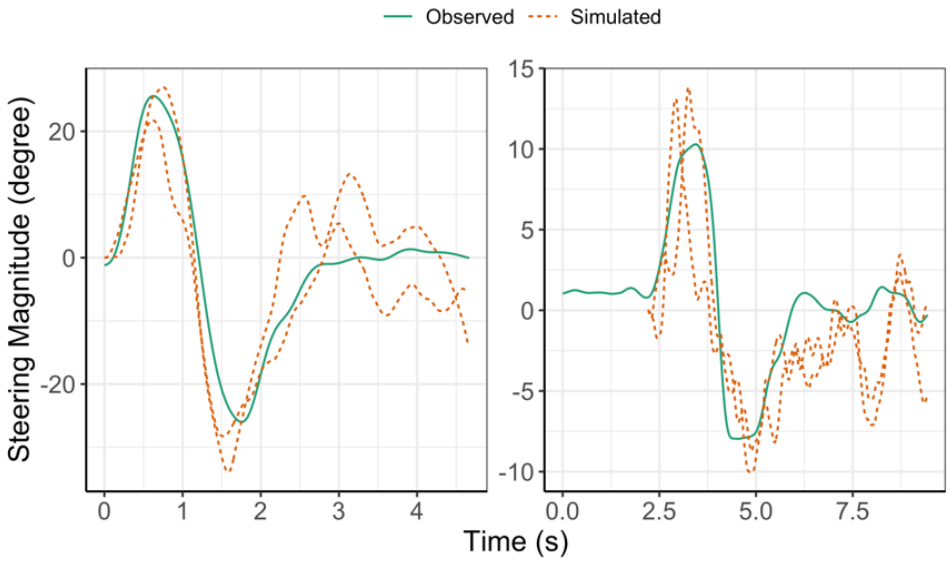

Figure 44. Examples of observed versus simulated steering responses.

5.3.2 Takeover Quality Metrics

Being able to model drivers' lateral control will allow us to evaluate drivers' lateral control across a variety of traffic conditions and in interaction with different design choices. Traditionally a simple metric to assess the quality of a drivers' takeover performance has been whether the response led to a collision, lane departure (lane depart in Figure 45), or a combination of both (LD-collision in Figure 45). Such measures are directly related to the safety of the drivers' takeover response. Figure 45 shows the frequency of each of these outcomes (safe, collision, lane depart, and LD-collision) across the different experimental conditions (time budget, visual demand, and event type, which was restricted to slow lead and revealed stopped vehicle events). The longer time budgets, especially the slow lead vehicle, in which the threat

was visible to the drivers, had safer takeover responses (100% safe). The shortest time budget of 3 s, especially for the sudden revealed vehicle event, led to the most unsuccessful takeovers.

Overall, based on Figure 45, as expected, drivers need a reasonable time budget to have a safe takeover response, and 3 s seems insufficient. Second, with the sudden revealed vehicle event, the threat associated with the takeover request is not initially visible. When the lead vehicle suddenly changes lanes revealing the stopped car, there is an element of surprise affecting the drivers' takeover response. This surprise could cause drivers to override their initial planned takeover response leading to a delayed or abrupt takeover, which might be unsafe.

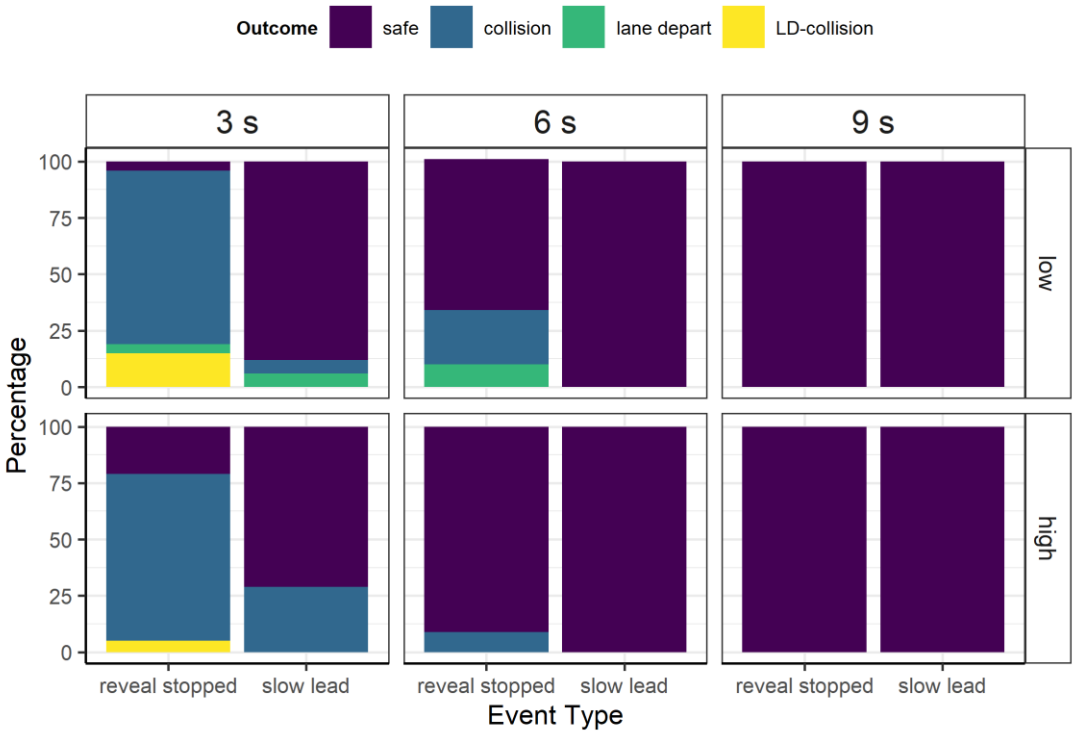

Figure 45. Frequency of successful and unsuccessful takeover responses across different conditions. Time Budgets: 3, 6, and 9 s - Visual demand: low and high.

Setting aside the success of a takeover, which is the most obvious metric of takeover quality, other potential metrics can describe both the safety and smoothness of drivers' takeover behavior in more detail. These metrics typically involve summary statistics of the time series of drivers' lateral and longitudinal control. According to Figure 38, most drivers seem to brake first when receiving a takeover request. Figure 38 only captures a snapshot of the whole takeover maneuver by simply showing the drivers' initial control choice while driving is an iterative process requiring us to broaden the analysis's time window. In this analysis specifically, we know that

even though most drivers started their takeovers by braking, it was followed by a lane change (lateral control response). Therefore, it only seems reasonable to evaluate both drivers' lateral and longitudinal control responses together. We propose four variables for measuring the quality of lateral and longitudinal control of drivers' takeover behavior: 1) minimum speed, 2) maximum inverse tau, 3) steering magnitude at the end of the analysis time window, and 4) the number of steering corrections. This last metric is a newly proposed quality measure for drivers' lateral control behavior, which will be discussed in the following section.

5.3.2.1 Lateral Quality Metrics: Chain corrections

With drivers' lateral control responses, some of the typical summary statistics to capture the characteristics of the steering profile include the maximum or minimum steering magnitude, the mean and standard deviation of the steering signal. Such measures could be used to measure the quality of drivers' lateral control. In this chapter, we will further explore the dynamics of the steering response using another metric based on the peaks and valleys of the steering profile. Dinparastdjadid et al. (2018) defined this measure as one-time versus chain corrections with Figure 46, providing an overview of this metric.

The premise of chain corrections is based on drivers' overshooting in their initial steering response leading to excessive steering corrections. In this dissertation, we have defined an overshoot as a peak or valley that is greater than 5 degrees and is followed by another peak or valley that is also greater than 5 degrees. In Figure 46, the dashed horizontal red lines are the ± 5 boundaries. An example of a smooth lateral control response would be Figure 46(a), in which there is a shallow valley at around 2 s, but the vehicle stays within the boundaries of ± 5, and there is not followed by another peak outside the boundaries.

In Figure 46(b) and (c), the chain corrections have been shown with a red dot. For example, in Figure 46(b), the first red dot is at a peak greater than 5 degrees and is followed by a valley outside the boundary. There is however, another peak at around 3 s, in Figure 46(b), but because it is not followed by a valley outside the boundary, it is not considered as a chain correction. In a one-time correction, which is a more stable steering response, the steering profile can have a peak or valley that has an absolute value greater than 5 degrees, but it should be followed by a stabilization period in which the steering wheel angle approaches zero, similar to the last peak in Figure 46(b).

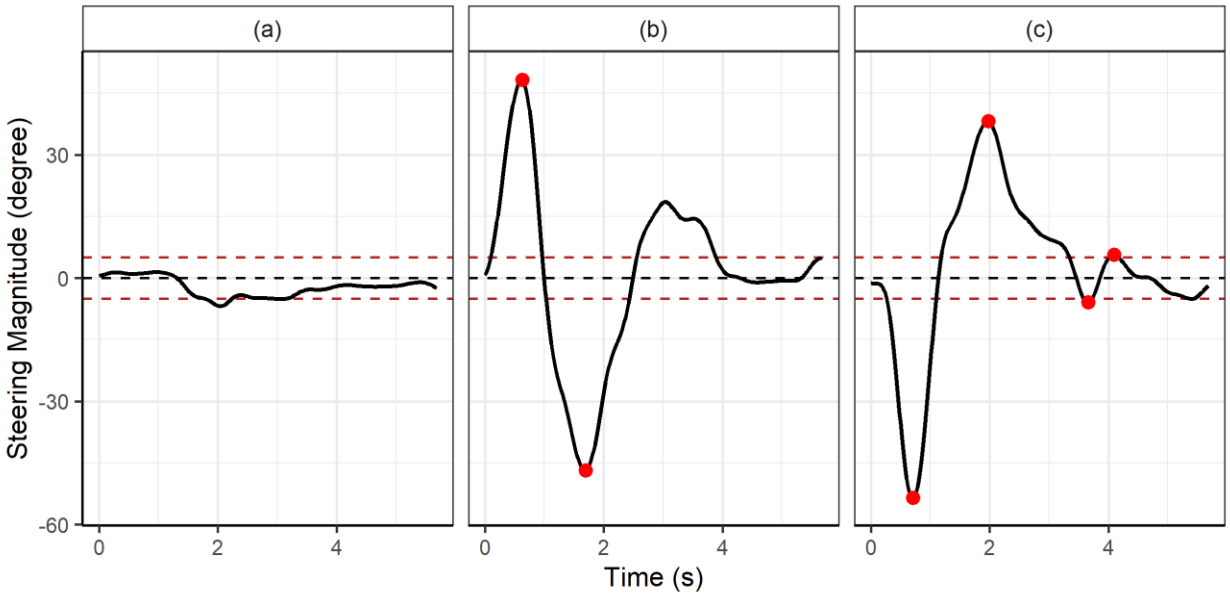

Figure 46. Example of smooth vs. chain steering maneuver. Red dots are chain corrections, and the horizontal red lines are the ±5 boundaries for a peak or valley to be considered as a chain response.

Chain corrections indicate that the driver overshot in their initial steering response, requiring a series of subsequent peaks and valleys to correct the initial excessive lateral input. Chain corrections can be indicative of an unstable takeover response, which has the potential to become a safety risk, making it a suitable metric to evaluate the quality of drivers' lateral takeover control. The peaks and valleys and when a steering response is initiated can also aid the modeling of steering profiles by defining the boundaries between when the driver switches from evidence accumulation to a steering response and modeling its magnitude.

When a steering control response is initiated, it can involve either a small steering adjustment or include a series of peaks and valleys, followed by a stabilization period. Regardless of the details of the steering profile, in a smooth takeover response, the steering wheel angle's value should stabilize to a value near zero soon after the driver resumes manual control. This would be the one-time correction, which, even with an initial high magnitude response, would be considered a stable maneuver relative to a steering profile with chain corrections. This is particularly important in lane change scenarios for which values such as maximum lane deviation or steering magnitude might not indicate a poor takeover. A lane change might require a larger steering input causing a bigger deviation from the center of the original lane, while still being a planned,

smooth, and successful maneuver. For the sake of comparison, we also included the absolute maximum steering value as another quality metric for lateral control.

5.3.2.2 Longitudinal Quality Metrics

In this analysis, maximum inverse tau and minimum speed during the window between the driver resuming manual control and 3 s after the hazard landmark was considered as metrics that reflect the quality of the drivers' longitudinal control behavior.

Inverse tau is similar to time to collision and shows the urgency of the situation with bigger inverse tau values indicating a higher degree of threat and urgency regarding a collision with a lead vehicle. With maximum inverse tau, we have a metric that directly assesses the urgency of the scenario and is closely tied to the safety of the takeover maneuver. On the other hand, the second longitudinal quality metric, the minimum speed is more focused on the smoothness of the takeover response rather than its safety and success. If a takeover response is timely and well thought through (assuming drivers were given a reasonable time budget for a takeover), the driver should not need to slam on the breaks to avoid a collision. A sudden drop in the vehicle's speed, especially when it goes to zero, can be traced back to either the driver or the automated system. If the automated system fails to warn the driver promptly, it can be expected that the driver would have to resort to sudden actions such as braking to avoid a collision. If the driver is given ample time and still has a sudden deceleration/brake response, it could be due to the drivers' lack of situation awareness to have a timely and deliberate response. We hypothesize that such sudden drops in speed can happen due to both a delayed response, leading to a vehicle being near the threat, or due to a quick and panicked takeover response that is executed poorly. In other words, as stated in the introduction of this chapter, both the timeliness and the quality of execution can be a culprit in an unsuccessful takeover response.

5.3.2.3 Quality Metrics and Takeover Time

In applying the four metrics to the data from drivers' takeover responses, the aim was to assess the quality of takeover behaviors across different experimental conditions while also examining the association between these metrics and drivers' takeover time. In other words, this section tries to answer whether these metrics complement takeover time.

In Figure 47, the color used for the filling of each point indicates the event type (slow lead vs. reveal stopped vehicle), while the shape and color of the point's border reflect the success of the

takeover response. A circle point with a black border means a safe takeover, and a diamond-shaped point indicates an unsuccessful takeover with the border color reflecting the type of failure. To better assess these metrics, and their association with takeover time, specific regions of interest were defined using the grey and red rectangles shown in Figure 47. The grey regions are supposed to represent clusters of takeover behavior that score well on both the timeliness of the takeover and the quality of its execution. The red rectangles describe clusters of behavior that capture the worst of both, which are delayed takeover times and poor quality. The height of these regions can change based on the specific combination of experimental conditions. For example, the 9 s time budget has an overall smaller absolute maximum steering value than the 3 s time budget, which is evident by the height of its red region being shorter.

Looking at the top row of Figure 47, the grey rectangle captures cases in which drivers responded quickly while maintaining their initial speed to a good degree. The red rectangle is the exact opposite, with a delayed response that led to a sudden drop in speed even as far as a full stop in response to the takeover request. With delayed responses, the silver lining should be that the driver was taking their time gathering information about the scene to make a more well-calibrated response. In the case of the minimum speed quality metric, this would mean the regions above the red rectangles. For minimum speed, the threshold is at 30 mph, for maximum inverse tau, ten $s^{-1,}$ for the number of steering corrections 1, and for absolute maximum steering wheel angle magnitude 30 degrees.

Figure 47 shows that the shortest time budget (3 s) accounts for most of the unsuccessful takeover responses. Specifically, in the right half of the plots in the 3 s time budget column, most failed takeovers happen after the takeover time's halfway point of about 1.5 s. As we move towards the bigger time budgets (6 and 9 s), the number of failed takeovers for delayed takeover times decreases. Summarizing these observations, it can be stated that in time-pressured situations, a delayed takeover time has a high probability of turning into an unsuccessful takeover, while providing the driver with enough time like the 9 s budget can reduce failure cases even when a delayed response occurs.

Most of the delayed takeover times that were also unsuccessful can be traced back to the revealed stopped event (black diamonds in Figure 47). It can be assumed that the lack of threat visibility after receiving the takeover request delays drivers' takeover time. This could be due to

the uncertainty around the threat that requires a reaction and control response. As seen in the 3 s time budget column, most of the reveal stopped vehicle events are delayed and led to a failed takeover regardless of whether the driver slammed on the brakes reducing speed or not. This is evident by looking at the max inverse tau grid for the 3-second time budget. Most of the black points (reveal stopped event), are diamond-shaped (failed takeover) and fall into the red rectangle. Overall, it can be concluded that sudden events, such as the reveal of a stopped lead vehicle, carry a level of surprise that, if combined with a short time budget can lead to unsuccessful takeovers. Such sudden events that are not visually obvious when drivers take over seem to be handled better when the driver has been brought back into the driving loop a few seconds prior to the surprising event like the longer time budgets.

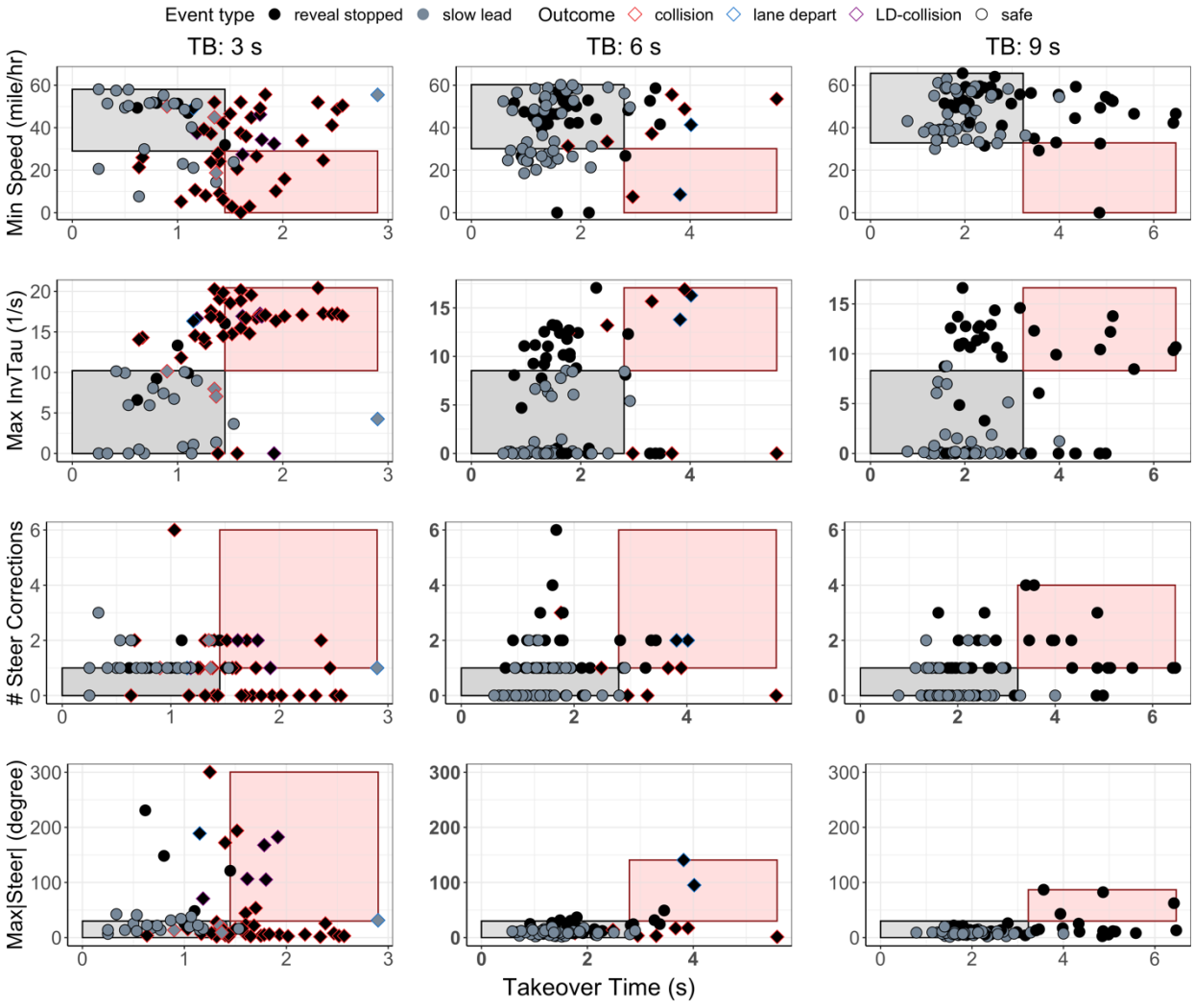

Figure 47. Takeover quality metrics across different time budgets and event types.

Focusing only on the left-hand side of each plot (takeover times less than the middle point), the vertical distribution of the points reflects a combination of speedy and both well and poorly executed takeover responses. This further shows that examining takeover time in isolation to evaluate drivers' takeover behavior is not enough. In other words, the points towards the left of the middle point in Figure 47, which are shorter takeover times, will not always lead to a safe and smooth takeover experience, as shown by the points outside of the grey rectangle.

5.4 Discussion

The success of Level 3 automated vehicles is closely tied to the drivers' takeover performance, creating a series of Human Factors challenges. The safety of the takeover process is an important design consideration for different aspects of the human-machine-interface and the automated driving system itself (C. Gold et al., 2018). Drivers' takeover time has been the center of many studies on evaluating drivers' takeover performance (Zhang et al., 2019). While knowing the drivers' takeover time is important, especially for the design of warning interfaces, takeover time alone is not the only measure to reflect the drivers' understanding of the situation and readiness to take over (Louw, Kountouriotis, et al., 2015). Even though the timing of a takeover is crucial, simply resuming manual control does not guarantee that the driver will be able to have a safe and successful takeover response (Louw, Markkula, et al., 2017). Studying takeover time in combination with the quality of drivers' takeover control maneuvers can provide a more comprehensive indicator of drivers' takeover performance.

A straightforward indicator of the quality of a takeover maneuver is simply the success of the takeover response and whether it led to failed executions causing a collision, road departure, or a combination of both. In this study, it was realized that the time budget given to the driver affects the safety of the takeover response, especially when combined with a surprising event like a sudden revealed stopped vehicle. Takeovers for such events that are not visually salient when the takeover request is issued tend to lead to delayed takeover times that are also executed poorly. A delayed takeover time due to surprising events with a short time budget accounted for the highest percentage of failed takeover times. The same surprising events with a longer time budget had no failed takeovers, which could be explained by higher levels of situation awareness due to being brought back into the driving loop for an extended amount of time.

Assessing the quality of how drivers executed a control response, we examined four metrics that looked at both lateral and longitudinal control. These metrics were maximum inverse tau, minimum speed, absolute maximum steering wheel angle magnitude, and our newly proposed metric, the number of steering chain correction with the first two focusing on longitudinal control while the latter two dealing with lateral control. These metrics complement takeover time and takeover success measures by examining the dynamics of drivers' control response. Also, these metrics offer two new opportunities in studying the quality drivers' takeover behavior.

First, by using takeover time in isolation, there is no guarantee that drivers will be able to have a smooth and successful takeover maneuver. The results of this analysis further asserted this claim, hence pointing to the need for post takeover measures that compliment a timely takeover for a more comprehensive assessment of any new design in the vehicle to aid drivers' takeover maneuvers. On the other hand, using high-level metrics such as safe vs. failed do not explore the dynamics of what led to the failed response, which could provide insight into where drivers usually fail. Looking at the time series of drivers' lateral and longitudinal control and using summary statistics such as the number of chain corrections that was introduced in this chapter provide real-time indicators of the safety and success of the takeover maneuver to guide the design of new safety systems.

The second offering of such metrics is that they not only explore the safety and riskiness of a takeover maneuver, but they also examine the smoothness and experience of the takeover. This becomes especially important for passengers inside the vehicle and other road users interacting with the ego vehicle. For example, when a driver suddenly brakes in response to a takeover request, this could affect the vehicle following from behind, while also making the passengers uncomfortable. Such sudden responses might lead second-hand users (passengers, other road users) to believe that the automated driving system cannot properly inform and guide the driver during a takeover. In this study, the response to visually obvious events, like the slow lead vehicle, tends to have a smoother longitudinal and lateral response. In addition, a longer time budget regardless of event type seems to play an important role in having both a smooth and safe takeover.

Being able to simulate drivers' takeover control behavior will allow us to generalize these quality metrics to takeover scenarios beyond what was considered in this analysis. We proposed and

validated a model of drivers' lateral takeover control using the perceptual cues, far and near point angles. With such a model, summary statistics such as the maximum steering magnitude and the number of chain corrections can be extracted from the simulated time series steering profile to evaluate the success and smoothness of drivers' lateral control. Future work can consider combining this model with a model of drivers' longitudinal control like a braking model introduced in Svärd et al. (2020), to simulate drivers' overall takeover response.

In addition, simulating drivers' steering response, it was found that a steering decision should be tied to which lane the driver is considering to be in after performing their lateral control maneuver. If after the drivers' evidence accumulation process ends and the selected decision alternative is to steer, that would not be enough to model the drivers consecutive steering behavior, since it lacks information on the lane center from which the near and far point angles should be calculated. We propose that models of evidence accumulation divide the steering response into in-lane adjustments and lane-change maneuvers with the first having the original lane as the reference, while the latter having an adjacent lane's center as its reference.

5.5 Conclusion

Considering the possibility of having SAE Level 3 automated driving systems on the road, it is crucial to understand drivers' takeover performance across a variety of situations and in interaction with different design alternatives. Takeover time, though being the most frequently used measure of takeover quality (Zhang et al., 2019), cannot provide a complete estimate of drivers' takeover behavior and how they balance the speed versus accuracy of their takeover response. This points to the need to also explore drivers' lateral and longitudinal control behavior after resuming manual control in combination with takeover time.

In this chapter, we introduced a new metric, the number of chain corrections to capture the instability of drivers' steering control maneuvers during a takeover. We also explored the relationship between takeover time and our new quality metric along with other more common takeover quality metrics like maximum steering input and speed drop. It was found that low-quality takeovers can occur in both tails of drivers' takeover time (short and long takeovers). In addition, we found that drivers might start their takeover response with a high-quality takeover, but the delayed appearance of a surprising event like a suddenly revealed stopped vehicle could lead to evasive control maneuvers. This further points to the importance of being able to simulate

drivers' takeover control behavior across a variety of scenarios. To this end, we developed a model of drivers' steering behavior that captured their takeover lateral control response. This model complements the evidence accumulation model from Chapter 4, allowing us to simulate the whole takeover process minus drivers' braking control response.

Based on our assessment of the speed-accuracy tradeoff of drivers' takeover behavior in this chapter, we recommend that if possible, Level 3 automated driving systems provide drivers with contextual information on the type of hazard causing the takeover request to improve their situation awareness and the quality of their subsequent takeover response.

6 General Conclusions and Recommendations for Future Work

The term “automated driving” can encompass many different meanings that depend on how function allocation distributes responsibility between the automated system and the driver. An incorrect or inaccurate understanding of these function allocations could lead to many human-factors related issues (Inagaki & Sheridan, 2019). In conditionally automated driving, SAE Level 3, the driving task changes from that of continuous control in manual driving to only intervening when a takeover is issued. With SAE Level 3, the driver can delegate lateral and longitudinal control of the vehicle to the automated driving system, and it does not require supervision. The driver, however, is expected to be ready to resume manual control when a takeover request warning is issued by the automated system. In such cases, the takeover request is supposed to provide the driver with sufficient time to take back vehicle control (SAE International, 2018). Increased levels of automation are commonly believed to reduce drivers’ interaction with, and control of, certain driving tasks, negatively impacting the drivers’ ability to intervene and have a timely and appropriate response to safety critical events. This phenomenon, relating to how road vehicle automation will influence driver performance and behavior has been termed “Out of the Loop” (OOTL) (Merat et al., 2018). This raises the question of whether the driver will be prepared to be the system’s fallback in all circumstances and whether the driver will be able to take over safely.

After drivers receive the takeover request, they will sample and process information from the surroundings and integrate it into a coherent image that can guide a safe and successful takeover response. However, given a short time buffer, drivers can choose to increase the speed of their decision-making process, but this usually comes at the cost of lower precision (Dambacher & Hübner, 2014). Understanding and simulating the underlying process of how drivers’ balance the tradeoff between speed and accuracy across a variety of takeover situations is critical when evaluating different design alternatives for conditional automated vehicles.

Reviewing the literature on drivers’ takeover behavior and other relevant fields of research in Chapter 2, we identified a series of gaps in the literature leading to three research questions including, 1) does mean takeover time misrepresent drivers’ takeover behavior?, 2) can evidence accumulation models capture the underlying processes that influence drivers’ takeover time and control choice?, and 3) is there a relationship between takeover time and lateral and longitudinal

performance quality metrics? And can we model drivers' lateral takeover control based on the drivers' takeover time and the kinematics of the driving scenario? These questions were addressed using empirical data from a driving simulator studies in chapters 3 through 5

6.1 Limitations and Future Work

Takeover time was one of the core concepts, both explored and modeled in this dissertation. The interpretation of the effect of independent variables (time budget, level of visual demand, and event type) on the tails of drivers' takeover time distributions should be tempered by the fact that the experiments were performed in a driving simulator. A possible side effect of studying driver takeover behavior in simulators is that it could potentially accentuate longer response times due to the minimal consequences in comparison to the real world. Therefore, in generalizing the results from any simulator study to the roadway, it should be noted that the drivers' response distributions might not be as skewed. Regardless, knowing that the tails could lead to extreme consequences, quantile regression provides a tool to assess the effect of different variables on the distribution of driver response time to ensure that vehicle automation provides the driver with sufficient time during a takeover. A similar sentiment regarding driving simulators can be extended to drivers' control behavior, particularly their steering behavior. For example, drivers' personal vehicle's steering wheel might have a different stiffness level than the driving simulator, potentially causing them to either oversteer or understeer. Such issues can be ameliorated with the initial practice session participants receive upon arriving for the experiment, but in general, the lack of extended exposure to the system and its functionalities are a limitation.

Along these lines, having limited exposure to the system is another limitation of any short-term experimental study like the one in this dissertation. Over time, as drivers use their personal SAE Level 3 vehicle, they become more accustomed to its warning system, functionalities, capabilities, and limitations. This concept was also discussed as the drivers' hierarchical generative model being better attuned as the driver learns about the system's boundaries of operation (Engström et al., 2018). As a result, drivers will better perceive irregularities in how the system interacts with the environment and what typically prompts the system to issue a takeover request, improving their takeover performance. Though a valid limitation, data from one-time simulator studies can serve a greater purpose. Typically, when users first interact with their semi-automated vehicle, they do not receive extensive training on their system at the

dealership. As a result, they will have to figure out their system and its capabilities/limitations and could encounter issues such as mode error. This cycle of learning could also re-occur as these systems self-update themselves and revise (Endsley, 2017a). Therefore, the specific issue of potential inconsistencies from simulator studies due to lack of exposure to the system would be a direct parallel to the initial stage of drivers becoming familiar with their new vehicle and its functionalities and limitations.

The opposite of this argument also stands, stating that since drivers are not very familiar with the simulator and its' boundaries of safe operation, they will act more cautious. With repeated exposure to their automated system, we could expect to observe inappropriate reliance on automation (i.e., misuse and disuse), which could negatively impact the safety and acceptance of these systems. Specifically in the context of this dissertation and takeover scenarios, having a system that mostly performs well could leave the driver ill-prepared and open to misuse which has been defined as failures in which users inadvertently violate critical assumptions about their system and rely on automation inappropriately (J. D. Lee & See, 2004; Parasuraman & Riley, 1997). Though having data from longitudinal studies on driver behavior over time is appealing, we believe that the general findings from research like this dissertation on takeover will still be applicable. In addition, incorporating phenomena like misuse into models of driver takeover behavior by extending the model and adjusting its parameters can be explored in future work.

Another limitation in Chapter 3 was excluding small takeover times (i.e., less than 0.2 s). The fast responses may have been due to the driver initiating the takeover process before the takeover request; specifically, the drivers may have noticed the hazard before the takeover request. This could be indicative of two different response mechanisms in the distribution, where drivers who began responding before the takeover request are combined with drivers responding to the takeover request. We treated these responses as arising from a single distribution to simplify the modeling process. However, future studies could apply more complex models, such as a mixture model, to address this limitation. Non-responses after a takeover request could also be added to the analysis of the continuous response distribution using models such as the two-part model that is used to study discrete-continuous data (Belotti et al., 2015; J. D. Lee et al., 2019).

One of the core contributions of this dissertation was applying evidence accumulation models to driver-automation interaction, specifically after receiving a takeover request warning from an

SAE Level 3 automated driving system. In Chapter 4, we found that the model performed better for the slow lead vehicle event in comparison to the reveal stopped vehicle event. Though both events involved a vehicle blocking the road ahead, one was visually salient while the other involved a surprising reveal. In the reveal stopped vehicle event, the original lead vehicle suddenly changes lanes making the stopped car visible. This change of stimulus is not considered in the current model setup except through the steep rise in looming. Future work could explore an additional parameter in the model, reflecting the delay in drivers' cognitive processes for encoding and incorporating the new stimulus after the surprising change happens. This delay could improve the model fit for the reveal stopped vehicle event, which showed to be skewed towards shorter takeover times (Holmes et al., 2016).

In addition to event type, another independent variable in this dissertation was traffic density that was distilled into the over-simplified construct of visual demand. Using the predictive processing framework, we can explore how traffic density influences the interplay between drivers' pragmatic and epistemic actions. For example, in scenarios where there is traffic in the adjacent lanes of the ego vehicle, epistemic actions such as checking the side mirrors can increase the precision of the drivers' predictions. This can also be framed into how drivers will balance the tradeoff between speed (i.e., having a fast takeover time), and accuracy (i.e., takeover quality), while engaging in epistemic action in the presence of traffic and how human-machine interfaces (HMIs), can aid this process.

Figure 48 provides an overview of the potential future modeling work that could benefit from this dissertation and build on it. In this thesis, we explored drivers' takeover time distributions and control behavior across a variety of conditions. We also modeled drivers' evidence accumulation process leading to their takeover time and control choice, along with their consecutive lateral takeover maneuver. Building on the modeling platform from this dissertation along with the existing modeling efforts in the literature discussed in Chapter 2, we could create a virtual model of how humans drive in different scenarios ranging from routine driving to takeovers in extreme conditions.

In this dissertation, we only modeled the one-time decision after a takeover request is issued, which was the drivers' initial takeover control decision. However, the sequential sampling of evidence to guide driving does not simply terminate after drivers resume manual. In fact, as seen

in Figure 48, after the initial decision, drivers will continue to sample evidence from the driving scene, human-machine interface (if applicable to the design being analyzed) along with the addition of feedback regarding their own control input. For example, if the driver brakes in response to a slowing lead vehicle, they will accumulate evidence as to whether their steering is resolving the issue or not, or whether a lane change is needed and if the adjacent lanes are open. This is a continuous cycle, and while the effort in this dissertation is a step forward in this direction, it was a discrete simulation that needs to be extended.

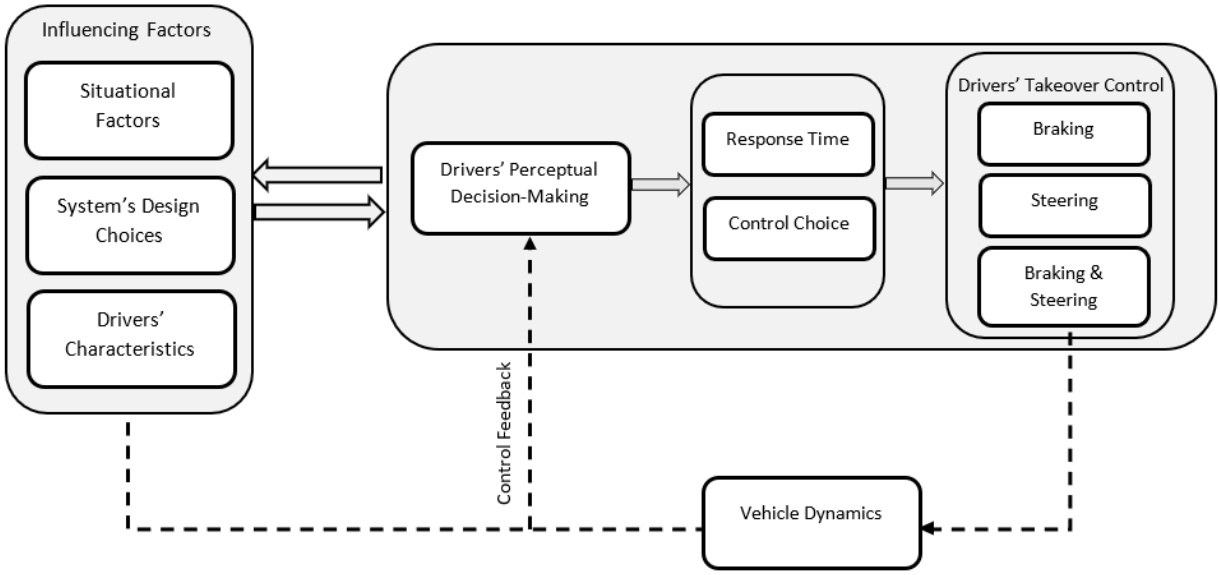

Figure 48. Overview of this dissertation and potential future work.

Another element from Figure 48 that points to future research is the addition of the combination of braking and steering as a takeover control response. Given that this was the first time two alternative control choices were simulated and validated using evidence accumulation models in the context of driving, we tried to simplify the model and consider only two control choices. However, as seen in the findings of this dissertation, sometimes the time difference between when drivers steer and brake is so small that they could potentially be considered as a single control response (e.g., as drivers press their feet on the brake pedal, they start moving the steering wheel). In future work, adding additional control choices like the combination of steering and braking to the decision-making process would lead to a more realistic simulation of drivers' takeover behavior. In addition, based on the findings of the lateral control model from Chapter 5, we proposed that the steering component in Figure 48, needs to convey whether a steering response it is an in-lane steering adjustment or lane change maneuver so that the steering

model uses the correct lane center as its reference for the near and far point angles (Salvucci & Gray, 2004). Another direct expansion of this work would be to include a model of drivers' longitudinal control behavior using a brake model similar to the validated model of Svärd et al. (2020) to complement our proposed lateral control model.

These control models could also benefit from a more sophisticated vehicle dynamics model, which is a component of Figure 48. In modeling drivers' steering behavior in this dissertation, we used a simplified version of a classic car model known as the 2D bicycle model. Though basic, this model does well at simulating vehicle motion in normal driving conditions. But future work could benefit from an advanced vehicle dynamics model which could convert the drivers' input (e.g., braking, steering), into a more accurate signal while also being able to reflect the characteristics of different vehicle models and the effect of roadway conditions.

Using the connectionist model proposed in Markkula et al. (2018) could be another next step to model drivers' situation awareness in a continuous manner as several interconnected units of perceptual decision-making with the decision-making model from this dissertation serving as one of its components. The general principles used in such a framework based on perceptual decision-making would not be limited to only the driver inside the vehicle but can also be extended to other agents interacting with automated vehicles on the road such as pedestrians and cyclists. Using this general framework, a virtual environment of interactions inside the vehicle with the driver and outside of it with other agents on the road can be created, serving as a tool for estimating and optimizing the impact of vehicle automation across a variety of scenarios.

Lastly, going back to the prediction processing framework discussed in the introduction, at first glance it may seem that sequential sampling models and predictive processing provide different accounts on how they approach perceptual decisions, whereas, under certain assumptions, they have been shown to be formally equivalent (Bitzer et al., 2014). Sequential sampling models rely on a feedforward readout and linear integration of noisy sensory information, while predictive processing's relies on a reciprocal exchange of top-down and bottom-up information, allowing us to explain away sensory inputs along with nonlinear dynamics of integration (Friston, 2005; Wacongne et al., 2012). In a predictive processing framework, evidence accumulation can be explained by an evolving probability distribution over multiple possible causes of sensation from the hierarchical generative model. Inference at different stages of the hierarchy includes

predictions from the immediately upper level (which from a Bayesian perspective are the priors) and sensory evidence from the level below (which from a Bayesian perspective are the likelihoods). Like the sequential sampling framework discussed in this thesis, beliefs are continuously updated, but in this context, it is done by comparing the predicted and observed sensory inputs. Beliefs are gradually refined until the sensory system settles on an interpretation of the inputs with the highest likelihood (Summerfield & De Lange, 2014). Future work can deepen our understanding of how each of these perspectives explains drivers' decision making in a variety of scenarios. This will allow us to create more accurate and theoretically plausible models of drivers' cognitive processes in complex scenarios.

6.2 Theoretical Contributions and Practical Implications

In this dissertation, we explored drivers' takeover behavior across a variety of conditions, including different time budgets, levels of visual demand (i.e., surrounding traffic density), and event types. This data was collected using a driving simulator with event types referring to the hazard awaiting the driver after resuming manual control in the simulated driving scene, like a pedestrian, lowing lead vehicle, or a work zone.

The first component was takeover time, which has been defined as the time between when a takeover request is issued, and the driver resuming manual control. Takeover time is the most frequently used measure in the literature to assess drivers' takeover responses (Zhang et al., 2019). With takeover time, one of the main gaps in the literature is the focus on reporting mean takeover times across different studies. This is especially important since the tails of the distribution can have a disproportionate effect on safety outcomes (Horrey & Wickens, 2007). To explore this point, we applied Bayesian quantile regression to our empirical data in Chapter 3 and found that different design and situational factors could influence the tails of the distributions differently than the mean. This suggests that the 85^{th} percentile of the response time may be a more relevant safety metric because it directly estimates the part of the distribution that is most directly related to safety.

Another gap in the literature is the limited number of modeling efforts to predict drivers' takeover behavior. There are infinite combinations of traffic situations, design choices, and driver-related factors that can affect drivers' takeover performance. Validated computational models will allow us to simulate drivers' takeover behavior across these different situations to

inform the design of automated vehicles and assure their safety (Markkula, Romano, et al., 2018). In Chapter 4, we propose a model of drivers' perceptual decision making to predict drivers' takeover time and control choice. An evidence accumulation model with a separate accumulator for each decision alternative (i.e., steer versus brake) with a linearly collapsing threshold was validated using the driving simulator's experimental data. The collapsing threshold allowed us to incorporate the effect of time pressure introduced by the takeover request, which created a deadline for drivers to take over. To the best of our knowledge, this is the first time such a model has been applied and validated to simulate drivers' takeover behavior in the presence of a takeover request warning.

After the drivers' evidence accumulation is over, and they decide on their initial control response, the final piece of the takeover is executing it. One of the gaps in the literature on takeover quality is the lack of diversity in the type of events explored. One solution to this problem is to rely on validated models of driver control behavior to simulate drivers' lateral and longitudinal control maneuvers across a variety of conditions. In Chapter 5, we proposed an algorithm that ties the evidence accumulation process to models of drivers' lateral control. In addition, we proposed a new metric for evaluating the stability of drivers' lateral control maneuvers, the number of chain corrections. This metric captures when drivers overshoot in their initial steering response and must correct it by consecutive steering maneuvers.

Overall, this dissertation found that lower time budgets have a higher rate of unsuccessful takeovers, while the visibility of the hazard after drivers received the takeover request influences both the timing and quality of their response. Specifically, we compared an event with a slowing lead vehicle to an event in which the lead vehicle suddenly changed lanes, revealing a stopped vehicle. With the latter, when the takeover request was issued, the hazard (stopped vehicle) was not visible, leading to both delayed and poor-quality takeovers (i.e., smaller minimum speed values, larger maximum steering values, and more chain corrections). Based on these observations, we recommend that, if possible, contextual information regarding the cause of the takeover request or obscured hazards be communicated to the driver with the takeover request. Another potential recommendation is that the vehicle slow down prior to the takeover request to aid drivers in having a smoother lateral maneuver in the face of a surprising reveal while simultaneously alerting drivers about a potential threat.

This dissertation was focused on understanding and modeling the speed-accuracy trade-off in drivers' takeover responses across a variety of takeover situations in interaction with different system design choices (i.e., time budget). The main theoretical contributions of this dissertation were modeling drivers' time-pressured perceptual decision making after a takeover request along with their subsequent lateral control and also introducing a new metric to assess the quality of drivers' lateral takeover control response. The main practical contributions included highlighting the need to consider the tails of takeover time distributions for safer automated system designs. And second, the models developed in this dissertation can be used as building blocks to create a comprehensive virtual environment that will allow the testing and validation of different design choices for automated vehicles.

The models of human behavior developed in this dissertation are not limited to Level 3 automated driving systems and can be used for higher levels of automated driving. Such models can provide a baseline of drivers' behavior across a variety of scenarios aiding the development of automated vehicles. In addition, they can be incorporated into a virtual testing platform to simulate complex interactions between automated vehicles and both drivers/riders inside the vehicle and incidental users on the road (e.g., pedestrians). The findings of this dissertation are also not restricted to the context of driving. The underlying cognitive processes for how agents balance speed versus accuracy in time-pressured situations explored in this dissertation can be applied to any domain that involves similar decision-making processes.

6.3 Conclusion

Increasingly capable automation is changing the role of the driver introducing new human factors challenges. SAE Level 3 automated driving systems enable drivers to engage in non-driving related tasks while automation is active, but drivers must resume manual control after receiving a takeover request (SAE International, 2018). The safety of such systems relies on the drivers' takeover response, making it critical to understand the underlying dynamics of drivers' takeover behavior and its influencing factors. A takeover can be assessed through the notion of speed versus accuracy with speed referring to the timeliness of the takeover response, and accuracy is the quality of its execution. Having delayed takeovers is synonymous with more extreme initial conditions. It could also be indicative of the driver taking more time to accumulate evidence from the driving scene to increase their situation awareness leading to a

higher quality takeover. On the other hand, with quicker takeovers, the driver might have to trade off gathering more information about the driving scene (e.g., checking mirrors), for a fast response, which could potentially suffer in its quality. This points to the need to look at takeover time and quality together to have a full picture of the takeover response.

In such explorations, it is essential to look at the whole distribution of drivers' behavior, specifically the tails of the distribution, which are typically associated with safety challenges. Failing to account for different quantiles of the distribution and how they are influenced by alternative design choices and situational factors will lead to misleading designs for the average user and average situation, underestimating safety-critical situations.

Lastly, this dissertation proposed and validated models of drivers' evidence accumulation processes after receiving a takeover request and their subsequent lateral control response. Having validated models of drivers' perceptual decision-making and control responses will allow us to expand our understanding of how drivers' will interact with automated driving systems beyond naturalistic and simulator studies by simulating their safety outcomes across a wider range of scenarios and design choices.

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