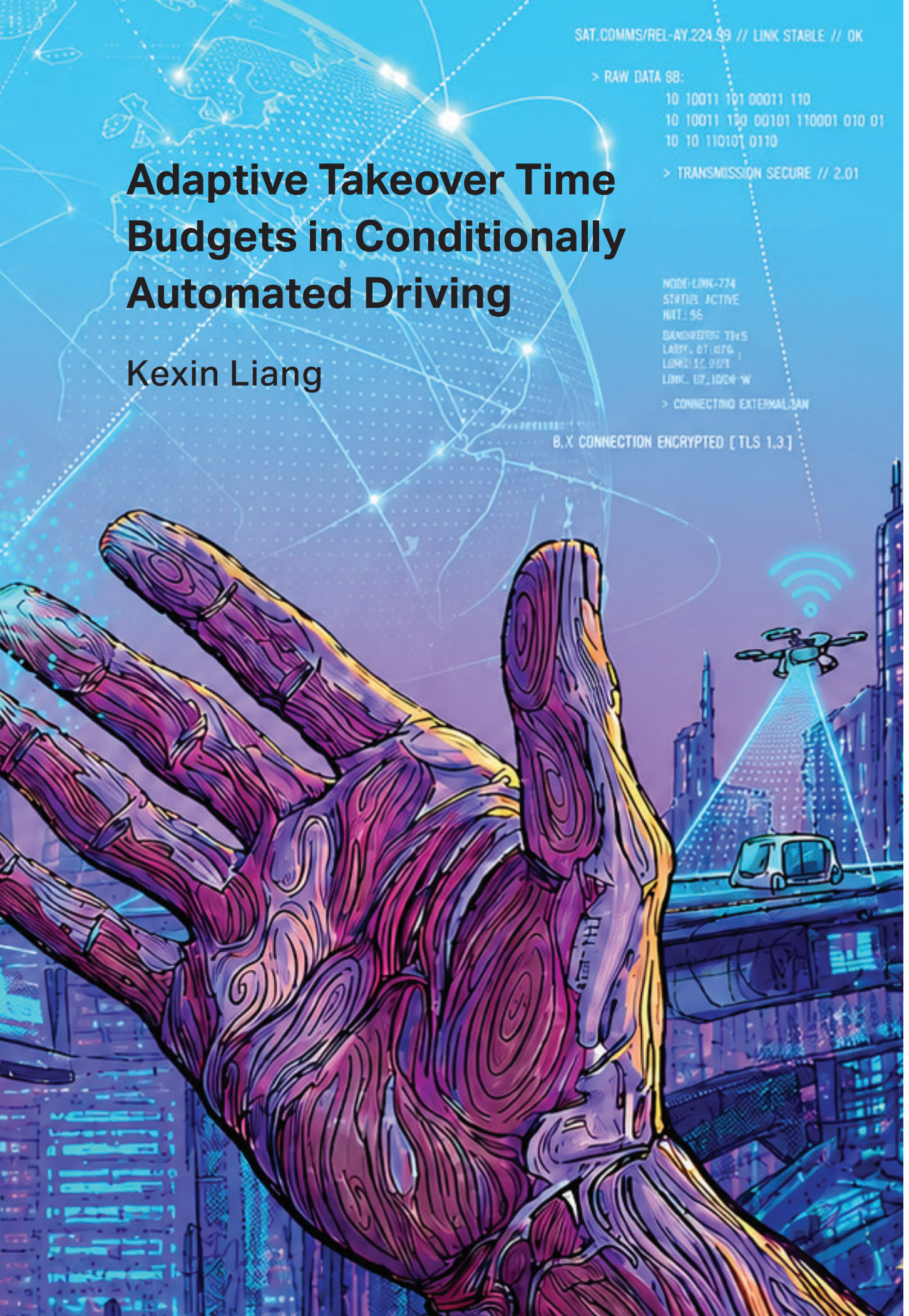
Adaptive Takeover Time Budgets in Conditionally Automated Driving

Kexin Liang



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KEXIN LIANG

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Dissertation

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The human brain is the most complex system we know,
and understanding human factors is key to designing better technology.

Donald Norman

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When I started my PhD, I was not really 100% sure that doing a PhD was something I truly wanted or whether it was the right decision for me. But reflecting on these past four years, I am genuinely happy that I made this choice. I have come to cherish both the achievements and the challenges I have faced, and I have grown tremendously as a researcher and as a person. The journey has not only shaped my academic skills but also taught me resilience, patience, and the importance of finding joy along the way.

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I would also like to thank my co-authors, Sina Nordhoff, Soyeon Kim and Chuheng Wei. Sina generously helped me develop the questionnaires, despite her own busy schedule, which was invaluable as I had little prior experience at that time. I also had the pleasure of conducting driving simulator experiments with Soyeon, whose many creative ideas and remarkable productivity I greatly admire. And I am grateful to Chuheng for including me as a co-author of your survey and for generously sharing thoughts about life and career. I am grateful for the opportunity to collaborate with all of you, and I hope we keep in touch.

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This thesis is a reflection not only of my own effort, but also of the guidance, support, and inspiration I have received from so many people along the way. The past four years have been full of challenges, uncertainties, and moments of self-doubt, but also of growth, joy, and meaningful connections. These experiences have taught me not only how to conduct research, but also how to embrace life with resilience and gratitude. As I close this chapter and look ahead to the next, I will keep moving forward, stay resilient, enjoy life, and love wholeheartedly.

Kexin Liang
Menlo Park, May 2026

CONTENTS

1

INTRODUCTION

1.1. BACKGROUND

AUTOMATED driving represents a key milestone in the evolution of intelligent transportation, aiming to improve traffic safety, efficiency, and driver experience. Despite continued advancements, human drivers remain an indispensable part of the driving loop, serving as a safety backup in situations that exceed the system's operational limits. A typical example arises in conditionally automated driving, where the system issues takeover requests in scenarios beyond its capabilities, requiring drivers to regain control within limited time budgets. Ensuring the smoothness of such control transitions is therefore critical for preventing hazards and maintaining driving comfort.

Providing drivers with sufficient time budgets is essential to support safe and comfortable transitions (Li, Wang, Wang, Zeng, Li, *et al.* 2021; Weaver and DeLucia 2020), as they enable drivers to effectively shift from passive monitoring or non-driving tasks to active control (Hu, Cai, *et al.* 2023; Lu, Happee, *et al.* 2016). This process takes time and cognitive effort to assess the situation and respond effectively. Delays or poor-quality takeover operations not only increase safety risks (Karimi *et al.* 2025; Roche, Thüring, and Trukenbrod 2020) but also undermine users' experience and reduce their willingness to engage with automation (Ma and Zhang 2021; Parasuraman and Riley 1997).

The sufficiency of time budgets depends on their relationship with drivers' Takeover Time (ToT) (Marberger *et al.* 2018), which is defined as the interval from the initiation of a takeover request to the resumption of manual control by drivers (ISO 21959:2020 2020). To distinguish between the two concepts, time budget refers to the amount of time drivers are allocated for the takeover task, whereas ToT is the actual time drivers require to complete this task. Tight time budgets that cannot accommodate the required ToT can increase the risk of accidents (Gold, Damböck, *et al.* 2013), as drivers lack adequate time for proper responses. Conversely, time budgets that significantly exceed the required ToT may also pose risks, particularly when the out-of-capability situations are not readily perceivable to drivers. Because such takeover requests can be perceived as false alarms (Huang and Pitts 2022; Skrickij, Šabanovič, and Žuraulis 2020), leading to reduced attention and potential

dangers. Thus, the determination of sufficient time budgets should be guided by drivers' ToT to achieve targeted performance. This applies particularly to planned, low-urgency takeover situations where the system detects an upcoming boundary condition sufficiently in advance to issue a timely request, such as approaching the end of a motorway automation zone, entering a construction area, or encountering severe weather conditions. In such scenarios, the system has enough foresight to offer the driver a meaningful time budget, making the determination of sufficient time budgets both feasible and safety-critical. On the other hand, in unplanned, high-urgency scenarios, such as a lead vehicle suddenly braking or an unexpected obstacle entering the lane, the available time budget becomes extremely limited. These high-urgency scenarios require automated fallback strategies or minimum-risk maneuvers and are beyond the scope of this thesis, representing a separate and critical research topic.

A widely recognized transition time in the literature for drivers to resume vehicle control is seven seconds (Gold, Damböck, *et al.* 2013), which has been adopted in numerous takeover experiments (Gold, Körber, *et al.* 2016; Jarosch, Bellem, and Bengler 2019; Körber *et al.* 2016; Li, Hou, *et al.* 2021). In on-road situations, Mercedes-Benz offers drivers ten seconds to resume vehicle control [1]. However, ToT varies significantly across different drivers and scenarios. For example, Favarò, Eurich, and Rizvi (2019) examined field tests of autonomous vehicles conducted in California by four manufacturers and found that drivers' ToT ranged from 0.83 s to 3.10 s across 1,143 takeover cases, highlighting the influence of driver trust and experience. Zhang, De Winter, *et al.* (2019) conducted a literature review on the determinants of ToT and reported that drivers' ToT ranged from 0.69 s to 19.79 s across 520 takeovers among 129 studies, exhibiting a long right-tailed distribution. Several tentative explanations have been proposed for this wide variability in ToT, which are discussed in detail in Chapter 2. Given the substantial variability in ToT, assigning fixed time budgets to accommodate diverse driver and situation demands introduces critical safety risks, especially in complex driving contexts and for drivers who need more time to complete the takeover.

Therefore, a key design question arises:

> *What is the most efficient method for computing time budgets that accommodate drivers' various takeover times during control transitions?*

A promising solution to this question is to provide adaptive time budgets, allowing drivers to perform flexible takeovers that are tailored to specific scenarios. De Winter *et al.* (2014) conducted a meta-analysis on the effects of automated driving on drivers' workload and situational awareness. They stated that adaptive automation is a feasible approach to maintaining drivers' situational awareness at a necessary level to keep them in the driving loop. Similarly, Huang and Pitts (2022) examined the effects of time budgets on takeover performance and suggested that the time budget should be adjusted based on the urgency of the situation, ensuring drivers have sufficient time to perform safe and smooth takeovers. Such adaptive time budgets

[1] https://abcnews.go.com/Business/future-driving-hands-off-eyes-off-mercedes-benz/story?id=103681808

have the potential to prompt better takeover performance and more human-centered automated driving compared with fixed time budgets. Thus, this thesis focuses on the critical design challenge of developing an adaptive time budget framework and presents a corresponding implementation roadmap in Section 1.2.

1.2. ADAPTIVE TIME BUDGET FRAMEWORK

This thesis proposes an adaptive time budget (TB) framework to accommodate drivers' various takeover times (ToT), thus supporting targeted takeover performance (ToP) across diverse drivers and situations. The central principle is risk mitigation: drivers require a proper TB that provides sufficient margin beyond their required ToT to ensure a safe transition, while avoiding excessively long intervals that may induce attention decay. I conceptualize the framework for determining adaptive TB as a closed control loop (see Figure 1.1). The automated driving system continuously predicts takeover time (ToT), adjusts the provided TB, monitors ToP, and updates the TB strategy accordingly. Over time, as more takeovers occur, the quantitative relationship among ToT, TB, and ToP becomes more precise, enhancing the effectiveness of the TB strategy and improving overall takeover performance.

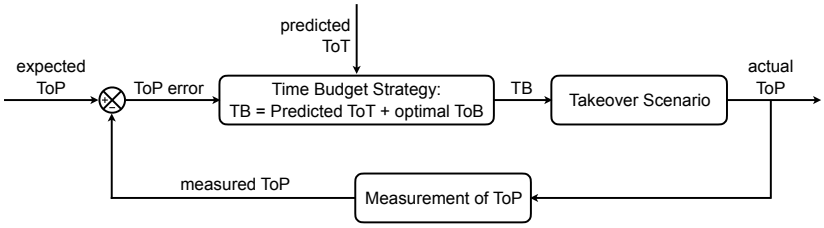


Figure 1.1: Adaptive time budget framework: a closed-loop control architecture.

Based on this framework, three complementary steps are required for application:

1 ToT prediction model: when a takeover request occurs, the driver's ToT in the current scenario needs to be predicted. The scenario reflects both the driver's individual capacity and the contextual task demands. Note that the consequences of prediction errors are asymmetrical: underestimating ToT risks insufficient time budget allocation for the driver to regain control and may lead to unsafe maneuvers, whereas overestimating ToT affects efficiency and driver comfort without substantially compromising safety. The design of an adaptive time budget should account for this asymmetry, prioritizing the avoidance of the potentially unsafe consequences of underestimated ToT.

2 ToP measurement criterion: For a given TB in a given scenario, the actual ToP for the driver performing the takeover task needs to be measured from multiple aspects, including response efficiency, operation quality, and driver experience. This is the basis for evaluating the sufficiency of TB for a predicted ToT.

3 TB determination methodology: To further mitigate the risk of allocating an insufficient time budget due to underestimated ToT, the conditionally automated driving system can determine an appropriate TB by adding a positive takeover buffer (ToB) to the predicted ToT. This requires a quantified relationship among ToT, ToB, and ToP, allowing the strategy to identify the ToB that yields estimated optimal ToP. Such methodology combines the ToT prediction model and ToP measurement to comprise an adaptive TB allocation system.

Based on the above steps in the adaptive time budget framework, this dissertation identifies four research gaps regarding quantifying the relationship among three takeover components (i.e., ToT, TB, and ToP), predicting drivers' ToT, evaluating their ToP, and determining appropriate ToB. Details are presented in Section 1.3.

1.3. RESEARCH GAPS

Four key research gaps have been identified in the design of adaptive time budget strategy that can accommodate the diverse demands of drivers and driving contexts, ensuring safe and comfortable vehicle control transitions. Specifically,

1 **Research on determining safety-critical time budgets that consider the full takeover sequence remains underdeveloped (Chapter 2).**

Takeover process is an integrated sequence where the time budget is closely interconnected with takeover time (i.e., the lower limit of sufficient time budgets) and takeover performance (i.e., the consequence of the supplied time budgets for given takeover time). Previous studies have examined time budgets as factors influencing takeover time and performance, which often overlooking the complexities of achieving a balance between timely control transitions and effective performance. A systematic research on designing adaptive time budgets that satisfy various driver needs and scenario demands, while considering the entire takeover process, remains limited.

2 **Developing adaptive time budget strategies demands more reliable and interpretable takeover time prediction models (Chapter 4).**

Estimation of ToT is a fundamental component of adaptive time budget. Existing models mainly predict average ToT or broad ToT intervals. This approach risks underestimating and/or overestimating drivers' actual ToT, increasing the likelihood of improper time budget allocation, which is safety-critical during takeovers. Besides, ToT is influenced by numerous factors (e.g., traffic density, distraction). A clear variable selection criterion is essential to enhance the interpretability of predictive algorithms.

3 **A thorough understanding of takeover performance requires further exploration of approaches combining objective metrics with subjective evaluations (Chapter 5).**

Takeover performance is generally evaluated using objective metrics such as lane deviation and time-to-collision. However, drivers' subjective experiences—such as perceived workload and satisfaction—are often overlooked. This gap underscores the need for integrated evaluation approaches that combine both objective and subjective measures to capture a more comprehensive understanding of takeover performance and better support the development of human-centered automated driving systems.

4 **Research on exploring the relationship between takeover time, time budget, and takeover performance is limited in the context of safe applications (Chapter 6).**

Significant research has examined how given time budgets affect drivers' ToT and takeover performance, while fewer studies have explored the reverse: leveraging predicted ToT to determine appropriate time budgets that optimize takeover performance. Establishing this connection would facilitate more precise, data-driven strategies for dynamically adjusting time budgets. This requires a well-defined quantitative relationship between ToT, time budget, and takeover performance, which remains underexplored.

Addressing the above research gaps is essential for advancing the development of adaptive time budgets, enhancing the safety and comfort of control transitions, and informing human-centered human-automation interaction designs. Based on these identified gaps, five research objectives are established to guide investigations into designing adaptive time budgets, which are detailed in Section 1.4.

1.4. RESEARCH OBJECTIVES

The overall objective of this dissertation is to **develop methodologies and models for providing sufficient time budgets to accommodate diverse driver needs and situational demands, thereby improving driving safety and driver comfort in takeovers.** To achieve this overall objective, five sub-objectives have been identified:

1 **Structure the conceptual relationships among time budget, takeover time, and takeover performance (Chapter 2).**

Time budget, takeover time, and takeover performance are closely interrelated within the takeover process. This objective aims to establish a clear theoretical framework for understanding their relationships, laying the foundation for developing strategies that allocate time budgets sufficiently exceeding drivers' required takeover time to achieve optimal performance.

2 **Collect comprehensive data on drivers' takeover behaviours across varying conditions (Chapter 3).**

This objective aims to gather empirical data on drivers' takeover behaviors under various conditions, capturing key factors such as takeover time, driver cognition, and individual driver characteristics. The collected data will serve

as a basis for developing predictive models, evaluating takeover performance, and refining time budget determination strategies.

3 **Develop a computational model for predicting takeover time with improved interpretability and reliability (Chapter 4).**

This objective focuses on constructing a computational model to predict drivers' takeover time based on various human factors, such as accumulated driving years, cognitive status, and takeover styles. The model aims to improve the reliability and interpretability of takeover time predictions, thereby enabling more accurate and personalized time budget allocations.

4 **Examine takeover performance from multiple dimensions (Chapter 5).**

This objective focuses on evaluating drivers' takeover performance across three dimensions: response efficiency, user experience, and operation quality. These three dimensions collectively capture the temporal, cognitive, and behavioral aspects of takeover, enabling a multidimensional understanding of how drivers adapt to control transitions under varying conditions.

5 **Quantify the relationship of takeover time, time budget, and takeover performance (Chapter 6).**

This objective aims to develop a quantitative framework that captures the interplay among takeover time, time budget, and takeover performance. The goal is to serve as the foundation for the core logic of the adaptive time budget strategy, which determines a sufficient time budget based on predicted takeover time to achieve desired performance.

These objectives collectively strive to deepen the understanding and implementation of adaptive time budgets, ultimately promoting safer and more comfortable vehicle control transitions.

1.5. RESEARCH QUESTIONS

The overall research question of this thesis is: **How can sufficient time budgets be determined to accommodate drivers' varying takeover times, ensuring safe and comfortable vehicle control transitions?** This chapter presents the five sub-questions that collectively address this central inquiry:

1 **What understanding of takeover time, time budget, and takeover performance can be drawn from existing literature to guide the design of sufficient time budgets (Chapter 2)?**

To design sufficient time budgets, it is essential to first understand what is already known about the key components involved—takeover time, time budget, and takeover performance. This research question examines how long drivers typically take to resume control, how time budgets are defined and operationalized, and how the corresponding takeover performance is measured through a systematic review of existing studies.

2 **How do different drivers respond to takeover requests under varying conditions (Chapter 3)?**

This research question requires a controlled driving simulator experiment that systematically varies contextual factors—such as traffic density and non-driving-related task—while collecting data on driver characteristics, cognition, and performance. The simulator offers a safe and controlled environment for examining how drivers with diverse profiles respond to takeover requests across varying conditions.

3 **How can takeover time prediction models be developed to achieve higher interpretability and reliability (Chapter 4)?**

This research question addresses how takeover time prediction models can be developed to enhance both interpretability and reliability. Specifically, the research explores how the careful selection of meaningful, human-interpretable features—such as task demand, driving experience, and takeover style—can enhance the model's decision-making transparency while improving its generalizability across diverse conditions.

4 **What role does driver cognition play in shaping multidimensional takeover performance (Chapter 5)?**

Cognitive factors such as situational awareness and spare capacity influence drivers' decision-making processes following takeover requests. This research question focuses on examining the underlying mechanisms through which driver cognition affects various aspects of takeover performance, taking individual driver characteristics as a baseline for comparison.

5 **How can the relationship among takeover time, time budget, and takeover performance be quantitatively characterized to inform an adaptive time budget strategy (Chapter 6)?**

A key concept in addressing this research question is the takeover buffer—the margin between the designed time budget and the driver's actual takeover time. Understanding and quantifying how varying buffer sizes impact takeover safety and user comfort is essential for developing an adaptive time budget strategy that dynamically adjusts the allocated time based on predicted takeover times to achieve optimal performance.

By combining the systematic review, empirical data collection, computational modeling, and quantitative analysis, this thesis aims to address the proposed research questions and establish a robust connection between takeover time prediction, dynamic time budget allocation, and the achievement of optimal performance.

1.6. CONTRIBUTIONS

This dissertation contributes to multiple aspects in methodological development and modeling of human-vehicle interactions for automated driving, which are deconstructed into scientific and practical contributions.

1.6.1. SCIENTIFIC CONTRIBUTIONS

1 **Conceptual frameworks and research gaps in sufficient time budget design**

This review advances the understanding of sufficient time budgets in conditionally automated driving by proposing two taxonomies (one for takeover time predictors and another for takeover performance measures), formulating a qualitative hypothesis about the relationship between takeover time, time budget, and takeover performance, and identifying key research gaps for designing sufficient time budgets that are adaptive to various situational demands. These contributions provide guidance for determining sufficient time budgets that enable achieving optimal takeover performance.

2 **Dataset from the driving simulator experiment**

This dissertation presents a comprehensive dataset collected from driving simulator experiments involving 57 participants. The experimental design includes three traffic densities and three types of non-driving-related tasks. The dataset comprises driver characteristics, drivers' perception of takeovers, eye-tracking data, and vehicle operation data. This dataset serves as the foundation for the analyses conducted in this dissertation and provides valuable resources for future empirical studies on human-automation interaction in conditionally automated driving.

3 **Takeover time prediction model**

A Category Boosting (CatBoost) model is developed to predict drivers' actual takeover time, rather than relying on average takeover times or takeover time intervals. The model incorporates driver characteristics and drivers' perceived spare capacity as input features. A key finding is that adding 13 driver characteristics does not significantly improve prediction accuracy when spare capacity is already considered, emphasizing the importance of feature selection in constructing reliable and interpretable takeover time prediction models.

4 **Multidimensional analysis of takeover performance**

This dissertation presents a multidimensional analysis of cognitive influences on takeover performance in conditionally automated driving. It examines how Situational Awareness (SA) and Spare Capacity (SC) distinctly affect response efficiency, user experience, and driving safety. The findings demonstrate that SA enhances response speed, particularly for reflexive actions, while SC more strongly influences overall takeover quality. These findings deepen the understanding of how key cognitive states shape different aspects of takeover performance, offering actionable guidance for the design of more adaptive and supportive automated driving systems.

5 **Quantified relation of takeover time, time budget, and takeover performance**

This dissertation introduces the concept of a takeover buffer (i.e., the additional time allocated beyond the takeover time in the time budget) to link takeover time, time budget, and takeover performance. Drivers' takeover performance

and preferences for time budget and takeover buffer are examined across diverse scenarios. Based on takeover time prediction models and the effects of takeover buffer alongside driver preferences, this dissertation proposes an adaptive time budget strategy that ensures targeted takeover performance as the estimated takeover time plus a driver-preferred buffer using a piecewise function. This contribution lays the groundwork for developing adaptive time budgets that optimize the safety and comfort of vehicle control transitions.

1.6.2. PRACTICAL CONTRIBUTIONS

1 **Enhancing driving safety through adaptive time budgets**

This dissertation contributes to improving driving safety by providing a data-driven approach for determining sufficient and adaptive time budgets for vehicle control transitions. By establishing a quantitative framework that links takeover time, time budget, and takeover performance, it supports the development of appropriate time budget allocations to accommodate real-time driver needs and situational demands. This approach helps reduce the risk of unsafe transitions, enabling drivers to have adequate time to regain control effectively, particularly in complex or high-risk scenarios.

2 **Improving driver experience with personalized takeover strategy**

By leveraging empirical data and predictive modeling, this dissertation highlights the role of perceived spare capacity in takeover time prediction and emphasizes the importance of individualized takeover strategies. The findings suggest that personalized takeover assistance—tailored to a driver's cognitive state—can create a more seamless transition between automation and manual control. These insights support the development of user-centered interfaces that enhance driver trust and comfort in conditionally automated vehicles.

3 **Advancing human-centered automated driving design**

This research promotes a more human-centered approach to automated driving by integrating driver characteristics and cognitive factors into the design of takeover management strategies. The findings show that perceived spare capacity plays a more critical role in determining drivers' takeover efficiency and quality than driver characteristics. This knowledge supports the development of adaptive automation systems that prioritize real-time assessments of driver state, leading to more intuitive and responsive human-automation interactions.

1.7. THESIS STRUCTURE

The structure of this dissertation is shown in Figure 1.2. **Chapter 2** provides a systematic review of the takeover sequence, identifies research gaps, and positions the current work within the broader scientific discourse; **Chapter 3** details the driving simulator experiment, explaining the experimental design, the use of questionnaires and eye-tracking glasses, and how empirical data were systematically collected and analyzed to address the research objectives; **Chapter 4** focuses on the prediction

of takeover time, specifically examining the contribution of various predictor sets. It explores how spare capacity and driver characteristics influence the speed and effectiveness of driver takeover responses; **Chapter 5** evaluates drivers' takeover performance from three key dimensions (i.e., response efficiency, user experience, and operation quality) to provide a comprehensive understanding of human-vehicle interactions during control transitions; **Chapter 6** addresses strategies for determining sufficient time budgets. This chapter investigates the impact of buffer times within the allocated time budget on takeover performance and driver preferences; and **Chapter 7** summarizes that the variability in takeover time underscores the need for adaptive, context-sensitive time budgets to achieve targeted performance, and provides future research recommendations.

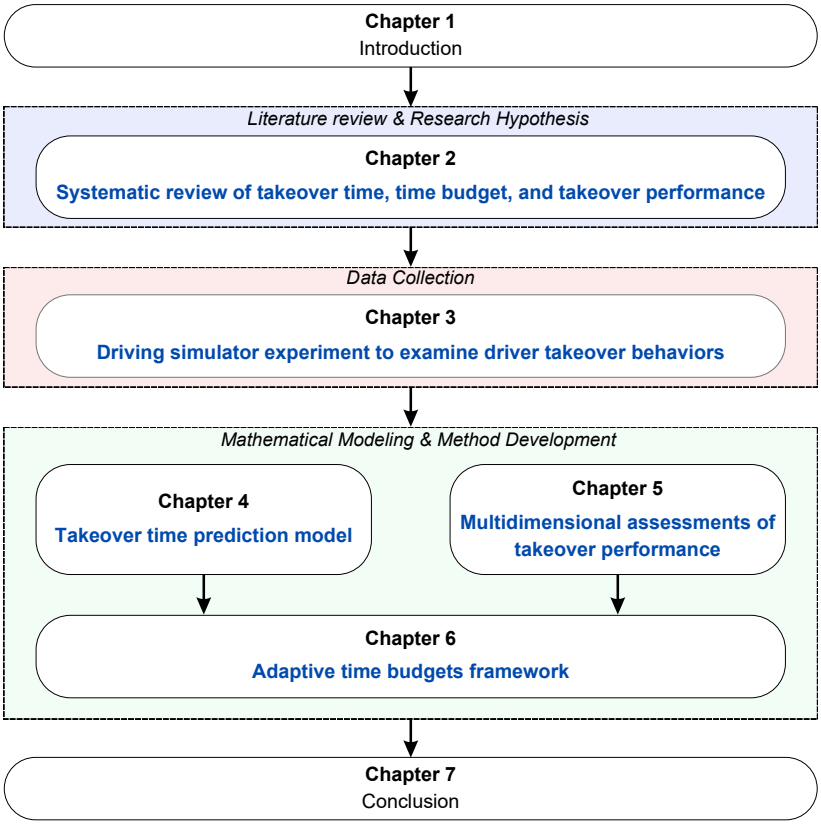


Figure 1.2: Structure of this dissertation.

2

SYSTEMATIC REVIEW OF TAKEOVER TIME, TIME BUDGET, AND OUTCOME

Chapter 1 identifies an overall research question for this dissertation, i.e., " how to determine sufficient time budgets to accommodate drivers' various takeover times, ensuring safe and comfortable vehicle control transitions". Here in this Chapter, I set out to answer this research question, beginning with a systematic review of the takeover sequence, including takeover time that drivers require for vehicle control transitions, the time budget that the automated driving systems provide for control transitions, and the corresponding takeover performance.

As conditionally automated driving systems require drivers to resume vehicle control when automation reaches its limits, ensuring safe and comfortable transitions is critical. While time budgets have been studied as factors influencing takeover time and performance, research on determining sufficient time budgets that can be adapted to meet the demands of diverse scenarios and drivers, while considering the entire takeover sequence, remains limited. This review (i) categorizes determinants of takeover time using the task-capability framework, (ii) examines existing research on fixed time budgets and highlights the importance of providing adaptive time budgets, (iii) proposes a taxonomy of takeover performance measures, and (iv) identifies six research agendas. The review offers insights to optimize takeover strategies, thus enhancing safety and comfort of vehicle control transitions.

This chapter is based on a journal article (Liang, Calvert, and van Lint 2026):

> Liang, K., Calvert, S., & van Lint, J. (2026). Towards Safe and Comfortable Control Transitions: A Systematic Review of takeover time, time budget, and takeover performance. Human Factors. In press.

2.1. INTRODUCTION

In conditionally automated driving, one primary safety consideration is the transition of vehicle control (ToC) from automation to human drivers. This ToC is critical in situations where automation's capabilities are exceeded, requiring drivers to promptly resume control within constrained time budgets as a safety fallback to minimize potential risks (SAE *et al.* 2021). However, the complexity of human-vehicle interactions can make ToCs demanding and potentially hazardous, leading to substantial variability in drivers' takeover time—the period required by drivers to regain control (Skrickij, Šabanovič, and Žuraulis 2020). This variability poses a significant challenge for conditionally automated driving systems (CADS), as they must provide sufficient time budgets to accommodate diverse driver needs during takeovers (Li, Wang, Wang, Zeng, Li, *et al.* 2021). Knowing what a sufficient amount of time is to perform ToCs is vital for driving safety and user comfort, and is the focus of this research.

Review articles have emerged to provide insights on facilitating smooth ToCs, such as driving states during ToC (Lu, Happee, *et al.* 2016), user interfaces (Kim, van Egmond, and Happee 2021), and takeover request designs (Miller, Nikan, and Zaki 2024). These reviews highlight the importance of designing CADS that align with drivers' cognition and demands. Zhang, De Winter, *et al.* (2019) performed a meta-analysis on takeover time and observed that longer time budgets that are available for drivers to resume vehicle control generally lead to longer takeover time and improved takeover performance when compared to shorter time budgets. This observation indicates that time budgets have significant influences on drivers' takeover time and takeover performance, which is also reported by McDonald *et al.* (2019) and Weaver and DeLucia (2022). Specifically, on one hand, tight time budgets can lead to short takeover times and poor takeover performance (Gold, Happee, and Bengler 2018), as drivers (especially those who are sensitive to risk) tend to conduct over-reactions. This can harm drivers' takeover experience and put them in serious danger of accidents (Gold, Damböck, *et al.* 2013). On the other hand, longer time budgets give drivers more time to respond to takeover requests and help them to achieve more stable takeover performance and lower accident rates (Wan and Wu 2018; Yin and Pan 2020). But if time budgets are excessively long, the safety of takeovers will not be improved significantly as time budgets increase (Huang and Pitts 2022; Wan and Wu 2018) because of the limitation of driver capabilities for fulfilling takeover tasks. Such excessively long time budgets can cause inefficiencies in takeovers and then in the general traffic system (Skrickij, Šabanovič, and Žuraulis 2020). Huang and Pitts (2022) stated that early requests for drivers to resume vehicle control can be taken as false alarms, which is dangerous if drivers decide not to respond. On these bases, we conclude that sufficient time budgets are vital for the safety and comfort of vehicle control transitions.

Therefore, a natural question to ask is:

> *How can time budgets be determined to sufficiently accommodate diverse scenarios and driver needs, ensuring safe and comfortable vehicle control transitions?*

To answer this open question, we conduct a systematic review that focuses on time budget, but also includes takeover time and takeover performance. While existing studies have investigated the relationships between time budgets and both takeover time and performance, there remains a critical gap in research addressing how to determine optimal time budgets that can sufficiently accommodate the diverse needs of different drivers across varying driving scenarios - particularly in the form of review papers. Additionally, the takeover process is an integrated sequence where the time budget is closely interconnected with takeover time (i.e., the lower limit of sufficient time budgets) and takeover performance (i.e., the consequence of the supplied time budgets for given takeover time). Studies examining related takeover time, takeover performance, and various factors impacting these elements, indirectly contribute valuable insights toward determining sufficient time budgets across diverse scenarios and drivers. However, a systematic review that examines these three elements as an integrated sequence is still missing. To fill in this gap, we break down our investigation on the determination of sufficient time budgets into three sub-questions:

- **Takeover Time:** *how long do drivers take to fulfill takeover tasks?*

  Takeover time is the lower limit for sufficient time budgets to ensure safe and driving (Marberger *et al.* 2018; Zhang, De Winter, *et al.* 2019). In this review, we examine the lengths of takeover time that are observed in empirical studies and find that drivers' takeover time varies significantly due to its complex causal relationships with numerous determinants. We investigate the effects of these determinants on takeover time across studies and synthesize the observed correlations between takeover time and its determinants. Further, we propose a taxonomy to structure these determinants based on the task-capability interface model in Fuller (2011) and partially capture the interplay of these determinants. This taxonomy aims to provide theoretical guidance for selecting predictors of takeover time considering the complex causal relationships between takeover time and its determinants.

- **Time Budget:** *how long do conditionally automated driving systems offer drivers for takeover tasks?*

  Time budget has a significant impact on drivers' takeover behaviors and subjective experience (Gold, Happee, and Bengler 2018; Wan and Wu 2018). In this review, we explore the research on fixed time budgets and adaptive time budgets respectively. We argue that adaptive time budgets provide promising possibilities for satisfying various takeover demands across different drivers and scenarios. To further the knowledge of adaptive time budgets, we formulate a hypothesis for the qualitative relationship between takeover time, time budget, and takeover performance, which can be considered as a starting point for future research on adaptive time budgets and needs to be validated and quantified. We think the quantified relationship can lay a foundation for determining sufficient time budgets that enables achieving optimal takeover performance for specific takeover time.

- **Takeover Performance:** *do the offered time budgets suffice?*

  Takeover performance can indicate the sufficiency of the time budget that is offered for specific takeover time (Huang and Pitts 2022; Tan and Zhang 2022). In this review, we look into the measures of takeover performance and extract related performance indicators. The extraction process reveals that the measures of takeover performance are imbalanced towards either objective driving performance from the vehicle perspective or subjective user experiences from the human perspective. These imbalanced measures can steer the studies that consider takeover performance as optimization goals toward skewed directions. We suggest standardized frameworks of takeover performance measures that bridge both the vehicle perspective and the human perspective are critical for developing safe and comfortable control transitions in conditionally automated driving. To lay the groundwork for such standard frameworks, we propose a taxonomy of the indicators of takeover performance and compare the suitability of various human-related performance indicators in practice, which can help readers select effective performance indicators in different contexts.

This review aims to provide valuable insights to readers seeking a systematic overview of human-vehicle interactions during control transitions and requiring guidance on designing human-centered conditionally automated driving systems.

2.2. METHODOLOGY

This systematic review exploits Scopus and Web of Science as they have relatively strict document inclusion criteria (Martín-Martín *et al.* 2019). Within these two databases, the search query is defined as TITLE-ABS-KEY ((human OR driver) AND (interact* OR cooperat*) AND ((auto* OR self) AND (driving OR vehicle OR car)) AND ((takeover OR transit*) control) AND (((takeover OR react* OR respon* OR lead) AND (time OR performance)) OR “time-budget”)). The time scope is limited to 2010 - 2025, considering that from around 2010 onwards the number of studies on control transitions has steeply increased (Lu, Happee, *et al.* 2016). As for document types, conference reviews are excluded because they add limited value when related conference papers are included. Additionally, only English articles are considered. This search strategy leads to 185 records in Scopus and 92 records in Web of Science. On this basis, a stratified process of filtering articles is performed following the guidelines of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Moher *et al.* 2009). After removing 74 duplicates, an additional 103 records are excluded for two reasons: not focusing on the Human-Vehicle Interactions (HVIs) during takeovers, e.g., constructing a framework for training automated driving models; and not discussing takeover time, time budget, or takeover performance, e.g., propose a taxonomy for takeovers. This filtering process results in 100 articles remaining.

For the analysis of these 100 articles, this review adopts a combined method of umbrella review and systematic review. Specifically, six review papers (Hu, Zhang,

et al. 2024; Hungund and Pradhan 2023; Martinez and Huang 2022; McDonald *et al.* 2019; Weaver and DeLucia 2022; Zhang, De Winter, *et al.* 2019) are examined to provide a high-level understanding of HVIs during takeovers via the umbrella review. Other involved research papers are also analyzed to supplement the results of the umbrella review. With this combined analysis method, we aim to provide a comprehensive overview of the state-of-the-art research on takeover time, time budget, and takeover performance, which can facilitate the explorations of sufficient time budgets for safe and comfortable takeovers.

2.3. TAKEOVER TIME

Takeover time refers to the amount of time that human drivers take to resume vehicle control from conditionally automated driving systems (Zhang, De Winter, *et al.* 2019). It is the minimum requirement to be met by sufficient time budgets (Marberger *et al.* 2018; Zhang, De Winter, *et al.* 2019), otherwise drivers may not have enough time to complete the takeover task both safely and comfortably. In this section, we clarify the concept of takeover time that is adopted in this review in Section 2.3.1, examine the lengths of takeover time observed in empirical studies in Section 2.3.2, and propose a taxonomy to structure the complex causal relationships between takeover time and its determinants in Section 2.3.3.

2.3.1. CONCEPT OF TAKEOVER TIME

Before delving deeper into takeover time, it is necessary to clarify its definition, as the takeover process consists of multiple overlapping intervals—such as takeover time, reaction time, and response time—that are generally used inconsistently in the literature (Huang, Fan, *et al.* 2024; Zeeb, Buchner, and Schrauf 2016). For example, the takeover time defined in Alambeigi and McDonald (2023) is called takeover reaction time in Wan and Wu (2018). To avoid potential misunderstandings of the temporal terminologies during takeovers, we examine the definitions of takeover time in the literature and clarify the specific concept adopted in this review. Studies employing alternative definitions are excluded from further analysis.

A well-accepted definition of takeover time is the interval from the initiation of a takeover request until the start of manual driving, according to ISO 21959:2020 (2020). "The start of manual driving" is generally interpreted in two ways. The first interpretation is the moment when the driver starts to physically control the vehicle, i.e., the start of motor readiness for resuming control (Seet *et al.* 2022). The second interpretation is the moment when the driver starts to consciously control the vehicle, i.e., the start of meaningful longitudinal/lateral inputs (Gold, Happee, and Bengler 2018). Here, we adopt the second interpretation for the following two reasons. On one hand, the first interpretation focuses more on drivers' physical behaviors, while Zeeb, Buchner, and Schrauf (2016) and Yoon and Ji (2019) noticed that the time drivers take to achieve motor readiness does not change significantly in different takeover scenarios. This might be due to the fact that motor readiness is more related to drivers' reflexive reaction (Zeeb, Buchner, and Schrauf 2016), especially in time-critical scenarios (Markkula *et al.* 2016). Such an

interval is beyond our research scope; On the contrary, the second interpretation focuses more on drivers' conscious behaviors which are the underlying reasons for how drivers respond physically (Merat *et al.* 2019; Xing *et al.* 2021). This second interpretation can help researchers to conduct in-depth investigations into the underlying mechanism of HVIs during takeovers and provide valuable insights into how to improve the safety and comfort of takeovers in conditionally automated driving (Du, Yang, and Zhou 2020). Thus, this review defines the takeover time as the interval between the takeover request and drivers' first conscious input. Such first conscious input is generally indicated by the angle of the steering wheel exceeding 2°or the position of the braking pedal exceeding 10 % (Gold, Damböck, *et al.* 2013; Li, Blythe, Guo, *et al.* 2019).

To illustrate the clarified takeover time, we describe a takeover process in a temporal sequence which is shown in Figure 2.1. The sequence begins with a conditionally automated driving system performing dynamic driving tasks (ISO 21959:2020 2020) and maintaining control of the vehicle, while the human driver is allowed to engage in non-driving-related tasks, such as watching videos. When the system encounters a situation beyond its operational design domain (ISO 21959:2020 2020)—a "system boundary" occurs—the system initiates a takeover request for the human driver to assume vehicle control and performs safety fallback actions, such as slowing down, to manage the transition. The timing of this takeover request establishes the available time budget before the system disengages. Upon receiving the request, the human driver must disengage from non-driving related tasks and begin to perceive, understand, and predict the scenario (Endsley 2021) to develop situational awareness. Typically, an "attention time lag" occurs due to competing information processing demands (Van Lint and Calvert 2018) before the driver assumes conscious control of the vehicle, i.e., meaningful human control of the vehicle (Calvert, Johnsen, and George 2024). If the time budget is insufficient for the driver to complete this cognitive process, they may be forced into a rushed response, known as "rush control". The duration of this process is referred to as the "takeover time" and is the focus of this review. To streamline the further discussion of the relationship between takeover time and time budget, we propose a concept - takeover buffer, which represents the interval left within the time budget after subtracting the takeover time. To achieve a safe and comfortable takeover performance, the takeover buffer is expected to be a small positive number for the efficiency (Doubek *et al.* 2020) and safety (Zhang, De Winter, *et al.* 2019) of takeovers. Note that this takeover buffer can also be negative, where the available time budget is shorter than the required takeover time. Such circumstances are hazardous, as drivers may lack the time needed to be physically and mentally prepared to resume control and undertake necessary evasive maneuvers. Thus, establishing an appropriate takeover buffer for a given takeover time is essential for designing sufficient time budgets.

2.3.2. LENGTHS OF TAKEOVER TIME

After the concept of takeover time is clarified in the above sub-section, we address the first research question of this review: how long do drivers take to fulfill takeover

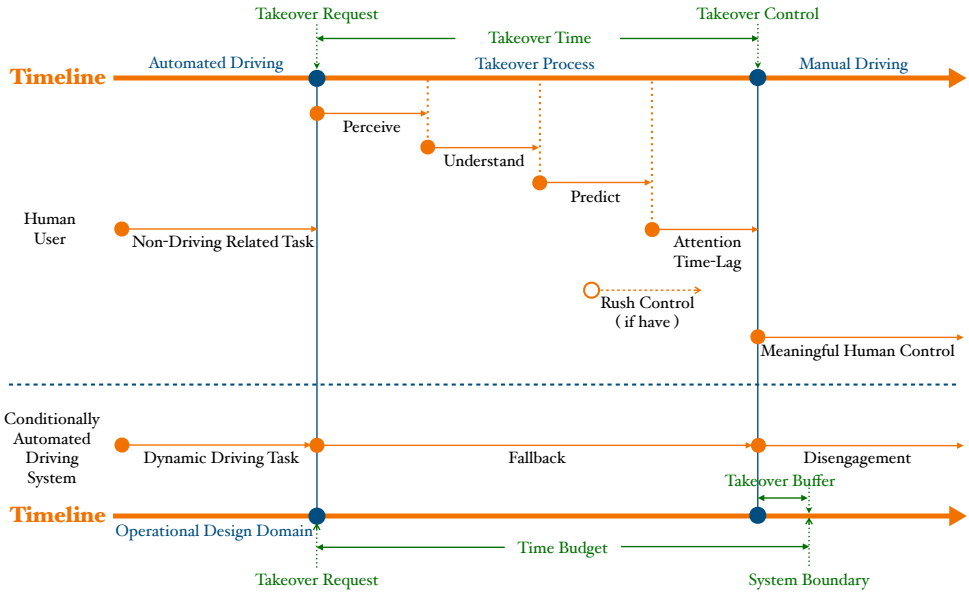


Figure 2.1: The timeline of a takeover process in conditionally automated driving.

tasks? To answer this question, we examine the studies of takeover time that are consistent with the above definition of takeover time, i.e., the interval between the takeover request and the first conscious input from human drivers.

To our knowledge, there is no consensus in the literature about a general takeover time that can be applied to all situations (Xing *et al.* 2021; Zeeb, Buchner, and Schrauf 2015). For example, Favarò, Eurich, and Rizvi (2019) reported 1143 takeover cases from four vehicle manufacturers and noted that drivers' mean takeover time varied across manufacturers, ranging from 0.83 to 3.10 seconds. Based on the data reported in Favarò, Eurich, and Rizvi (2019), we calculated an average mean takeover time of 1.14s. Meanwhile, Zhang, De Winter, *et al.* (2019) analyzed 520 takeover cases from the literature. Results show that the mean takeover time across studies varies from 0.69s to 19.79s and the average mean takeover time is 2.72s. To explore this further, we summarize the takeover time across 28 cases from three studies and list these examples in Table 2.1. This table details how takeover time varies across different driver characteristics and scenarios, capturing variations based on factors such as driver age, non-driving related tasks (NDRT), urgency of the takeover scenario, traffic density, and takeover request modality (TORM). The data reveal significant variability in ToT across studies and conditions. For instance, high-urgency scenarios generally prompt faster driver responses, while NDRTs—especially cognitively demanding tasks—tend to lengthen takeover time. There are also age-related differences: Li, Blythe, Guo, *et al.* (2018) found that older drivers typically require longer ToT than younger drivers under the same condition, whereas Körber *et al.* (2016) showed no significant age difference in ToT. These two

examples universally indicate that takeover time varies strongly over human drivers, driving contexts, and takeover scenarios (Delmas, Camps, and Lemercier 2022; Li, Blythe, Guo, *et al.* 2019; Wang, Xu, *et al.* 2025). Particularly, the comparison between Favarò, Eurich, and Rizvi (2019) and Zhang, De Winter, *et al.* (2019) reveals that the takeover times in real-car driving experiments can be very different from those observed in driving simulator experiments which have been widely used to explore human factors in automated driving (Du, Zhou, *et al.* 2020b; Gold, Happee, and Bengler 2018; Zhao, Geng, *et al.* 2023). Such differences should be considered when applying experimentally derived conclusions in practice.

Mean takeover times and their ranges provide useful insights into the overall duration of driver responses, but they fail to reflect the significant variability in takeover time consistently reported across studies (Delmas, Camps, and Lemercier 2022; Li, Blythe, Guo, *et al.* 2019). Research has shown that distributions of takeover time are typically right-skewed (Eriksson and Stanton 2017b; Rydström *et al.* 2022; Zhang, De Winter, *et al.* 2019), indicating that a significant portion of drivers require considerably more time than the average to regain control. Designing time budgets based solely on mean values risks underestimating the needs of slower responders, potentially placing them in unsafe situations where they may lack sufficient time to execute evasive actions. These findings highlight the need to move beyond averages and focus more on understanding the factors causing variability in takeover time, in order to inform the design of time budgets that can better accommodate diverse driver needs.

The variation in takeover time across different drivers and situations raises critical questions: what causes the variation in drivers' takeover time? More specifically, what are the determinants of takeover time, and how do they affect takeover time? We investigate this question in Section 2.3.3.

2.3.3. DETERMINANTS OF TAKEOVER TIME

Previous research has shown substantial variation in takeover time across drivers, driving contexts, and scenarios (Delmas, Camps, and Lemercier 2022; Wang, Xu, *et al.* 2025; Zhang, De Winter, *et al.* 2019). This variability complicates the determination of sufficient time budgets, which must account for takeover time as a lower bound. A clearer understanding of the factors influencing takeover time is essential for designing appropriate time budgets and improving takeover performance.

A growing body of studies on takeover time determinants has been executed on topics such as situational awareness (Chen, Zhao, Li, Gong, *et al.* 2024; Yang, Semiromi, *et al.* 2020), workload (Eriksson and Stanton 2017b; Oh, Yun, and Myung 2024), time budget (Li, Wang, Wang, Zeng, Li, *et al.* 2021), non-driving related task (Hu, Zhang, *et al.* 2024), etc. We notice that even for those studies that examine the same determinant(s), their experimental settings vary and consequently, their results can differ. These phenomena show that the studies of takeover time determinants are scattered and often lack comparability, which is also noticed by Zhang, De Winter, *et al.* (2019). We argue that two factors may be responsible for hindering comparative studies. First, determinants of takeover time are numerous (Zhang, De Winter, *et al.* 2019). It is unrealistic to investigate all determinants

Table 2.1: An overview of takeover times studied in the literature (examples).

Study	Age	NDRT	Urgency	Traffic Density	TORM	ToT(s)
Körber *et al.* (2016)	young	no	high	low	A	2.58(0.97)
	young	no	high	medium	A	3.32(1.44)
	young	no	high	high	A	3.52(1.17)
	young	phone call	high	low	A	2.76(0.88)
	young	phone call	high	medium	A	3.70(0.97)
	young	phone call	high	high	A	3.66(1.24)
	old	no	high	low	A	2.41(1.00)
	old	no	high	medium	A	3.41(1.34)
	old	no	high	high	A	3.41(1.39)
	old	phone call	high	low	A	2.62(1.29)
	old	phone call	high	medium	A	3.25(1.41)
	old	phone call	high	high	A	3.56(1.10)
Li, Blythe, Guo, *et al.* (2018)	young	reading	low	low	V + A	3.61(1.79)
	old	reading	low	low	V + A	4.33(1.84)
Yoon, Kim, and Ji (2019)	all	phone call	high	low	V	2.56(1.10)
	all	watching video	high	low	V	2.42(1.09)
	all	phone call	high	low	T	2.49(1.35)
	all	watching video	high	low	T	2.18(1.33)
	all	phone call	high	low	A	2.32(1.29)
	all	watching video	high	low	A	2.23(1.27)
	all	phone call	high	low	V + T	2.15(0.91)
	all	watching video	high	low	V + T	1.88(0.80)
	all	phone call	high	low	T + A	2.18(0.99)
	all	watching video	high	low	T + A	2.05(0.99)
	all	phone call	high	low	V + A	2.11(1.08)
	all	watching video	high	low	V + A	1.97(0.95)
	all	phone call	high	low	V+T+A	2.22(1.07)
	all	watching video	high	low	V+T+A	1.95(1.07)

* NDRT: non-driving related task; TORM: takeover request modality; A: auditory; V: visual; T: vibrotactile; ToT: takeover time, presented as "mean (SD)".
* Urgency of takeover scenarios is classified based on Zhang, De Winter, *et al.* (2019).

together. Second, these determinants are closely connected. Their interrelationships lead to potential confounding factors which make designs of controlled experiments challenging (Choi *et al.* 2020; Pipkorn, Tivesten, and Dozza 2022). Therefore, it is difficult to isolate individual determinants from the overall experimental set-ups and to make quantitative comparisons of their effects on takeover time across studies.

To alleviate the lack of comparative studies caused by the above two factors, we take two key steps:

First, we extract takeover time determinants through a combined umbrella and systematic review approach to ensure comprehensive coverage and methodological rigor. Specifically, we begin with an umbrella review (i.e., review of reviews) to extract the determinants of takeover time from review papers. Hu, Zhang, *et al.* (2024), Martinez and Huang (2022), Weaver and DeLucia (2022), Zhang, De Winter, *et al.* (2019), and McDonald *et al.* (2019) have provided valuable overviews and meta-analyses on takeover time and its influencing factors, serving as the primary foundation for constructing a comprehensive set of determinants. We then conduct a systematic review of additional studies to complement and refine the overview developed through the umbrella review (Agrawal and Peeta 2021; Chen, Lu, *et al.* 2021; Chen, Zhao, Li, Gong, *et al.* 2024; Dogan, Rahal, *et al.* 2017; Du, Zhou, *et al.* 2020a; Kim, Kim, *et al.* 2020; Li, Blythe, Zhang, *et al.* 2022; Lin *et al.* 2020; Oh, Yun, and Myung 2024; Roche, Somieski, and Brandenburg 2019; Ruscio, Bos, and Ciceri 2017; Stimm *et al.* 2019; Wu, Kihara, *et al.* 2019). This combined approach enables a comprehensive overview of the determinants of takeover time identified in the literature. After standardizing terminology and consolidating subcategories, 23 distinct determinants are identified and illustrated in Figure 2.2.

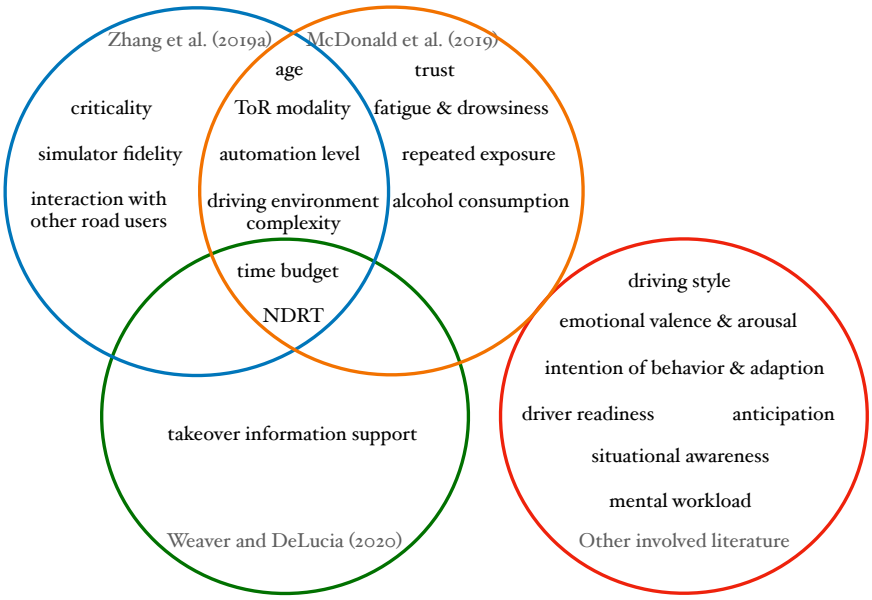


Figure 2.2: Collection of takeover time determinants.

We find that the takeover time determinants from the five reviews have both overlaps and differences, mainly due to their different focuses. For example, Zhang, De Winter, *et al.* (2019) synthesized quantitative studies of takeover time. McDonald *et al.* (2019) were interested in driver behavior models during takeovers. Weaver and DeLucia (2022) focused more on the designs of conditionally automated driving systems. The determinants from other literature are mainly related to human factors, such as situational awareness (Agrawal and Peeta 2021). This phenomenon suggests that not only review papers, but also related quantitative studies, driver behavior models, and conditionally automated driving designs, need to pay more attention to the influence of human factors on takeover time.

Second, we propose a structured taxonomy to organize the identified determinants, which not only brings conceptual clarity but also lays the foundation for investigating their interrelationships and complex effects on takeover time. To ground our taxonomy, we adopt the Task-Capability Interface (TCI) model (Fuller 2011), a well-established framework frequently used to explain driver behaviors (Calvert, Schakel, and van Lint 2020; Delmas, Camps, and Lemercier 2022; Oviedo-Trespalacios *et al.* 2019). The core concept is that drivers adjust their behavior to manage perceived risk based on their assessment of task demands and their own capabilities (Fuller 2011; Van Lint and Calvert 2018). In takeover contexts, we apply this model to categorize determinants of takeover time into two groups: takeover task demand determinants and driver takeover capability determinants, as shown in Figure 2.3.

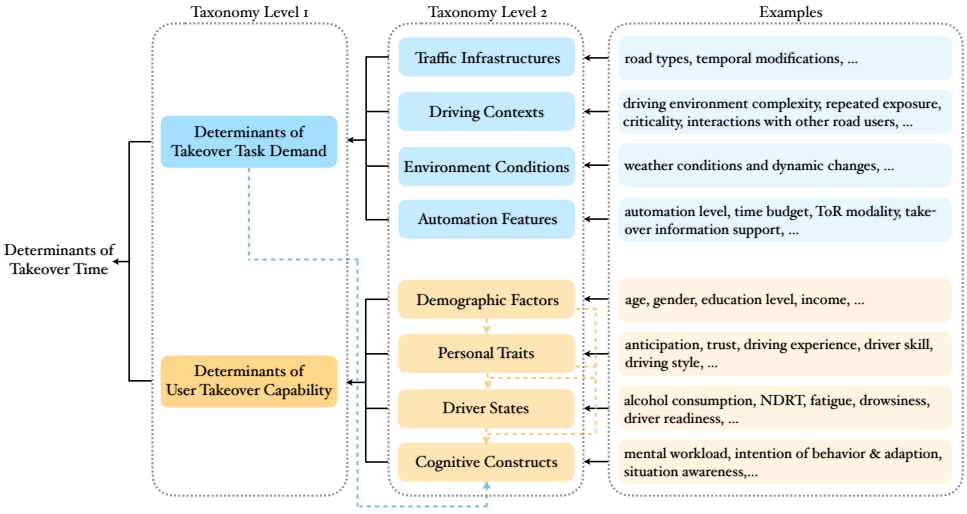


Figure 2.3: Taxonomy of takeover time determinants.

The determinants of takeover task demand reflect the requirements for various components of takeover scenarios, such as driving environment complexity. To further categorize these determinants, we modify the six-layer model for automated driving scenarios in Weber *et al.* (2019) and make the classification model suitable for takeover scenarios. Thus, a four-level classification for determinants of takeover task

demand is proposed, including traffic foundations, driving contexts, environment conditions, and automation features. The first classification (traffic foundations) is consolidated from the three layers (street layers, traffic infrastructures, and temporal modifications) in Weber *et al.* (2019) to streamline the structure. The second classification (driving contexts) is modified from the movable objects layer as this classification also includes other contextual factors, such as simulator fidelity. The third classification (environment conditions) remains consistent with the original model which involves weather conditions and the corresponding dynamic changes. And the fourth classification (automation features) encompasses not only the data and communications layer in Weber *et al.* (2019) but also takeover-related determinants, such as time budget and takeover request modality.

As for the determinants of driver takeover capability, they reflect drivers' competences in fulfilling takeover tasks. Fuller (2011) divided driver capability into related knowledge, skill, and other human factors, but this classification is ambiguous in the takeover context. Hence, we refer to the framework of human factors in traffic modeling in Sharma, Ali, *et al.* (2018) and reclassify the capability determinants into four categories: demographic factors, personal traits, driver states, and cognitive constructs. Specifically, demographic factors involve information that can delineate driver populations, such as age and gender. Personal traits refer to the enduring individual characteristics that have been developed over time, such as trust. Driver states represent drivers' situational physical and mental conditions, such as drowsiness. And cognitive constructs are constructs with regard to information processing and motivational procedures, such as workload. Note that these categories of driver takeover capability determinants have interdependent effects on one another. We suggest to understand this phenomenon by drawing on the relationship between long-term and short-term memory, as demographic factors and personal traits are relatively stable and relate to humans' long-term memory while driver states and cognitive constructs are situational and mainly affect short-term memory (Atkinson and Shiffrin 1968). Therefore, the relationships between these categories of driver takeover capability determinants can be understood as drivers' demographic factors and personal traits (long-term memory) provide knowledge and experience that guide the development of driver states and cognitive constructs (short-term memory), and driver states and cognitive constructs (short-term memory) can also strengthen and shape drivers' personal traits (long-term memory) in turn (Atkinson and Shiffrin 1968).

This taxonomy illustrates that the determinants of takeover task demand and driver takeover capability interface with each other through the cognition processes. We dive deeper into the cognitive constructs and try to partially capture their interrelationships along the human cognition process. Besides the TCI model, two other theories are adopted to provide theoretical support, namely, the attention mechanism in Wickens and Carswell (2021) and the situation model in Endsley (2021). Attention resources and their allocations have been proven to have a decisive impact on human behaviors (Parasuraman and Manzey 2010; Wickens, Clegg, *et al.* 2015; Yamani and Horrey 2018). Specifically, attention resources provide energy for cognitive activities and the attention allocations govern information

filtering processes in these activities (Wickens and Carswell 2021), including the three procedures of the situation model: perception, understanding, and projection (Fuller 2011). Here, a distinction has been made between the situation model and situational awareness. That is, the situation model refers to the information processing procedures that consist of human perception, understanding, and projection of surrounding environments (Endsley 2021). And situational awareness is considered as the product or knowledge of the situation model (Endsley 1995). Corresponding to the three procedures of the situation model, situational awareness can also be subdivided into three levels (Endsley 2021). In this case, the human cognition process and the interrelationships of cognitive constructs can be interpreted as when encountering takeover requests, human drivers first transfer the objective factors into perceived takeover task demands and perceived driver takeover capabilities and gain their level 1 situational awareness through the perception procedure. Then, the drivers compare these two aspects and recognize the mental workload required for the takeover tasks and gain their level 2 situational awareness through the understanding procedure. After that, the drivers project future situations, develop level 3 situational awareness, and make decisions about the intent of takeover behaviors and/or adaptions. During this process, attention resources and allocations determine cognitive abilities in each procedure and eventually lead to various takeover time. The above interpretation partially captures the interrelationship of determinants of takeover task demand and driver capability based on the attention theory (Wickens and Carswell 2021) and situation model (Endsley 2021), which can be improved and modified as research on human cognition theory processes.

We anticipate that the proposed taxonomy of takeover time determinants can help to elucidate the underlying mechanisms that govern drivers' takeover behaviors and facilitate the prediction of takeover time which is the lower limit to be satisfied by sufficient time budgets.

2.4. TIME BUDGET

It is crucial to ensure sufficient time budgets for the safety, quality, and efficiency of takeovers (Li, Wang, Wang, Zeng, Li, *et al.* 2021), which are the fundamental aspects that influence drivers' willingness to utilize automation (Parasuraman and Riley 1997). The sufficiency of time budgets is a relative concept, as it depends on the takeover time that drivers need to consciously control vehicle operations. On one hand, the time budget should be longer than the takeover time, so that drivers have enough time to respond and resume vehicles' control safely (Gold, Happee, and Bengler 2018). On the other hand, if the time budget is excessively long, the efficiency and comfort of the takeovers can be affected, and drivers may perceive the takeover request as a false alarm (Huang and Pitts 2022; Skrickij, Šabanovič, and Žuraulis 2020), which can also lead to potential risks to safe driving. This section delves deeper into the sufficiency of time budgets by exploring fixed time budgets that are tested and suggested in the literature in Section 2.4.1, and discussing the state-of-the-art adaptive time budgets research in Section 2.4.2.

2.4.1. FIXED TIME BUDGETS

Existing studies on time budgets often focus on how fixed durations accommodate various takeover scenarios (Dogan and Acarman 2025; Liu, Wu, *et al.* 2024). A commonly used time budget in the literature is 7 seconds for distracted drivers to resume vehicle control (Gold, Damböck, *et al.* 2013), and this value has been widely adopted in takeover experiments (Jarosch, Bellem, and Bengler 2019; Körber *et al.* 2016; Xu *et al.* 2024). However, Gold, Damböck, *et al.* (2013) pointed out that drivers exhibit low situational awareness under a 7-second time budget, indicating its potential inadequacy. Similarly, Eriksson and Stanton (2017a) reported that a 7-second budget may not satisfy the needs of most drivers in real takeover contexts. Supporting this concern, McDonald *et al.* (2019) found that the average time budget across studies is closer to 8 seconds. These findings suggest that longer time budgets may be necessary—especially in complex scenarios or for drivers with slower response times. Further research is needed to identify context-dependent thresholds for fixed time budgets that ensure both safety and comfort during control transitions.

We dive deeper into the fixed time budgets that have been tested in empirical studies and provide an overview of the suggested time budgets in different takeover scenarios. The corresponding takeover time and driving velocities in these studies are also listed in the overview to provide contextual information, as shown in Table 2.2. Such an overview can help readers to gain a better understanding of the context between time budgets and takeover times and identify potential research gaps with regard to the underdeveloped time budgets and takeover scenarios.

Table 2.2: An overview of the time budgets studied in the literature (examples).

Studies	tTB(s)	ToT(s)	V(km/h)	sTB(s)
Gold, Damböck, *et al.* (2013)	5, 7	mean=2.10, 2.89	120	≥ 7
Mok *et al.* (2015)	2, 5, 8	-	72	5
Melcher *et al.* (2015)	10	1.4-6.7, median=3.5	100	10
Körber *et al.* (2016)	7	1.91-4.28	120	>7
Clark and Feng (2017)	4.5, 7.5	mean=2.07, 1.91	72	7.5
Wan and Wu (2018)	3, 6, 10, 15, 30, 60	2.0*-3.0*	-	10
Du, Yang, and Zhou (2020)	4, 7	1.5*-3.5*	130	7
Dogan, Yousfi, *et al.* (2021)	4, 8	mean=2.28, 2.80	110	8
Huang and Pitts (2022)	4, 7	mean=1.75, 1.79	97	7
Shahini *et al.* (2023)	5, 8, 10	mean=2.05, 2.45, 2.60	64	≥ 8
Wu, Yao, *et al.* (2024)	3, 7, 11, 15	mean=2.07, 2.98, 3.47, 3.08	60	15

* tTB: tested Time Budget; ToT: Takeover Time; V: Velocity; sTB: suggested Time Budget.

* The takeover times with * marks are estimated according to the figures in the references because the specific numbers are not mentioned.

As shown in Table 2.2, the suggested time budgets in the literature vary significantly

from 5 to 15 seconds. We describe three reasons responsible for such variations in suggested time budgets:

- **High variability of takeover demands**: empirical studies on fixed time budgets have diverse experiment designs, involving different participants and takeover scenarios. As discussed in Section 2.3.3, this phenomenon leads to varied takeover times, i.e., varied takeover demands that need to be satisfied by time budgets. So when researchers test the time budgets of interest, the sufficient time budgets that meet varied demands are accordingly different. This means that researchers can come to distinct conclusions about the suggested time budgets when they test different scenarios on different participants.

- **Lack of consistent measures of takeover performance**: different studies adopt different criteria for suggesting time budgets as they have different research objectives. For example, Yin and Pan (2020) reported that a time budget of 45s was preferred over 15s based on the subjective experiences and feelings of the elderly, while Wan and Wu (2018) aimed to deliver a safe but also efficient takeover and they stated that a 10-second time budget is acceptable. This phenomenon reveals that standard measures for takeover performance are critical to improving the comparability of research on time budgets, which will be further discussed in Section 2.5.

- **Sufficient time budgets should not be fixed**: similar to the concept of Time To Collision (TTC) (Hayward 1972), time budget is the time to the detected system boundaries if the ego vehicle continues at its present speed on the same lane after the takeover request (Tanshi and Söffker 2022). This reveals that the time budget is subject to the relative distance and driving speed to the detected system boundaries. Tanshi and Söffker (2022) found that a 7-second time budget is too long when the ego vehicle drives at 80 km/h, but is suitable when the driving speed is between 100 km/h to 130 km/h. This example suggests that a sufficient time budget should not be applied indiscriminately, but be adjusted according to the relative distance and speed to system boundaries.

In conclusion, fixed time budgets entail inherent limitations in satisfying the diverse demands of human drivers and takeover scenarios. A fixed time budget that is inadequate to cover the required takeover time may endanger the safety of takeovers, whereas an excessively long fixed time budget may impede the efficiency of takeovers. In either case, the takeover experience of drivers will be compromised, which can lead to reduced trust and acceptance of conditionally automated driving. Therefore, it is imperative to dynamically tailor the time budget based on the needed takeover time to improve the performance and user experience of takeovers.

2.4.2. ADAPTIVE TIME BUDGETS

As fixed time budgets show weaknesses in satisfying various takeover demands (Eriksson and Stanton 2017b), we argue that the adaptive time budget is a promising direction for research on time budgets and human factors in takeovers as they can

facilitate human drivers to perform flexible takeovers that are tailored to specific contexts. Previous studies also support this argumentation. De Winter *et al.* (2014) performed a meta-analysis of the effects of automated driving on drivers' workload and situational awareness. They stated that adaptive automation is a feasible approach to maintaining drivers' situational awareness at a necessary level to keep them in the driving loop. Huang and Pitts (2022) analyzed the effects of time budgets on takeover performance and suggested that the automated driving system should adjust the time budget based on the urgency of the situation so that drivers can have enough time to perform safe and smooth takeovers. We argue that such adaptive time budgets have the potential to prompt better takeover performance and more human-centered conditionally automated driving compared with fixed time budgets.

Research on adaptive time budgets is emerging. Marberger *et al.* (2018) proposed to quantify driver availability for taking over vehicle control from conditionally automated driving systems by the difference between the available time budget and the time needed for a safe takeover process, i.e., drivers' takeover time plus intervention time. This method provides insights for research on adaptive time budgets, that is, if the preferred driver availability is preset, the sufficient time budget can be calculated as the sum of this preset driver availability and the needed time for safe takeovers. Similar to this idea, Li, Hou, *et al.* (2021) adjusted the time budget via a multiple regression model of the visual distraction degree of drivers, takeover repetition, and time to the boundary at takeover timing (TTBT, the same concept as the takeover buffer proposed in Section 2.3.1). The similarity between the above two studies can be understood as the first two input variables (i.e., drivers' visual distraction degree and takeover repetition) of the regression model in Li, Hou, *et al.* (2021) indicate the needed time for safe takeovers in Marberger *et al.* (2018). And the last variable (TTBT) of the regression model indicates driver availability. In a follow-up research of Li, Wang, Wang, Zeng, Li, *et al.*, they discussed the effects of fatigue state and traffic condition on the takeover performance and embedded these two factors into the former adaptive time budget model. This improved model not only complements the indicators of the needed takeover time by embedding fatigue state but also includes the traffic condition that relates to takeover task demand. The improved model is more in line with Fuller's TCI model which is used to interpret drivers' takeover time in Section 2.3.3. This finding provides additional evidence in favor of utilizing the TCI model for deciphering drivers' takeover time and reinforcing our belief that the sufficiency of time budgets is relative to the needed takeover time.

While previous research has made significant contributions to the determination of adaptive time budgets, we argue that the following two aspects can be further improved to enhance the interpretability and practicality of the adaptive strategies for determining sufficient time budgets:

- **Prediction of takeover time**: the discussions of adaptive time budget have an implicit precondition where drivers' takeover time is known before determining the timing of initiating takeover requests (while Li, Hou, *et al.* did not mention that they predicted drivers' takeover time, the input variables they chose for the regression model are predictors of takeover time). This requires timely and accurate prediction of drivers' takeover time before conditionally automated

driving systems initiate takeover requests, which is primarily achieved by neural network models. Rangesh *et al.* (2021a) utilized a long-short-term memory neural network to predict drivers' takeover time based on the time drivers need to be physically ready for manual driving (i.e., the time until drivers put their hands on the steering wheel, feet on a pedal, and eyes on the road). Pakdamanian *et al.* (2021) adopted a deep neural network method to predict drivers' takeover time based on the driving parameters of vehicles and the physio-psychological signals of drivers, such as galvanic skin responses. Results show that these AI-based approaches enable the valid prediction of takeover time. But the interpretability of these models is still a challenge (Ayoub, Du, *et al.* 2022; Li, Hou, *et al.* 2021; Pakdamanian *et al.* 2021). For example, why choose those variables as predictors of takeover time? Are those variables representative enough? Are there any other variables that should be considered? These open questions emphasize the importance of reinforcing theoretical bases and constructing interpretable prediction models of the takeover time, which is also mentioned in Section 2.3.3.

- **TTBT should be preset**: the TTBTs in the studies of Li, Hou, *et al.* (2021) were determined via post-analyses after the takeover process based on the subsequent takeover performance. Li, Wang, Wang, Zeng, Li, *et al.* (2021) provided four options for TTBT (3s, 4s, 5s, and 6s) and observed that the 4-second TTBT is the minimum interval that satisfies the preset collision rate. But considering that TTBT is an indispensable determinant of time budget, the lengths of TTBT should be preset before the takeover process actually happens, so that conditionally automated driving systems can combine the preset TTBT and the predicted takeover time, then determine the timing of initiating the takeover request, i.e., the time budget. That means the TTBTs should come from prior analyses of takeover performance instead of post-analyses. Similarly, this principle also applies to driver availability in Marberger *et al.* (2018) as the driver availability should also be preset and then added to the predicted takeover time to determine time budgets. Further research on the determination of TTBT and driver availability is necessary to facilitate the application of the adaptive time budget model in practice and thereby enhance its social significance.

We notice that most studies of takeovers involve both time budgets and takeover times, yet few of these studies report the values of TTBTs which represent the differences between time budgets and takeover times. Happee *et al.* (2017) referred to TTBT as the remaining time within the time budget and observed that this limited remaining time affects drivers' performance of evasive maneuvers. Marberger *et al.* (2018) referred to TTBT as drivers' intervention time and used it to measure driver availability. Tanshi and Söffker (2022) referred to TTBT as the maneuver response time which is similar to the intervention time in Marberger *et al.* (2018) and considered it as a determinant of time budgets. We argue that these terms do not fully reflect the intentions of embedding such an interval in the time budget. For instance, the terms "TTBT" and "remaining time " merely describe the position

of this interval in the time budget sequence and they do not capture the design intentions of embedding this interval in time budgets. While the "intervention time" and "maneuver response time" partially reflect the intention of providing a time window for human intervention in vehicle operations to ensure the safety of takeovers, it fails to convey the other intended benefits of this interval. For instance, this interval can help to improve tolerance for deviations in the predicted takeover time to enhance the robustness of adaptive time budget strategies (Marberger *et al.* 2018) and protect drivers from excessive time pressures to regain control to ensure the safety and comfort of takeovers (Melcher *et al.* 2015). Therefore, we propose the term "takeover buffer" to describe such an interval as the buffer time to the takeover time in the time budget. The concept of takeover buffer aligns with ISO 21959:2020 (2020), where the total time budget is composed of driver takeover time, driver intervention time, and remaining action time. Specifically, in this study, the sum of the driver intervention time and remaining action time constitutes the takeover buffer. The term "buffer" is defined as "something or someone that helps protect from harm" in Cambridge Dictionary where the "harm" can be interpreted as failures to provide sufficient time budgets. Therefore, we think the proposed time buffer aptly captures the aforementioned intentions which are to offer a time window for human interventions, enhance the robustness of adaptive strategies, and ensure takeover safety.

To explore the takeover buffers in other studies, we leverage the records in Table 2.2 and subtract the mean/median takeover times from the suggested time budgets. Mok *et al.* (2015) is excluded because it did not report takeover times. The takeover times in Körber *et al.* (2016), Wan and Wu (2018), and Du, Yang, and Zhou (2020) are taken as the average of the maximum and minimum values because these two studies only reported ranges of takeover times. Results show that the mean takeover buffer is 6.00s while the average mean takeover time is 2.65s. This suggests that the optimal takeover buffer can be two to three times the takeover time, which accounts for a large part of the time budget and thus requires closer examination. This leads to the question: how to determine a sufficient takeover buffer?

The answer to this question is critical to determine a sufficient time budget that can optimize takeover performance, considering the time budget is determined by the predicted takeover time and the takeover buffer in research of adaptive time budgets (Li, Hou, *et al.* 2021; Marberger *et al.* 2018). This determination strategy of time budgets indicates that the sufficiency of the takeover buffer is interdependent with the takeover time and the time budget which can be reflected by the corresponding takeover performance. A quantitative relationship between takeover time, time budget, and takeover performance is necessary to determine a sufficient takeover buffer, which is also applicable to determining a sufficient time budget but has yet to be comprehensively examined (Gold, Happee, and Bengler 2018; Tanshi and Söffker 2022). Therefore, we propose a hypothesis for a qualitative relationship between takeover time, time budget, and takeover performance in Section 2.6.1 which can serve as a starting point for future research on sufficient and/or adaptive time budgets.

2.5. TAKEOVER PERFORMANCE

Takeover performance aids in understanding the mechanism factors in the takeover process (Gold, Happee, and Bengler 2018) and serves as an optimization target for research that aims to improve the safety and comfort of conditionally automated driving (Li, Wang, Wang, Zeng, Wu, *et al.* 2023), which includes the studies of sufficient time budgets. In this section, we synthesize measures of takeover performance to clarify the suitability of various evaluation criteria. This can also facilitate the development of the relationship between takeover time, time budget, and takeover performance in Section 2.6.1, as takeover performance is an important variable in this relationship that needs to be quantified. Specifically, we examine measures and the corresponding indicators of takeover performance in the literature in Section 2.5.1, propose a taxonomy to structure these performance measures and indicators in Section 2.5.2, and compare the pros and cons of various human-related performance measures in Section 2.5.3.

2.5.1. MEASURES OF TAKEOVER PERFORMANCE

Research on takeovers has extensively explored how various factors influence takeover performance (Hwang, Choi, and Kim 2025; Lin *et al.* 2020). These studies generally employ different performance indicators and evaluation thresholds (Li, Wang, Wang, Zeng, Wu, *et al.* 2023), resulting in a lack of consensus on how takeover performance should be measured. For example, Eriksson and Stanton (2017a) employed the standard deviation of the steering wheel angle to indicate drivers' workload and used the mean absolute lateral position to assess drivers' lane-keeping accuracy. Alrefaie, Summerskill, and Jackon (2019) quantified the quality of takeovers based on the mean percentage change of vehicles' speed and heading angle during the takeover process. These two examples show that there are multiple measures of takeover performance yet a well-accepted criterion for measuring takeover performance is missing (Cao *et al.* 2021). This issue brings about a lack of comparability in research related to takeovers, which can introduce biases in quantitative studies of takeover performance and can even lead to opposite conclusions. As exemplified in Section 2.4.1, we find that different time budgets are suggested for similar takeover time. We suspect that this is because the related studies aim to improve different aspects of takeover performance, such as safety (Gold, Damböck, *et al.* 2013) and efficiency (Clark and Feng 2017). Different measures of takeover performance are adopted across studies, which accordingly leads to varied evaluation results that are used to suggest sufficient time budgets. This case shows that the lack of a well-accepted measure of takeover performance poses a challenge to determining sufficient time budgets. To address this issue, it is essential to improve the clarity on the suitability of evaluation criteria for takeover performance and explore how to validly measure takeover performance.

A valid measure of takeover performance requires a systematic overview of performance indicators so that researchers can compare the pros and cons of these indicators and then develop standard measures of takeover performance (Li, Wang, Wang, Zeng, Wu, *et al.* 2023). To provide such an overview, we synthesize the studies of takeover performance and extract the related performance indicators via

the combined approach of umbrella review and systematic review. Specifically, an initial indicator set of takeover performance is constructed by an umbrella review on four review papers, i.e., McDonald *et al.* (2019), Cao *et al.* (2021), Weaver and DeLucia (2022), and Chen, Zhao, Chen, *et al.* (2025). Additional indicators from other involved literature (such as Gold, Körber, *et al.* (2016), Beggiato, Hartwich, and Krems (2018), and Huang, Fan, *et al.* (2024)) are also included to complement the indicator set. The applied indicator extraction process is shown in Figure 2.4, where 38 performance indicators are identified.

Figure 2.4: Extraction of takeover performance indicators.

These four review papers cover both vehicle-based metrics (e.g., lateral acceleration) and human-based reaction times (e.g., the time taken to return hands to the steering wheel). However, they place less emphasis on drivers' subjective experiences (such as workload and user comfort), which are primarily drawn from other involved literature to supplement the performance indicator set. These experiential factors are crucial for driver acceptance of automated vehicles and ultimately influence users' willingness to adopt the technology. This phenomenon implies an imbalance in how objective and subjective performance measures are being considered in the literature, as some studies focus on driver experience (Li, Hou, *et al.* 2021; Li, Wang, Wang, Zeng, Wu, *et al.* 2023), while others emphasize vehicle performance (Happee *et al.* 2017; Li, Blythe, Guo, *et al.* 2018; Lu, He, *et al.* 2021), leading to a fragmented view of what constitutes successful takeover performance. This disparity can bias the direction of studies that use takeover performance as an optimization goal. For instance, Gold, Körber, *et al.* (2016) considered a long minimum Time To Collision (TTC) as a marker of high-quality takeover performance—a valid metric

from a vehicle-centric perspective, as it reflects a lower risk of collision. However, Radlmayr *et al.* (2018) argued that achieving a longer minimum TTC often involves abrupt braking, which can result in an unnatural and uncomfortable experience for the driver. Such discomfort may undermine trust in the automation and reduce long-term acceptance (Ma and Zhang 2021). Therefore, using minimum TTC as a standalone indicator may be insufficient or even misleading from a human-centered perspective. Therefore, it is important to develop integrated performance measures that capture both the human perspective and the vehicle perspective to optimize the safety and comfort of takeovers.

Considering the diversity of the extracted performance indicators, it is essential to categorize these indicators to provide an overview of the different branches of takeover performance. This can help to improve the comparability of related studies and facilitate the development of standard measures of takeover performance.

2.5.2. TAXONOMY OF TAKEOVER PERFORMANCE INDICATORS

A variety of performance measures has been used in studies of takeovers (Alrefaie, Summerskill, and Jackon 2019; Eriksson and Stanton 2017a), while a standardized and agreed-upon criterion for measuring takeover performance is still missing in the literature (Li, Wang, Wang, Zeng, Wu, *et al.* 2023). This makes it difficult to consolidate the results across studies of takeovers and draw consistent conclusions. In this case, it is necessary to provide a taxonomy of the existing measures of takeover performance, which can help to clarify the suitability of the evaluation criteria and guide the development of new measures of takeover performance.

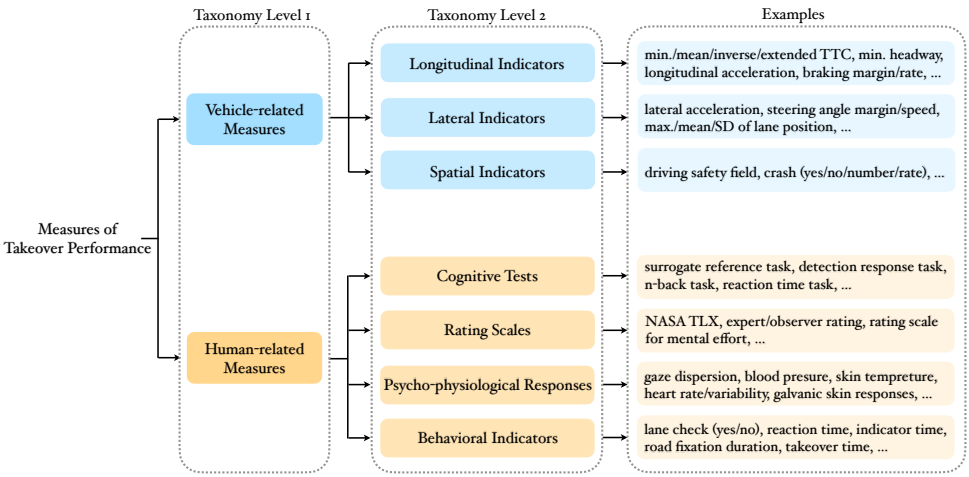


Figure 2.5: Taxonomy of takeover performance measures.

This review proposes a taxonomy to categorize measures of takeover performance as shown in Figure 2.5. Given that takeover is an interaction between vehicles and humans, we divide the measures of takeover performance into two categories

- vehicle-related measures and human-related measures. Specifically, vehicle-related measures are based on driving parameters, such as lateral acceleration (McDonald *et al.* 2019). And human-related measures are based on individual behaviors and subjective feedback, such as heart rate variability (Hecht *et al.* 2018). These two categories are not contradictions but complement each other, and the indicators within each category are further classified below:

In terms of vehicle-related measures, Cao *et al.* (2021) proposed a framework for categorizing these metrics into time and quality dimensions through a literature review of takeover performance. While this framework offers useful insights, some metrics may span both categories, making their classification less straightforward. For instance, Time to Collision (TTC) is typically defined as the time remaining before the ego vehicle would collide with an obstacle ahead if it maintains its current speed and trajectory (Hayward 1972), clearly placing it within the time dimension. However, TTC is also often interpreted as a safety indicator—smaller values indicate higher collision risk—highlighting its relevance to takeover quality as well (Wan and Wu 2018). This example illustrates the potential overlap between dimensions, suggesting that some metrics resist strict categorization. To reduce such ambiguities in classification results, we propose to divide vehicle-related indicators into longitudinal, lateral, and spatial indicators according to their application scope, i.e., the specific dimensions of takeover performance that these indicators measure. Here, spatial indicators refer to the metrics that comprehensively measure the takeover performance from both longitudinal and lateral dimensions, such as the driving safety field (Wang, Wu, and Li 2015). Collision-related metrics are also categorized into spatial indicators as collision is the result of operational failures in both longitudinal and lateral dimensions, i.e., drivers fail to either brake or change lanes in time to avoid crashes. We notice a common trend in previous research that vehicle-related takeover performance is measured by longitudinal and lateral indicators respectively (Lin *et al.* 2020; Lu, He, *et al.* 2021). For example, Shahini *et al.* (2023) utilized minimum TTC and maximum lateral acceleration to indicate the vehicle's longitudinal and lateral performance during takeovers. This may be due to that vehicles' driving behaviors during takeovers can be decoupled into longitudinal and lateral operations (Jin *et al.* 2021). But the decoupled measures of takeover performance may not capture the overall safety and quality of takeovers well as they can bring potential biases that arise from focusing only on either the longitudinal or lateral dimensions of the takeover performance. Hence, we suggest that researchers give more attention to spatial indicators of vehicle-related takeover performance to provide a comprehensive and integrated understanding of the entire takeover process, which is especially crucial in highly complex takeover scenarios (Wang, Wu, and Li 2015).

As for human-related indicators, we propose to further divide them into four categories according to the type of data that are collected and analyzed, namely cognition tests, rating scales, psychophysiological responses, and behavioral indicators. Specifically, cognition tests ask drivers to perform specific tasks to measure human mental functions, such as using detection response tasks to measure drivers' workload (Conti-Kufner 2017). Rating scales assess multiple aspects of

takeover performance via questionnaires. Related questions are answered either based on the memories of drivers (i.e., self-rating) (Li, Wang, Wang, Zeng, Wu, *et al.* 2023), or the observations of other experts (i.e., expert/observer rating) (Jarosch and Bengler 2019). Psychophysiological responses reflect the psychological activities of drivers via the changes in physiological response, such as heart rate variations (Alrefaie, Summerskill, and Jackon 2019). And behavioral indicators are derived from drivers' takeover behaviors, such as takeover time (Müller *et al.* 2021). Note that even though some behavioral indicators are measures based on vehicle-related parameters (such as steering wheel angles), human cognitive activities and the corresponding behaviors are the key determinants of these indicators. Therefore, we categorize such behavioral indicators as part of human-related measures rather than vehicle-related measures. Besides, it is important to distinguish these human-related performance measures from the determinants of driver takeover capability in Section 2.3.3. While these two categories are both related to human factors, human-related performance measures reflect the outcomes of the takeover process (i.e., how drivers respond and feel during and after takeovers) and determinants of driver capability refer to individual characteristics (e.g., age, experience, fatigue) that influence how drivers perceive, interpret, and act during a takeover. In other words, human-related performance measures evaluate the effects of a takeover on the driver, whereas driver capability determinants represent the preconditions that shape those effects.

Based on the proposed taxonomy in Figure 2.5, we notice that vehicle-related measures and human-related measures are keyed to different aspects of takeover performance. On one hand, vehicle-related measures generally reflect the safety and quality of takeovers. These measures are based on objective driving parameters, which are called surrogate measures of safety in Lu, He, *et al.* (2021). For instance, Wan and Wu (2018) used the minimum TTC and lateral acceleration to indicate the quality of post-takeover control. Jin *et al.* (2021) utilized maximum longitudinal deceleration, maximum lateral acceleration, and standard deviation of lane position as indicators to assess the longitudinal and lateral stability of evasive maneuvers during takeovers. On the other hand, human-related measures reflect drivers' takeover experience and their subjective assessments of takeover performance by tracking the changes in driver states and cognitive constructs. Wu, Kihara, *et al.* (2019) utilized drivers' eyeblink duration and Karolinska Sleepiness Scale to measure the observed and perceived drowsiness levels during takeovers respectively. Agrawal and Peeta (2021) monitored the changes in drivers' heart rates to track their mental stress during takeovers and they found that these changes have a significant negative effect on the safety and quality of takeover performance. This finding reveals that there is a correlation between the two categories of takeover performance measures, as the changes measured by human-related indicators can impact the performance measured by vehicle-related indicators. Additional support for this finding is a convergence between drivers' physiological changes and the quality of vehicle operations during takeovers, which is reported in Alrefaie, Summerskill, and Jackon (2019). They concluded that drivers' heart rates and pupil diameters can be used to predict the stability of the ego vehicle's speed and heading angle during evasive maneuvers which are important vehicle-related indicators of takeover performance.

This further emphasizes that the imbalanced consideration of vehicle-related and human-related measures of takeover performance is a crucial issue that needs to be addressed as the lack of integration between the two perspectives can lead to a distorted and incomplete understanding of the takeover process and its outcomes, which ultimately affects user trust and acceptance of conditionally automated driving (Li, Wang, Wang, Zeng, Wu, *et al.* 2023; Ma and Zhang 2021).

We argue that a more balanced measure of takeover performance, that integrates vehicles' objective driving performance and human drivers' subjective experience, is essential for the development and widespread adoption of conditionally automated driving systems. To address this issue, we propose a taxonomy of takeover performance indicators, which includes both vehicle-related indicators and human-related indicators. This taxonomy can provide a comprehensive understanding of the measures of takeover performance, guide the development of standardized performance measures, and then improve the comparability of studies of takeovers.

2.5.3. COMPARISON OF HUMAN-RELATED PERFORMANCE MEASURES

When it comes to takeover performance, the objects that are measured by human-related indicators are not as straightforward as those indicated by vehicle-related indicators. Specifically, as shown in Figure 2.5, vehicle-related indicators are further categorized into longitudinal, lateral, and spatial indicators according to the objects that they intend to measure, i.e., the specific dimensions of takeover performance. This classification criterion is not applicable to human-related indicators as these indicators have complex causal relationships with human cognitive constructs (Zhang, De Winter, *et al.* 2019). This is also one of the reasons for dividing human-related indicators of takeover performance according to the data collection methods, as not only a construct can be measured by multiple human-related indicators but a human-related indicator can be used to measure various constructs (Hecht *et al.* 2018). For example, drivers' heart rate and its variability are psycho-physiological responses that can be used to measure drowsiness (Fujiwara *et al.* 2018) and workload (Du, Yang, and Zhou 2020) while the workload can also be evaluated via self-rating questionnaires like NASA-Task Load Index (Yoon and Ji 2019). Taken the complex relationships between human constructs and human-related indicators of takeover performance, it is essential to clarify the suitability of these indicators and compare their pros and cons collectively. This will help readers to build a comprehensive understanding of human-related measures of takeover performance and identify suitable indicators for different research contexts.

In this section, we synthesize the analysis of various human-related measures of takeover performance based on the review paper of Hecht *et al.* together with other research articles such as Pakdamanian *et al.* (2021), Marberger *et al.* (2018), and Conti-Kufner (2017). We compare the four categories of human-related measures in Figure 2.5 from five perspectives, namely timeliness, robustness, implementability, intrusiveness, and validity. These perspectives are important properties that need to be considered when selecting of measures of takeover performance in empirical studies and practical applications of conditionally automated driving (Hecht *et al.* 2018). Specifically, timeliness refers to how quickly these human-related measures

can be obtained and processed, which is crucial for real-time evaluations of takeover performance and driver state monitoring (Marberger *et al.* 2018). Robustness refers to the degree of reliability and consistency that measurements can maintain across different takeover scenarios and environmental conditions, which plays an important role in the usefulness of these human-related measures of takeover performance (Yi *et al.* 2022). Implementability refers to the feasibility of incorporating the equipment for human-related measures into existing driving systems, which needs to be accomplished for measuring takeover performance in practical applications (Feldhütter, Feierle, *et al.* 2018). Intrusiveness relates to the degree of distraction and discomfort caused to drivers during the data collection process and should be kept at a low level to ensure that the processing of these human-related performance measures does not interfere with the drivers' driving abilities (Hecht *et al.* 2018). Finally, validity reflects the accuracy and the effectiveness of using these human-related measures to represent the intended constructs and evaluate the takeover performance in conditionally automated driving (Hecht *et al.* 2018). These five properties can provide guidance for readers to select appropriate and effective human-related measures of takeover performance in different research contexts. We have therefore carried out a comparative analysis of these properties of four categories of human-related takeover performance measures, as discussed below.

- **Timeliness:** psycho-physiological responses are real-time indicators that can be monitored during the takeover process; observer-rating scales and behavioral indicators can be obtained after specific takeover behaviors are completed; cognition tests and self-rating questionnaires are conducted after takeovers.

- **Robustness:** cognition tests and self-rating scales are robust to withstand interferences as long as the questions and tasks are well designed; results of observer rating can differ depending on observers; psycho-physiological responses and behavioral indicators are subject to environmental factors, such as lighting conditions.

- **Implementability:** cognition tests and rating scales are easy to implement in a vehicle as they quantify mental constructs by task performances and questionnaires; behavioral indicators require sensors to detect the thresholds of specific actions (e.g., the steering wheel angle and the head pitch angle) to turn on/off the timer; psycho-physiological responses are recorded by sophisticated instruments that can precisely capture the changes of physiological signals.

- **Intrusiveness:** cognition tests, rating scales, and behavioral indicators are generally non-intrusive; psycho-physiological responses are measured by attaching electrodes directly to human skin, such as scalps.

- **Validity:** cognition tests ask drivers to complete specific tasks, which thus brings extra workload to drivers. This property needs to be considered carefully when researchers use cognition tests to measure workload-related constructs; results of rating scales can deviate from driver perceptions, either by drivers themselves (who lack self-assessment abilities) or observers (who

hold personal judgments). These deviations can be reduced by well-designed questionnaires; psycho-physiological responses are proven to be closely related to human mental activities but need further validation through theoretical research; behavioral indicators are derived from physical takeover behaviors, which are surrogate performance indicators based on specific assumptions.

The above comparison provides an overview of five properties of human-related measures of takeover performance. Given that each measure has its pros and cons, we suggest that a hybrid approach that combines indicators from multiple categories can be valid for measuring the takeover performance from the human perspective. This approach provides a comprehensive assessment of human-related takeover performance and can reduce false detection rates by integrating multi-dimensional measurements, which is especially important when adaptive systems rely on potentially imperfect assessments of driver states. This is in line with the conclusions of Hecht *et al.* (2018) and Lu, He, *et al.* (2021) as they suggested that a combination of measurements is necessary to capture the full range of driver state and driving performance, especially in complex scenarios. Note that among the four categories of human-related measures in Figure 2.5, psycho-physiological responses have sophisticated causal relationships with human constructs. These relationships need to be further investigated to provide guidance for selecting proper psycho-physiological indicators and alleviate the disruptions of noisy signals in developing standard measures of takeover performance. To overcome these challenges, further research should focus on creating validated metrics that consistently reflect takeover performance across various driving contexts and on refining measurement techniques for both real-world and simulated driving contexts. Such advancements are essential for harnessing physiological data to improve adaptive human-vehicle interaction strategies.

2.6. DISCUSSION AND LIMITATIONS

To determine how to find sufficient time budgets for safe and comfortable takeovers, a systematic review has been conducted of existing research on takeover time (Section 2.3), time budget (Section 2.4), and takeover performance (Section 2.5) as the sufficiency of time budgets is subject to the required takeover time and the corresponding takeover performance (Marberger *et al.* 2018). Based on the analyses and findings of Section 2.3, 2.4, and 2.5, we suggest a potential solution for determining sufficient time budgets. That is, conditionally automated driving systems predict drivers' takeover time before takeovers start, and then find the optimal time budgets according to the quantified relationship between takeover time, time budget, and takeover performance. In this section, we propose a hypothetical relationship between takeover time, time budget, and takeover performance in Section 2.6.1, outlines a research agenda for sufficient time budgets in Section 2.6.2, and discuss limitations of this study in Section 2.6.3.

2.6.1. HYPOTHETICAL RELATIONSHIP BETWEEN TAKEOVER TIME, TIME BUDGET, AND TAKEOVER PERFORMANCE

Time budgets are dynamically adjusted to satisfy the demands of varied takeover times in research on adaptive time budgets (Li, Wang, Wang, Zeng, Li, *et al.* 2021; Marberger *et al.* 2018), so that such time budgets can be sufficient for human drivers to safely and comfortably take over vehicle control in various scenarios (Huang and Pitts 2022; Shahini *et al.* 2023). This indicates that the sufficiency of the time budget is a relative concept of the offered time budget and the needed takeover time, which can be reflected by the corresponding takeover performance (Tanshi and Söffker 2022). In this case, research on sufficient time budgets requires a clear quantitative relationship between takeover time, time budget, and takeover performance, based on which conditionally automated driving systems can accordingly adjust the time budget for the predicted takeover time to optimize the takeover performance.

We propose a hypothesis about the qualitative relationship between takeover time, time budget, and takeover performance in Figure 2.6, serving as a starting point for future research on sufficient or adaptive time budgets. The vertical lines are illustrative examples of a predicted takeover time and an estimated sufficient time budget. The inverted U-shaped relationship shown in the figure pertains to this specific takeover time. For any predicted takeover time, a sufficient time budget is determined to achieve the desired performance within the acceptable performance margin, based on the corresponding U-shaped relationship. Note that the takeover performance here embodies not only objective assessments of the safety and quality of takeovers based on driving parameters but also subjective assessments of experiences and feelings from human drivers. As time budget increases, performance initially improves but declines after a certain point due to reduced engagement or frustration (Huang and Pitts 2022; Skrickij, Šabanovič, and Žuraulis 2020). However, this decline is estimated to eventually level off, reflecting that while overly long time budgets may diminish subjective experience, they still satisfy safety requirements and maintain acceptable objective performance.

As shown in Figure 2.6, when conditionally automated driving systems predict that human drivers need a specific takeover time, if the offered time budget is much shorter than the takeover time, the takeover performance is generally poor because drivers do not have enough time to resume control and return to their normal driving level (Gold, Happee, and Bengler 2018). This situation can lead to over-reactions and even collisions in the worst case (Gold, Damböck, *et al.* 2013). Then, with the increase of the time budget, the takeover performance will improve first because drivers have more time to respond and develop situation awareness (Endsley 2021). Consequently, the safety, quality, and comfort of the takeover process will be enhanced (Wan and Wu 2018; Yin and Pan 2020) during which process the time budget gradually exceeds the takeover time. After the takeover performance rises to a peak, the time budget will become unnecessarily long as it continues to increase. During this process, the safety and quality of the takeover will not be improved significantly due to the limitations of driver takeover capabilities (Huang and Pitts 2022; Wan and Wu 2018). On the contrary, the overall takeover performance will gradually drop, as the takeover process becomes inefficient which can harm

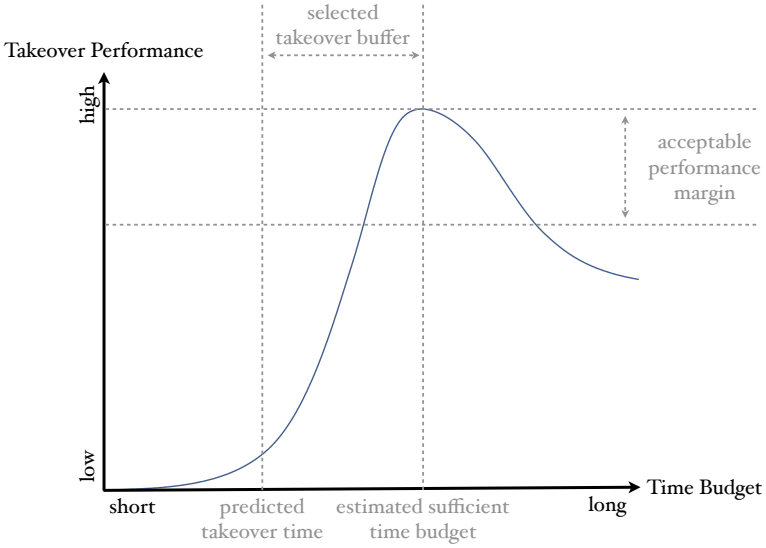


Figure 2.6: Hypothesis of the qualitative relationship between takeover time, time budget, and takeover performance.

drivers' takeover experience (Gold, Damböck, *et al.* 2013; Zhang, De Winter, *et al.* 2019). Considering the safety and quality of takeover are maintained at a high level, the takeover performance declines at a moderate rate after the peak.

While this roughly inverted U-shaped relationship has been acknowledged in several studies, Figure 2.6 provides new insights from the following three aspects:

- **Highlights the role of the takeover buffer:** We emphasize the essential role of the takeover buffer in the interplay between takeover time, time budget, and takeover performance. For a predicted takeover time within a specific context, selecting an appropriate takeover buffer is crucial to defining a time budget that is estimated to be sufficient to achieve the desired takeover performance. Therefore, the selection of a takeover buffer is fundamental to ensuring that the time budget adequately supports the takeover task.
- **Proposes an acceptable performance margin:** Rather than focusing solely on the peak point where performance may decline with an extended time budget, we suggest that research explore establishing an acceptable margin for takeover performance that a substantial portion of drivers can reliably achieve. This approach ensures that any reduction in takeover performance due to a prolonged time budget remains within an acceptable threshold. Within this margin, time budgets can be adjusted to optimize user experience without compromising essential performance standards.
- **Extends to a three-dimensional relationship model:** We propose that the relationship between time budget and takeover performance may shift with

varying takeover times. Based on suggested time budgets and takeover times (see Table 2.2), we find that drivers tend to prefer longer buffers as their takeover time increases. This may occur because longer takeover times often accompany more complex tasks, which demand additional buffers for a safe and effective takeover. Consequently, peak takeover performance and the curve's shape may adjust with different takeover times. Zhang, De Winter, *et al.* (2019) supported this view, noting that drivers take longer to resume control when provided with more time. This two-dimensional model of time budget and takeover performance can be expanded to three dimensions by incorporating takeover time. Additional research is necessary to further test and quantify this model for safe and comfortable takeovers.

These considerations contribute to a more refined understanding of the relationship between takeover time, time budget, and takeover performance, outlining how adaptive time budgets can be tailored to diverse driving scenarios.

Besides, such a relationship between takeover time, time budget, and takeover performance is not universal. For example, drivers adapt their takeover behaviors as they are getting used to interacting with automated driving systems (Stimm *et al.* 2019). Accordingly, the required takeover time and the preferred time budget that leads to the optimal takeover performance may vary depending on drivers' takeover behaviors and preferences, even in an identical takeover scenario. This implies that the relationship between takeover time, time budget, and takeover performance should also be updated over time to align with drivers' adapted takeover behaviors and preferences of time budgets. Such a relationship can also facilitate future research on developing flexible, context-sensitive, and personalized takeovers.

2.6.2. RESEARCH AGENDA

Based on the findings of Section 2.3, 2.4, and 2.5, we propose six possibilities from three aspects for further extension work to advance the knowledge and understanding in the determination of sufficient time budgets in conditionally automated driving, as discussed below.

In terms of the determinants of takeover time,

- this systematic review adopts the Task-Capability Interface (TCI) model to categorize the determinants of takeover time. The assumption is that human drivers make their decisions to maintain a relatively stable mental workload, based on the perceived takeover demand and the perceived driver capability (Endsley 2021; Van Lint and Calvert 2018). But to our knowledge, the TCI model has not been thoroughly investigated in the context of takeover research. Therefore, the validity of using the TCI model to interpret drivers' takeover behaviors and the corresponding takeover time needs further investigation.

- cognitive constructs (such as situation awareness) are mainly studied by empirical analysis at a higher abstraction level (Fernandez *et al.* 2017). That means experiments reveal the correlations between specific cognitive constructs and takeover time while the interplay of these constructs has

not yet been fully explored. In this review, we try to partially capture the relationships among these constructs based on the TCI model, situation model, and attention mechanism. Closer examinations of human cognition theories are desirable to reveal and validate the interplay of cognitive constructs and the influence mechanisms underlying drivers' takeover behaviors.

In terms of the determination strategies of time budget,

- considering the intra-heterogeneity of driver behaviors, drivers' behavioral adaptations and self-regulations can use more attention in the research of sufficient time budgets. Such adaptations and self-regulation are in line with the TCI theory because they can be regarded as compensation behaviors for maintaining the preferred safety margin. That means the takeover time that drivers need and their preferences of takeover buffer can change over time and space, which accordingly affects sufficient time budgets. Research on how to iterate the determination strategies of time budgets is necessary to maintain the high quality of takeovers, which requires to monitor driver states and track takeover performance.

- considering the inter-heterogeneity of driver behaviors, personalizing time budget strategies can be a lever to optimize human drivers' takeover experience as drivers with different driving styles, backgrounds, and ages can be catered for without discrimination. This needs further investigation on diverse interactions between human cognition and conditionally automated driving. How to customize explainable human-vehicle interaction models for individual drivers and take advantage of them to personalize the time budget strategy is an open challenge. Explorations can start with the adaptive time budget strategy.

In terms of measures of takeover performance,

- research on how to combine multiple perspectives of takeover performance is needed. Particularly, in-depth exploration is expected to bridge the vehicle perspective (objective assessments) and the human perspective (subjective assessments) of takeover performance. This is a potential reason that a standardized or well-accepted measure for takeover performance is still missing. An avenue lies in introducing fuzzy theories or probability methods in designing such a multi-perspective measure of takeover performance.

- takeover performance is generally measured on the microscopic level with a focus on the driving performance of the ego vehicle and the personal experience of its driver. Little is known about how the safety and quality of takeovers will influence the general traffic flow at the mesoscopic or macroscopic level. Research in this direction can help to examine the optimization of takeovers from a holistic perspective and provide insights into the overall traffic planning in the context of conditionally automated driving, which is important for policymakers.

This research agenda provides a potential direction for future studies on determination strategies of sufficient time budgets in conditionally automated driving. Through a systematic review of the literature on takeover time, time budget, and takeover performance, six research gaps have been identified. Further investigations aligned with this research agenda are expected to improve the safety and comfort of takeover maneuvers. This will contribute to the advancement of human-vehicle interactions and the optimization of the design of conditionally automated driving systems.

2.6.3. LIMITATIONS

Due to the limitation of time scope, databases, and search queries in Section 2.2, not all studies of takeover time, time budget, and takeover performance are included. Also, new materials will be supplemented all the time, so the investigation can be endless. But considering the significant account of the literature included, we think this systematic review is reliable and reaches relatively robust conclusions at least for the foreseeable future. The proposed frameworks of takeover time determinants and takeover performance measures can also be updated and expanded as related research progresses and new insights emerge, especially when more evidence of human cognitive interactions with conditionally automated driving is found.

Given the complex interplay of multiple influencing factors, designing sufficient time budgets through a comprehensive set of deterministic rules presents significant challenges. Similar to how the design of auditory alerts requires balancing factors like frequency, pulse rate, and loudness to convey an appropriate sense of urgency, our approach to determining sufficient time budgets considers the interdependence of various determinants. Consequently, we propose a flexible, adaptable framework that can be tailored to diverse and context-specific takeover scenarios. Specifically, we define a sufficient time budget as the predicted takeover time combined with an appropriate takeover buffer. This flexibility in adjusting the takeover buffer allows for a balanced approach that supports safe and effective driver responses across a range of conditions, avoiding the limitations of rigid, one-size-fits-all rules.

Moreover, the maximum limit of sufficient time budgets discussed in this review is subject to the abilities of automated driving systems to detect system boundaries. For instance, if a 7-second time budget is provided at a speed of 120 km/h, the conditionally automated driving systems would need to successfully detect the dangers that are at least 233m ahead. While the requirements for detecting system boundaries in this given relative speed and distance situation can already be met by current sensing technologies (Marti *et al.* 2019), the discussion of longer time budgets may necessitate further developments in sensing technology. Similarly, communication with other vehicles (V2V) and intelligent infrastructure (V2I) can also facilitate early initiations of takeover requests as other vehicles and infrastructures can send traffic information to the conditionally automated driving system even when the ego vehicle is at a distance. For example, manufacturers like General Motors and Ford have already begun integrating V2V systems into their vehicles, facilitating real-time exchange of critical safety information. Research by Kim, Liu, *et al.* (2015) shows that cooperative perception can extend the perception range

up to the boundary of connected vehicles, enabling proactive decision-making and planning in automated driving. Therefore, we argue that advancements in sensing and detection technologies, along with V2V and V2I communications, can enhance the situational awareness ability and operational flexibility of automated driving systems, thus expanding the scope of available time budgets and allowing further discussion of sufficient time budgets based on situational demands.

Other limitations of this review come from the common constraints in the involved literature. For internal validity, an unavoidable threat is participants get more and more familiar with the conditionally automated driving systems during experiment processes. Such habituation should be considered when drawing conclusions. As for external validity, most of the involved research in the reviewed papers is performed based on driving simulator experiments, which can limit their accuracy in replicating actual driving behaviors. Such impacts are mitigated in this review by mainly focusing on the temporal factors (such as takeover time and time budget) but the impacts still exist. Also, the findings of the reviewed research papers may not extrapolate well to a larger population as often sample sizes of these papers are relatively small (less than 200). But considering we synthesize the results of considerable experiments, the cumulative number of participants virtually increases the population validity as a whole.

2.7. CONCLUSIONS

Despite the acknowledgment of time budgets as a crucial factor, research specifically focused on determining what constitutes a sufficient time budget remains limited. Studies have concentrated on minimizing takeover time, often overlooking the complexities of achieving a balance between timely control transitions and effective performance. This gap in the literature prompts a fundamental question: How can sufficient time budgets be established for safe and comfortable vehicle control transitions across various drivers and scenarios? To answer this open question, this study considers the takeover process as an integrated sequence where takeover time serves as the lower limit of sufficient time budgets and takeover performance is the consequence of the supplied time budgets. We systematically examine the research on the takeover time, time budget, and takeover performance in conditionally automated driving.

Takeover Time: We find that drivers' takeover time varies significantly due to its complex causal relationships with numerous determinants. Thus, we synthesize the correlations between takeover time and its determinants. On this basis, we propose a taxonomy to structure these determinants based on the task-capability interface model (Fuller 2011) and partially capture the interplay of cognition determinants based on the attention mechanism (Wickens and Carswell 2021) and situation model (Endsley 2021), providing theoretical guidance to select takeover time predictors.

Time Budget: We define the takeover buffer as the interval left within the time budget after subtracting the takeover time, which can advance the understanding of the relationship between takeover time and time budget. Besides, we find that the fixed time budget is sub-optimal in meeting various takeover demands compared

with the adaptive time budget and point out several opportunities for research on adaptive time budget.

Takeover Performance: We find the imbalance of indicators between vehicle perspective and human perspective in measuring takeover performance, which can steer the studies that consider takeover performance as optimization goals toward skewed directions. Therefore, we propose a taxonomy to structure these performance measures, which helps to clarify the suitability of the evaluation criteria and guide the development of standard measures of takeover performance. We also compare human-related measures of takeover performance, which helps to build a comprehensive understanding of human-related measures and identify suitable indicators for different research contexts.

Based on these findings, we propose a hypothesis on the relationship between takeover time, time budget, and takeover performance. Rather than prescribing fixed time budget values, we establish a flexible and adaptable framework that estimates sufficient time budgets by combining the predicted takeover time with an appropriate takeover buffer to achieve desired performance outcomes. Thus, our contribution lies not in a precise calculation but in providing a structured method adaptable to a variety of contexts, offering a foundation for future research on adaptive time budgets for safe and comfortable takeovers. We also propose a research agenda for determining sufficient time budgets following adaptive time budget strategies, which covers determinants of takeover time, the determination strategies of time budget, and measures of takeover performance.

In summary, this systematic review investigates the sufficiency of the time budget by examining its determinant (takeover time) and the corresponding result (takeover performance). The proposed frameworks of takeover time determinants and takeover performance measures as well as the discussion about adaptive time budgets provide a promising research avenue for optimizing human-vehicle interactions. This will contribute to the safety and comfort of takeovers and stimulate widespread human trust and acceptance of conditionally automated driving.

3

DRIVING SIMULATOR EXPERIMENT TO UNRAVEL THE RELATIONSHIP BETWEEN TAKEOVER TIME, TIME BUDGET AND TAKEOVER PERFORMANCE

The literature review in Chapter 2 offers a comprehensive examination of the takeover sequence, proposing a methodological framework for dynamic time budgets that can be adapted to meet varying driver demands across diverse scenarios. With a clearer understanding of the current state of research and its limitations, Chapter 3 introduces a driving simulator study aimed at collecting data to inform the development of dynamic time budget strategies. This leads to a comprehensive dataset including driver characteristics, driving trajectory, driver perception, and eye movements, which is fundamental for the studies in Chapter 4, 5, and 6.

This chapter outlines the experimental design in detail, including the development of driving scenarios, the use of various questionnaires to capture driver characteristics and cognitive states, the procedures for data collection, and an overview of collected data. The experiment conducted in this chapter serves as the empirical foundation for the predictive modeling and conceptual analysis presented in the subsequent chapters, allowing for a more robust understanding of driver responses to takeover requests in conditionally autonomous driving.

This chapter is based on a journal article (Liang, Calvert, Nordhoff, and van Lint 2025):

> Liang, K., Calvert, S., Nordhoff, S., & van Lint, J. (2025). A Multimodal Dataset on Drivers' Responses to Takeover Requests in Conditionally Automated Driving. Under review.

3.1. INTRODUCTION

In conditionally automated driving, drivers must respond to takeover requests when the automated driving system reaches its limits (i.e. is outside of its Operational Design Domain (ODD)) and resume meaningful human control of the vehicle within limited time budgets (ISO 21959:2020 2020). This vehicle control transition is essential for both driving safety and user comfort, yet it is cognitively demanding, requiring prompt and effective driver reactions (Lu, Happee, *et al.* 2016). To optimize human-vehicle interaction across various conditions, it is essential to develop a deep understanding of drivers' takeover behaviors and the corresponding driving mechanisms. This requires a controlled driving simulator experiment that systematically manipulates contextual factors—such as traffic density and non-driving-related tasks—in a safe, repeatable environment, enabling the study of how drivers with diverse profiles respond to takeover requests under varying conditions. Taken from the driving simulator experiment, this dataset includes data on driver characteristics, subjective experience (indicated by questionnaire ratings and physiological signals), and objective operations. Together, these data offer a comprehensive view of drivers' takeover behaviors and influencing factors. The data can serve as a basis for developing takeover time prediction models, evaluating takeover performance, and refining time budget determination strategies, thus advancing safer and more effective control transitions.

The dataset was collected to investigate how to provide sufficient time budgets for drivers to take over vehicle control from Conditionally Automated Driving Systems (CADS) both safely and comfortably. Specifically, we have (1) developed models to predict drivers' actual takeover time, (2) evaluated takeover performance from both objective quality and subjective experience aspects, (3) quantified the relationship between takeover time, time budget, and takeover performance, and (4) proposed an adaptive time budget strategy to suffice divers driver and situation needs. The dataset comprises refined recordings from 57 drivers who experienced nine different takeover scenarios designed to vary in traffic density and non-driving related tasks. The sample is fairly evenly distributed by gender (33 males and 24 females) with respondents from across the adult lifespan (age: 38.51 ± 17.23). The order of nine scenarios was balanced using a Latin Square design, thereby reducing the potential order and learning effects and enhancing the dataset's reliability for experimental replication and the development of generalizable models. The dataset combines five data streams, including (1) driver characteristics (takeover style, risk-taking attitude, etc.), (2) scenario information (traffic density and non-driving-related task), (3) vehicle operational data (velocity, acceleration, steering wheel angle, etc.), (4) subjective scenario experience (situational awareness, spare capacity, etc.), and (5) physiological signals (eye movements and heart rate).

Researchers and practitioners can use this dataset to develop and validate models of takeover behavior and driver state estimation, as well as to analyze how individual traits, driver state, and contextual factors interact to shape takeover performance and driver experience.

A specification table of the dataset is shown in Table 3.1.

Table 3.1: Specification table of the dataset

Subject	Computer Sciences
Specific subject area	Driver characteristics and takeover behaviours during vehicle control transitions
Type of data	Tables (.csv), with sensitive personal information removed and participants anonymized; Text (.txt)
Data collection	Data was collected during a driving simulator experiment conducted on the campus of Delft University of Technology. Participants were recruited through both online channels (emails and LinkedIn) and offline methods (flyers). Eligibility criteria required possession of a valid driver's license and normal or corrected-to-normal vision (excluding the use of glasses). The utilized questionnaires were adapted from established instruments, including the NASA Task Load Index, Driving Activity Load Index, and Driver Skill Inventory. Physiological signals were recorded using Pupil Invisible eye-tracking glasses and the Fitbit Charge 5. Vehicle operational data were obtained from a fixed-base, medium-fidelity driving simulator.
Data source location	Institution: Delft University of Technology
City	Delft
Country	Netherlands
Latitude and longitude for collected samples/data	51.99924150127068, 4.3754366314098885
Data accessibility	Repository name: 4TU.ResearchData; Data identification number: https://doi.org/10.4121/e853b4e6-cba0-4e13-ac4b-506716ddd0fb.v1; Direct URL to data: https://data.4tu.nl/datasets/e853b4e6-cba0-4e13-ac4b-506716ddd0fb.
Related research article	1. K. Liang, S.C. Calvert, S. Nordhoff, M. Li, J.W.C. van Lint. Predicting drivers' takeover time for safe and comfortable vehicle control transitions: the role of spare capacity and driver characteristics. Applied Ergonomics 129 (2025): 104603. 2. K. Liang, J.L. Kästle, B. Anvari, S.C. Calvert, J.W.C. van Lint. Multidimensional Assessment of Takeover Performance in Conditionally Automated Driving. Transportation research part F: traffic psychology and behaviour. Under Review. 3. K. Liang, S.C. Calvert, J.W.C. van Lint. Adaptive time budgets for safe and comfortable vehicle control transition in conditionally automated driving. IEEE Transactions on Intelligent Transportation Systems. Under Review.

3.2. PARTICIPANT RECRUITMENT

Participants were recruited through both online (emails and LinkedIn) and offline (flyers) channels. Eligibility criteria require individuals to possess a valid driver's license and the ability to drive without glasses. Details about the study, encompassing research objectives, experimental procedures, anticipated duration, and data anonymization principles, were conveyed to participants through Informed Consent Forms. Additionally, participants were informed of the financial compensation, with each participant receiving a 20-euro voucher for their participation.

The target sample size for this study was 40 participants, based on practical considerations (e.g., participant availability and experimental resources) and reference to comparable driving simulator studies in takeover time prediction. For example, Yoon, Lee, and Ji (2021) modeled takeover time using multiple linear regression with 30 participants; Liu, Wu, *et al.* (2024) adopted a Latin square design with 37 participants to explore takeover time using Convolutional Neural Networks (CNN); and Liu, Liu, *et al.* (2025) predicted takeover time using a Deep Learning framework distilled by Gradient Boosting Decision Tree (DeepGBM), with an average of 27 data points per variable across 15 features. To enhance statistical robustness and account for participant variability, we actively recruited beyond the initial target and ultimately included 57 valid participants in the final analysis. We believe our sample provides a strong basis for exploratory modeling and interpretation, though we also acknowledge its limitations and highlight the value of larger samples in future research.

3.3. EXPERIMENTAL DESIGN, MATERIALS AND METHODS

This experiment required participants to detach from non-driving-related tasks and resume vehicle control from a simulated Conditionally Automated Driving System (CADS) across nine scenarios. Participants completed a "spare capacity" questionnaire after each takeover event and another post-experiment questionnaire detailing their takeover-related driver characteristics. Further information on the driving simulator experiment and the employed questionnaires is provided below.

3.3.1. EXPERIMENT INSTRUMENTATION

The experiment was conducted in a fixed-base, medium-fidelity driving simulator located at Delft University of Technology. A demonstration overview of the simulator is shown in Figure 3.1. The forward and side views are displayed on three 4K-resolution monitors. The simulator setup includes standard vehicle components such as a driver seat, a steering wheel, three pedals, a turn signal lever, and a mock dashboard positioned beneath the central screen to resemble a real vehicle interior. The experimental scenarios were developed and executed using SCANeR Studio on a Windows 10 PC.

Drivers' eye movements were recorded using the Pupil Invisible eye tracking system by Pupil Labs (Tonsen, Baumann, and Dierkes 2020), which leverages deep learning technology. As illustrated in Figure 3.2, the Pupil Invisible glasses feature:

Figure 3.1: The driving simulator at Delft University of Technology.

(i) a pair of infrared binocular cameras that track eye movements at 200 Hz with a resolution of 192×192 pixels, (ii) a scene camera that captures the surrounding driving environment at 30 Hz with a resolution of 1088×1080 pixels, and (iii) an Inertial Measurement Unit (IMU) that measures rotational velocity and translational acceleration of the glasses.

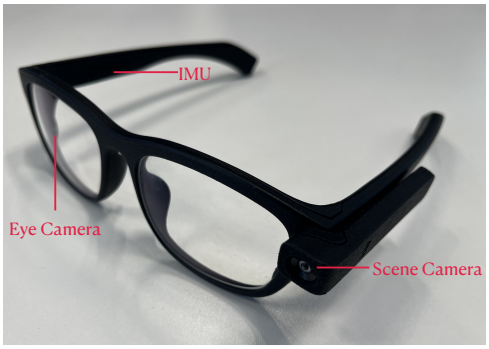


Figure 3.2: Pupil Invisible eye tracking glasses.

In addition, drivers' heart rates were monitored using the Fitbit Charge 5, which utilizes PurePulse® technology for continuous heart rate tracking. The heart rate data were recorded at approximately three-second intervals throughout the experiment.

3.3.2. EXPERIMENT DESIGN

The experiment simulates a two-lane motorway with a speed limit of 100 km/h, consistent with daytime regulations on Dutch motorways. The CADS enables participants to engage in non-driving-related activities in the automated mode. The boundary of the system's Operational Design Domain (ODD) is defined as the

moment the CADS detects a simulated obstacle—specifically, two vehicles that have collided and blocked the ego vehicle's path. A takeover request is triggered when the time gap between the ego vehicle and the crash site reaches seven seconds, a commonly adopted time budget in takeover research (Deniel, Schnebelen, *et al.* 2024; Gold, Damböck, *et al.* 2013). The request is communicated by three auditory beeps and three visual alerts "Please Take Over!" in the top-left corner of the central monitor. To reduce the risk of simulator sickness, all takeover requests are programmed to only occur on straight road segments (Hock *et al.* 2018).

The experiment systematically generates nine takeover scenarios by combining three traffic densities with three Non-Driving-Related tasks (NDRT). Three traffic density levels (low/medium/high) are manipulated by generating 0/10/20 vehicles per kilometer. Three NDRT levels (low/medium/high) are controlled by assigning participants to n-back tasks (n = 0, 1, 2) that demand varying cognitive workloads. Specifically, in n-back tasks, participants observe a sequence of positions of a blue box and are instructed to press a button when the current position is the same as the one shown n steps earlier. Examples of the 1-back and 2-back tasks are illustrated in Figure 3.3, while the 0-back task serves as a baseline condition and does not require sequence recall.

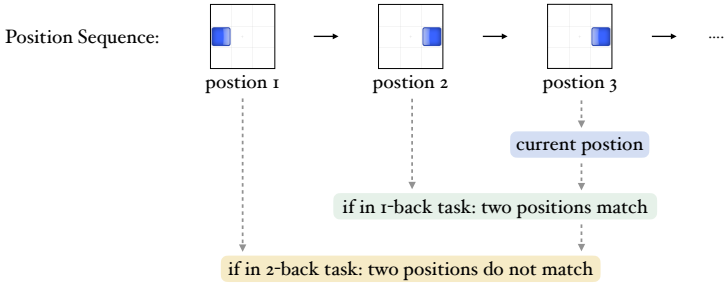


Figure 3.3: Demonstration of the n-back task: examples of 1-back and 2-back tasks.

To minimize potential order and learning effects, nine takeover scenarios are arranged using a Latin Square design (Calvert, Taale, *et al.* 2014), ensuring that each scenario appears equally across all ordinal positions (from first to ninth). Given the odd number of scenarios (nine), achieving full pairwise balance (i.e., each scenario both precedes and follows every other scenario an equal number of times) requires 18 unique ordering groups. The complete set of Latin Square orderings is presented in Table 3.2.

3.3.3. EXPERIMENT PROCEDURES

The experiment followed three procedures: the preparation procedure, the takeover procedure, and the post-experiment questionnaire procedure.

(1) Preparation procedure: Participants were briefed on the capabilities and limitations of the CADS, along with instructions for performing the n-back tasks. They then completed a ten-minute practice drive to become familiar with the driving

Table 3.2: Latin Square Order Groups for the Nine Takeover Scenarios

Group/Order	1	2	3	4	5	6	7	8	9
1	A	B	I	C	H	D	G	E	F
2	G	F	H	E	I	D	A	C	B
3	C	D	B	E	A	F	I	G	H
4	I	H	A	G	B	F	C	E	D
5	E	F	D	G	C	H	B	I	A
6	B	A	C	I	D	H	E	G	F
7	G	H	F	I	E	A	D	B	C
8	D	C	E	B	F	A	G	I	H
9	I	A	H	B	G	C	F	D	E
10	F	E	G	D	H	C	I	B	A
11	B	C	A	D	I	E	H	F	G
12	H	G	I	F	A	E	B	D	C
13	D	E	C	F	B	G	A	H	I
14	A	I	B	H	C	G	D	F	E
15	F	G	E	H	D	I	C	A	B
16	C	B	D	A	E	I	F	H	G
17	H	I	G	A	F	B	E	C	D
18	E	D	F	C	G	B	H	A	I

Note: Letters A–I represent the nine experimental conditions:
A = (0 veh/km, 0-back), B = (0 veh/km, 1-back), C = (0 veh/km, 2-back),
D = (10 veh/km, 0-back), E = (10 veh/km, 1-back), F = (10 veh/km, 2-back),
G = (20 veh/km, 0-back), H = (20 veh/km, 1-back), I = (20 veh/km, 2-back).

simulator and the takeover process, helping to mitigate learning effects during the actual trials (Radhakrishnan *et al.* 2023). Additional practice time was offered upon request until participants felt confident handling the simulator. They were also asked whether they experienced any discomfort while using the simulator and were advised to alert the experimenter if any symptoms occurred or worsened.

(2) Takeover procedure: Participant experienced nine takeover events, each consisting of the following five sequential phases. (i) Automated mode: Each takeover event began with the vehicle operating in automated mode where participants were performing the assigned n-back task. (ii) Takeover request: The takeover request was triggered at a random point between 30 and 60 seconds after entering automated mode (Eriksson and Stanton 2017b). This randomized interval ensured participants had enough time to both engage with the n-back task and manage takeover process and stabilize the ego vehicle afterwards, while also reducing the predictability of takeover requests. (iii) Takeover: Upon receiving the takeover request, participants were expected to immediately disengage from the n-back task and resume control of the vehicle. Takeover time was defined as the duration between the takeover request and the first manual input—operationalized as either a steering wheel angle exceeding 2 degrees or brake/gas pedal position surpassing 10% (Gold, Damböck,

et al. 2013; Liang, Calvert, Nordhoff, Li, *et al.* 2025). (iv) Manual mode: After regaining conscious control of the ego vehicle, participants were tasked with an evasive manoeuvre, which involved pulling out to the left lane, overtaking the detected collision ahead, and pulling over to the right lane after bypassing the collision. (v) Handover: Participants were instructed to hand over vehicle control back to the CADS when they felt conditions were safe to do so after stabilizing the vehicle on the right-hand lane, thus ending this takeover event in 30 seconds. A flow chart of such a sequential takeover event is presented in Figure 3.4. The total duration of each takeover event varies, as it starts from a randomized automated driving period (30–60 seconds), followed by the driver's takeover time (variable), a period of manual driving (variable), and a concluding fixed 30-second interval of automated driving.

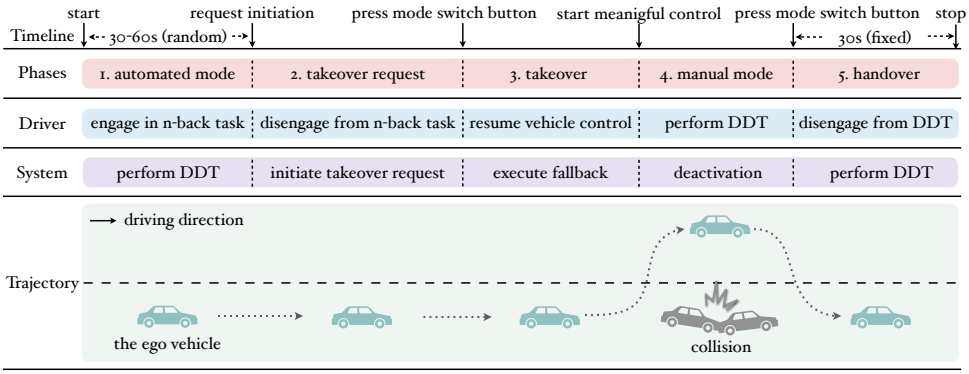


Figure 3.4: The flowchart of a takeover event (DDT: Dynamic Driving Task).

After completing each scenario, participants took a brief break and filled out a scenario experience questionnaire which evaluates their Situational Awareness (SA) and Spare Capacity (SC) during the takeover. Here, SA reflects how well a driver perceives, understands, and projects the surrounding environment (Endsley 2020; Van Lint and Calvert 2018). And SC is derived from Task-Capability Interface (TCI) theory (Fuller 2005), suggesting that drivers adjust their behaviors based on the dynamic interactions between their perceived task capability (TC) and task demands (TD) to maintain their perceived safety margin at an acceptable level. The questionnaire was specifically adapted for takeover situations, incorporating items from established scales including Situation Awareness Rating Technique (SART) (Taylor 2017), NASA Task Load Index (NASA-TLX) (Hart and Staveland 1988), Driving Activity Load Index (DALI) (Pauzié 2008), and Driver Skill Inventory (DSI) (Martinussen, Møller, and Prato 2014). The questionnaire is available in the accompanying Data Repository (Scenario Experience Questionnaire).

(3) Post-questionnaire procedure: Upon completing nine takeover events, drivers were requested to fill in a questionnaire capturing key driver characteristics. This includes demographic details (e.g., age, gender) and adapted questions regarding risk-taking attitude (Ma, Yan, *et al.* 2010), takeover skill (Martinussen, Møller, and

Prato 2014), takeover style (Taubman-Ben-Ari, Mikulincer, and Gillath 2004), and trust in the CADS (Nordhoff *et al.* 2021). The full questionnaire can be found in the accompanying Data Repository (Driver Characteristic Questionnaire).

A comprehensive overview of the experiment's three procedures is illustrated in Figure 3.5, offering methodological clarity and supporting the reproducibility.

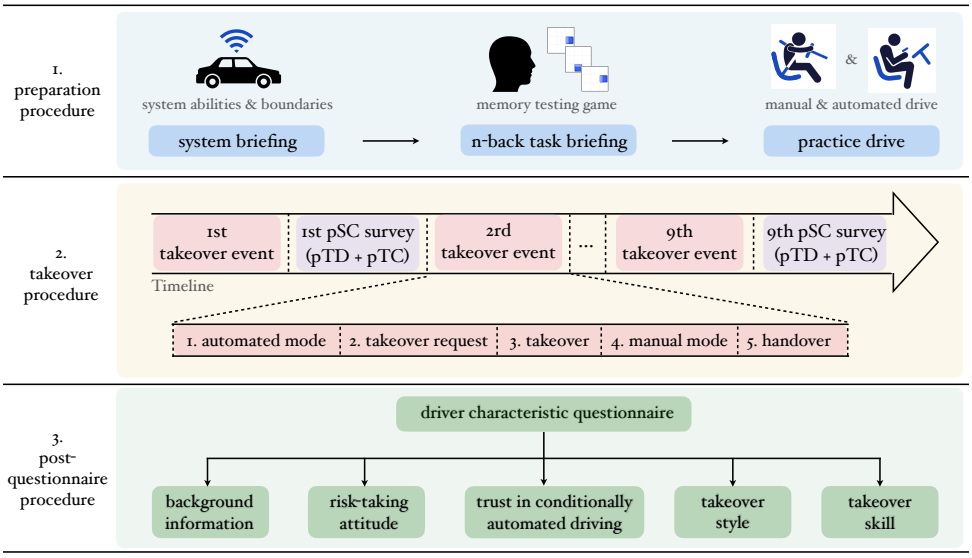


Figure 3.5: Overview of the experiment procedures: (1) preparation, (2) takeover, and (3) post-questionnaire.

3.4. DATASET DESCRIPTION

The dataset is organized into the following five main components, allowing researchers to efficiently access participant information, subjective perception, behavioral driving metrics, and physiological signals across nine takeover scenarios in a simulated conditionally automated driving environment.

0. readme.txt

This file provides an overview of the dataset, including its background and guidance for navigation.

1. data_description.csv

This file offers a variable-level summary of all data included. It contains metadata such as variable names, descriptions, data types, and units (where applicable).

2. driver_characteristics/

This folder includes two files, including (i) 2.1 driver_characteristic_questionnaire.csv which lists all questionnaire items used to assess driver characteristics, and (ii) 2.2 driver_characteristic_answers.csv which provides the corresponding responses from each participant (identified anonymously).

3. scenario_experience/

This folder stores drivers' self-reported personal assessments for each takeover. Specifically, 3.1 scenario_experience_questionnaire.csv contains the items measuring driver cognition (such as situational awareness and task demand) for each takeover. 3.2 scenario_experience_data.csv provides participant responses for each question across nine scenarios.

4. simulator_data/

This folder contains vehicle operation data recorded from the driving simulator. It is subdivided into nine folders, one for each scenario configuration (i.e., combinations of traffic density and n-back task). Each subfolder includes multiple .csv files, where each file corresponds to a takeover instance. File names follow the convention: density_[i]_nback_[j]_id_[n]_simulator_data.csv, where i indicates traffic density level (0, 10, 20 vehicles/km), j refers to the n-back task level (0, 1, 2), and n is the participant ID. Each file records detailed time-series data, e.g., vehicle speed, steering wheel angle, and lane position.

5. physiological_signals

This folder includes 5.1 eye_movement/ and 5.2 heart_rate/. Each contains nine scenario-specific folders, holding multiple .csv files labeled by scenario and participant. These files capture eye movement metrics (such as gaze coordinates and blink events) and heart rate. The sample is fairly evenly distributed by gender (33 males and 24 females) with respondents from across the adult lifespan (age: 38.51 ± 17.23). The distribution of individual driver characteristics is illustrated in Figure 3.6, which further demonstrates diversity across a wide range of relevant attributes.

The structure of the dataset is illustrated in Figure 3.7 for an overview.

3.5. LIMITATIONS

This dataset has several limitations to consider when interpreting or reusing the data. First, although the sample size of 57 participants is comparable to similar studies, a larger and more diverse sample—particularly including more drivers who self-identify as inexperienced—would improve representativeness and allow for broader generalization. Second, data were collected in a medium-fidelity driving simulator using structured, non-time-critical takeover scenarios. While simulators enable controlled data collection, user behaviour and perception may differ under real-world or high-urgency conditions. Users should be cautious with this when applying the dataset. Third, repeated exposure to similar takeover events within the experiment may introduce learning effects or adaptation, potentially influencing behavioural and subjective measures. Although the scenario order was counterbalanced using Latin Square design and takeover requests were randomized to mitigate predictability, some residual order effects may remain. Lastly, self-reported measures of cognitive state and workload were collected using adapted versions of validated instruments. While these tools offer valuable subjective insights, users should be aware that the adapted forms may require further validation for specific applications. We recommend considering these limitations when using the dataset for modeling, analysis, or experimental replication.

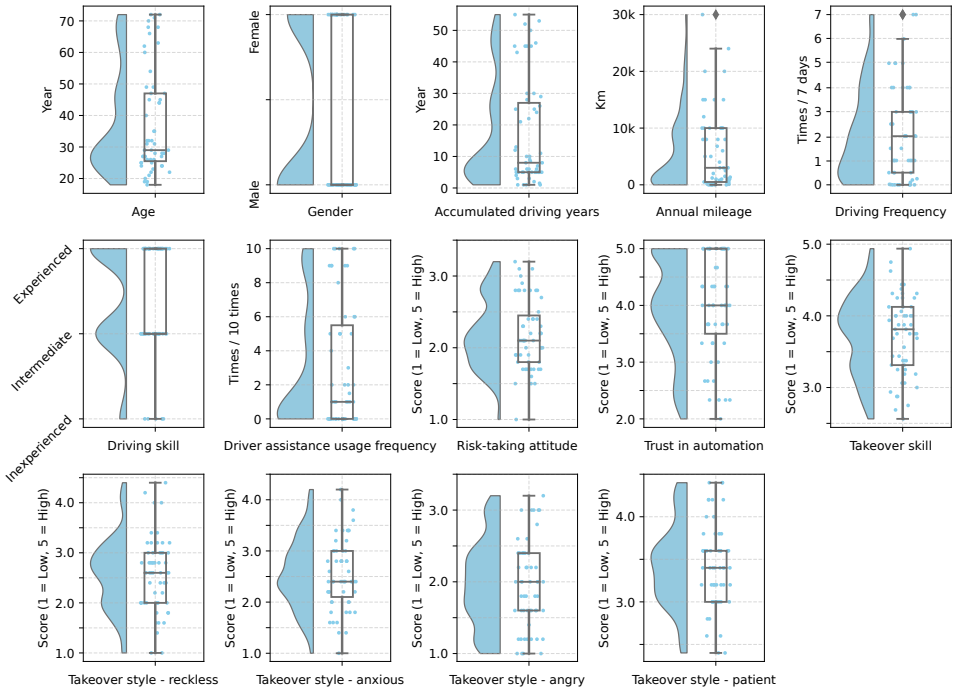


Figure 3.6: Distribution of driver characteristics among participants.

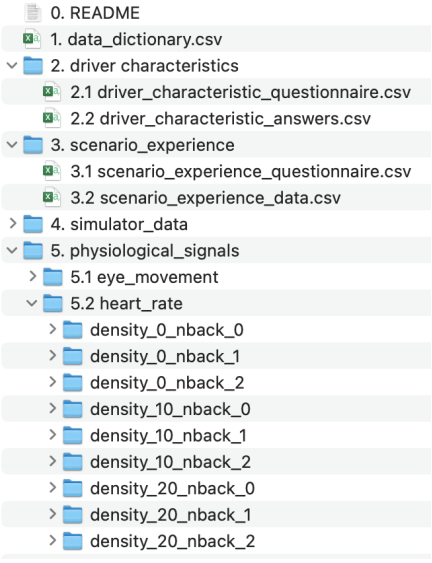


Figure 3.7: Overview of the Dataset Structure and File Organization.

3.6. CONCLUSION

Conditionally automated driving systems issue takeover requests when encountering situations beyond their operational capabilities, requiring drivers to promptly resume vehicle control and respond effectively. Understanding drivers' takeover responses is essential for optimizing human-automation interactions, improving driving safety during control transitions, and enhancing overall user experience. This paper presents a comprehensive multimodal dataset collected through a driving simulator experiment. 57 drivers (33 males and 24 females, age: 38.51 ± 17.23) participated in the experiment. Each participant experienced nine distinct takeover scenarios. The dataset integrates five structured streams: (i) driver characteristics, such as demographics, driving experience, risk-taking attitude, and takeover style; (ii) scenario information, including three traffic densities and three non-driving-related tasks; (iii) vehicle operations from the driving simulator, such as speed, acceleration, and steering wheel angle; (iv) scenario experience data, such as situational awareness and spare capacity for each scenario assessed via questionnaires; (v) psycho-physiological signals, including heart rate and eye movements.

This dataset enables in-depth analysis of factors influencing both takeover performance and driver experience. Researchers and practitioners in human-machine interactions, human factors, and user interface designs can use it to explore effective interaction strategies, personalized in-vehicle systems, and human-centered feature designs. The dataset is publicly available to foster transparency, interdisciplinary collaboration, and progress toward safer, more effective, and more comfortable vehicle control transitions in conditionally automated driving.

3.7. ETHICS STATEMENT

This driving simulator experiment is approved by the Human Research Ethics Committee (HREC) of Delft University of Technology (ID: 3499). We confirm that relevant informed consent was obtained from all subjects.

4

TAKEOVER TIME PREDICTION: ROLE OF SPARE CAPACITY AND DRIVER CHARACTERISTICS

Building on the driver characteristics, driving trajectory, and driver perception collected from the driving simulator experiment in Chapter 3, this Chapter shifts the focus to predictive modelling of drivers' takeover time (ToT). Such predictive models are critical for providing dynamic time budgets, as takeover time represents the minimum value that a time budget must accommodate to ensure the safety of vehicle control transitions across various scenarios.

This chapter addresses enduring challenges in reliability and interpretability of ToT prediction models by optimizing predictor selection. The relationship between ToT, driver characteristics, and perceived Spare Capacity (pSC, a cognitive construct from Task-Capability Interface theory) is examined using Category Boosting models. Results show that (i) incorporating 13 additional driver characteristics does not significantly improve prediction accuracy when pSC is already considered; and (ii) individual characteristics influence how drivers cognitively process takeover scenarios, and their predictive contribution likely overlaps with pSC. These findings suggest that monitoring cognitive states may be more effective for ToT prediction than extensive profiling of driver characteristics. This chapter provides a critical first step toward predictive frameworks for adaptive takeover strategies and offers guidance for designing personalized human–vehicle interactions.

This chapter is based on a journal article (Liang, Calvert, Nordhoff, Li, *et al.* 2025):

> Liang, K., Calvert, S. C., Nordhoff, S., Li, M., & van Lint, J. W. C. (2025). Predicting drivers' takeover time for safe and comfortable vehicle control transitions: The role of spare capacity and driver characteristics. Applied Ergonomics, 129, 104603.

4.1. INTRODUCTION

In conditionally automated driving, one primary concern pertains to the transition of vehicle control (ToC) between human drivers and automation. This transition contains complex human-automation interactions (Lu, Happee, *et al.* 2016), especially during takeovers when drivers must promptly detach from non-driving-related activities and resume active driving within constrained time budgets. Ensuring safety and comfort during ToC requires providing sufficient time budgets (Weaver and DeLucia 2022) to accommodate drivers' takeover time (ToT, the interval between the initiation of a takeover request and drivers' resumption of manual vehicle control (ISO 21959:2020 2020)). Tight time budgets that fail to allow drivers' required ToT can elevate accident risks and compromise driver comfort (Gold, Damböck, *et al.* 2013). Time budgets that excessively exceed the necessary ToT may be perceived as false alarms, resulting in decreased vigilance and increased danger (Huang and Pitts 2022), particularly when the out-of-capability situations are not readily perceivable to drivers. Thus, determining sufficient time budgets necessitates a deep understanding and precise prediction of drivers' ToT.

Predicting drivers' ToT can facilitate the development of adaptive takeover strategies (Du, Zhou, *et al.* 2020b), particularly by tailoring time budgets to accommodate drivers' varied needs across diverse scenarios. To our knowledge, research on predicting drivers' ToT is limited in both reliability (consistency and accuracy across scenarios and drivers) and interoperability (clarity in how input features influence predictions). Specifically, (i) concerning model inputs, existing literature have identified diverse predictors for ToT. For example, Huang, Yang, and Nakano (2023) broadly classified influencing factors into system-, scenario-, and human-related categories, emphasizing the complexity of thoroughly examining human-related factors. Chen, Zhao, Li, Gong, *et al.* (2024) developed a comprehensive ToT prediction model using 18 predictive features, including individual traits, environment, and situation awareness. Despite these contributions, the dynamic and complex nature of real-world driving suggests further refinement of feature selection is needed to enhance model reliability and generalizability; (ii) regarding model outputs, existing studies have made notable contributions to ToT, particularly through classification and average-based approaches. For instance, Pakdamanian *et al.* (2021) proposed a Deep Neural Network (DNN)-based model that achieved high accuracy (93%) in classifying ToTs into three intervals: short (< 3 s), medium (3–7 s), and long (>7 s). Similarly, Ayoub, Du, *et al.* (2022) applied an eXtreme Gradient Boosting (XGBoost) model to predict average ToT using literature data, reporting an RMSE of 0.806 and an MAE of 0.505. These models offer useful insights and represent meaningful steps forward in the field. However, ToT is known to vary widely across drivers and scenarios. For example, Zhang, De Winter, *et al.* (2019) observed a range from 0.69 s to 19.79 s across 520 takeovers. The classification and average-based predictions therefore oversimplify this variability and risk overlooking individual differences. In sum, improving drivers' actual ToT prediction models with reliable and interpretable feature selection is critical for aligning adaptive strategies with drivers' cognitive capacities and situational demands, ultimately enhancing the safety and comfort of Conditionally Automated Driving Systems (CADS).

This study takes a fundamental step toward improving the reliability and interpretability of ToT prediction models by optimizing input feature selection. We examine the influence of both latent cognitive constructs and observable driver characteristics. Guided by Fuller's Task-Capacity Interface (TCI) model, our findings in Liang, Calvert, Nordhoff, Li, *et al.* (2025) suggest that ToT is negatively correlated with perceived spare task capacity (pSC), that is, the difference between the total cognitive and perceptual-motor resources drivers believe they have available for a specific task (pTC) and the amount of those resources they perceive the task to demand (pTD). In the current study, we therefore consider pSC (=pTC-pTD) as an explanatory variable to predict ToT, which can help to reveal the underlying influencing mechanisms behind drivers' ToT and improve the interpretability of the prediction models. Besides, we conduct a comprehensive investigation of inter-driver heterogeneity in ToT by examining 13 driver characteristics (covering demographic, skill-related, and style-related factors) using tailored questionnaires. Based on data from a driving simulator experiment, we propose CatToT, a CatBoost-based ToT prediction model, to analyze the relationship among drivers' ToT, pSC, and driver characteristics using feature importance and SHapley Additive exPlanations (SHAP).

This study has three main contributions:

- provides more contextually relevant and valid tools for assessing driver profiles in takeover scenarios;
- reveals the cognitive mechanism underlying takeover behaviors and supports the development of dynamic time budget strategies that accommodate individual driver needs across various scenarios; and
- contributes to understanding inter-driver heterogeneity in cognitive responses, informing the design of more personalized and adaptive conditionally automated driving systems.

The findings provide valuable insights to readers who are interested in drivers' heterogeneous takeover behaviors and their implications for designing personalized interventions and training strategies tailored to diverse driver needs.

4.2. RELATED WORK

Predicting drivers' actual takeover time (ToT) necessitates a thorough understanding of driver heterogeneity, as it accounts for the diverse range of behaviors exhibited by drivers (Ansar, Alsaleh, and Farooq 2024; Sharma, Ali, *et al.* 2018). From this point of view, we examine previous studies on ToT predictions from two dimensions: inter-driver heterogeneity and intra-driver heterogeneity.

In terms of inter-driver heterogeneity, driver characteristics have been shown to affect drivers' behaviors and performance in various driving contexts (Eboli, Mazzulla, and Pungillo 2017; Zhao, Xu, *et al.* 2019). Differences in driver characteristics will thus likely affect drivers' responses to takeover requests. Zhang, Ma, Qu, *et al.* (2024) observed that different driving styles lead to varied ToT, where defensive drivers exhibited shorter ToT compared to aggressive drivers. However,

such characteristics have not been sufficiently considered in ToT prediction models. Gold, Happee, and Bengler (2018) integrated age in a generalized non-linear model and argued that drivers' age is correlated to their reaction time, physical skills and driving experience. Results show that drivers' age has a positive correlation with their ToT. Ayoub, Du, *et al.* (2022) considered gender as an important input in a deep neural network-based ToT prediction model which achieved accurate (93%) prediction of ToT intervals. Investigations of integrating other driver characteristics (such as drivers' driving skills and trust in conditionally automated driving) in ToT prediction models are required to capture drivers' attributes from diverse aspects. Therefore, this study constructs a prediction model for drivers' actual ToT with 13 driver characteristics, which is critical for the reliability of the prediction model across diverse drivers.

As for intra-driver heterogeneity, previous studies on ToT predictions have primarily focused on situational factors which can be divided into objective and subjective situational factors. Objective situational factors are derived from vehicle and environment settings. Yoon, Lee, and Ji (2021) modeled drivers' ToT with physical, visual, and cognitive attributes of non-driving related tasks using multiple linear regression analysis. The prediction results are generally shorter than the drivers' actual ToT. Ayoub, Du, *et al.* (2022) considered 17 scenario settings in predicting drivers' average ToT, including automation level, situation complexity, etc. While many factors are already considered, drivers' ToT can be affected by other objective situational factors, such as takeover information support (Weaver and DeLucia 2022). Given the multitude of these objective situational factors, selecting appropriate objective situational features for ToT prediction models is crucial for ensuring the models' reliability and practical feasibility. Meanwhile, subjective situational factors are derived from human drivers, typically including drivers' psycho-physiological and/or behavioral data. Rangesh *et al.* (2021b) trained a Long Short Term Memory (LSTM) model using drivers' eyes-on-road time, foot-on-pedal time, and hands-on-wheel time before takeover requests. Results show that the proposed model can achieve continuous predictions of ToT under various secondary activity conditions. Du, Zhou, *et al.* (2020b) employed drivers' gaze behaviors, heart rates, and galvanic skin responses to predict ToT and identified average heart rate as well as maximum and average phasic GSRs are important physiological factors for drivers' ToT. Such subjective situational factors-based models generally possess two limitations: (i) potential lurking factors behind the changes in physiological signals and behaviors may reduce the reliability of prediction results (McDonald *et al.* 2019), and (ii) the opacity of these models diminishes both algorithm interpretability and result reliability. These limitations can introduce uncertainties and safety risks to control transitions. This study emphasizes the importance of integrating cognitive constructs into ToT prediction models, as cognitive constructs: (i) represent drivers' comprehensive understanding of the entire objective scenarios, which synthetically reflect the effects of all related objective situational factors. (ii) play a decisive role in drivers' decision-making process (Endsley 2021), which are responsible for the changes in drivers' physiological signals and behaviors. We argue that cognitive constructs hold the potential to be reliable predictors for drivers' actual ToT, thus

improving the reliability and interpretability of the prediction models.

4.3. METHOD

4.3.1. DRIVING SIMULATOR EXPERIMENT

The experiment was conducted in a fixed-base, medium-fidelity driving simulator on the campus of Delft University of Technology. Participants were instructed to detach from non-driving related tasks (NDRTs) and take over vehicle control from a simulated Conditionally Automated Driving System (CADS) across nine scenarios (three traffic densities * three NDRTs). Specifically, three traffic density levels (low/medium/high) are manipulated by generating 0/10/20 vehicles per kilometer. Three NDRT levels (low/medium/high) are controlled by assigning participants to n-back tasks (n = 0, 1, 2) that demand varying cognitive workloads. Participants were required to complete a spare capacity survey after each takeover and another post-experiment questionnaire detailing their takeover-related characteristics. Details of the experiment instrumentation and procedures can be found in Chapter 3. With the collected data, the relationship between participants' ToT, perceived spare capacity, and driver characteristics was analyzed by the method in Section 6.3.2.

4.3.2. CATBOOST-BASED TAKEOVER TIME PREDICTION MODEL

To better understand the mechanisms shaping drivers' takeover time (ToT), we developed CatBoost models to predict ToT based on perceived spare capacity (pSC) and driver characteristics (Section 4.3.2). Model performance is evaluated using four metrics (Section 4.3.2), and interpretability is enhanced through feature importance and SHAP analysis (Section 4.3.2).

MODEL DEVELOPMENT

CatBoost is a high-performance gradient boosting algorithm that reduces overfitting and delivers strong predictive accuracy with minimal tuning (Kulkarni 2022; Prokhorenkova *et al.* 2018). It has been applied successfully in ranking, classification, and regression tasks (Li, Wang, Yang, *et al.* 2023; Liu, Deng, *et al.* 2020; Ma, Mei, and Cuomo 2021). While ToT prediction has typically used XGBoost (Ayoub, Du, *et al.* 2022; Chen, Zhao, Li, Gong, *et al.* 2024; Wang, Han, *et al.* 2024), CatBoost offers key advantages: (i) efficient handling of categorical features common in driver data, (ii) reduced gradient bias and prediction shift, and (iii) faster training suited for large-scale and real-time applications (Dorogush, Ershov, and Gulin 2018). These strengths make CatBoost well-suited for predicting drivers' ToT.

Assume that a dataset is given as $D = \{X_i, y_i\}_{i=1,2,\ldots,n}$ where $X_i = \{x_i^k\}_{k=1,2,\ldots,m}$ is a vector of m input variables that include both numerical and categorical features; $y_i \in \mathbb{R}$ is a target variable; and n is the total number of the observations. In this study, the dataset is randomly split into a training set D_{train} (80%) and a test set D_{test} (20%). To process features containing both categorical and numerical data, CatBoost (i) performs a random permutation of the dataset as $\sigma = (\sigma_1, \ldots, \sigma_n)$; and (ii) substitutes the categorical feature x_i^k with a new numerical feature calculated

by the corresponding Ordered Target Statistics (TS) on a subset of examples $\mathscr{D}_i = \{X_j : \sigma_j < \sigma_i\}$:

$$\hat{x}_i^k = \frac{\sum_{X_j \in \mathscr{D}_i} \left[x_j^k = x_i^k\right] * y_j + \alpha \cdot P}{\sum_{X_j \in \mathscr{D}_i} \left[x_j^k = x_i^k\right] + \alpha} \tag{4.1}$$

where P represents the prior value, which is typically set to the average target value (Micci-Barreca 2001); parameter α (>0) signifies the weight of the prior; and $[\cdot]$ denotes Iverson brackets, i.e., $\left[x_j^k = x_i^k\right] = 1$ if $x_j^k = x_i^k$ and 0 otherwise.

Catboost uses oblivious decision trees as base predictors, where all decision nodes employ the same splitting criteria at every depth level. This symmetrical approach helps mitigate over-fitting and enhances execution speed. On this basis, CatBoost iteratively builds a sequence of approximations to minimize the expected loss, which is Root Mean Squared Error (RMSE) in this study:

$$Loss^{(t)} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i^{(t)}\right)^2} + \Omega(f_t) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[y_i - (\hat{y}_i^{(t-1)} + f_t(x_i^k))\right]^2} + \Omega(f_t) \tag{4.2}$$

where N is the number of samples; y_i is the true target value; $\hat{y}_i^{(t)}$ and $\hat{y}_i^{(t-1)}$ are the predicted target values for sample i at the t-th and (t-1)-th iterations respectively; $f_t(x_i^k)$ is the t-th tree to be added; and $\Omega(f_t)$ is the regularization term to avoid over-fitting.

This study develops three CatBoost-based models for predicting ToT: CatToT$_{dc}$, incorporating 13 driver characteristics as inputs, CatToT$_{sc}$, utilizing drivers' pSC as the only input, and CatToT$_{dc+sc}$, incorporating both driver characteristics and pSC. Similarly, we construct another three CatBoost-based models for predicting drivers' pSC: CatSC$_{dc}$, which leverages 13 driver characteristics as inputs, CatSC$_{dn}$, which incorporates only $density$ and $ndrt$ as inputs, and CatSC$_{dc+dn}$, which integrates 13 driver characteristics, $density$, and $ndrt$. To achieve stable model performance, this study runs the 10-fold cross-validation 100 times during training.

MODEL EVALUATION

The performance of the CatBoost-based models is studied using multiple metrics to provide a comprehensive assessment of their predictive capabilities. Following previous research (Antypas *et al.* 2024; Ayoub, Du, *et al.* 2022; Yang, Zheng, *et al.* 2021), four metrics are selected: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2), and Pearson Correlation Coefficient (r). By using a combination of these metrics, this study assesses the models' predictive capabilities across different aspects of their performance. A better prediction performance is indicated by lower RMSE, lower MAE, higher R^2, and higher absolute value of r.

MODEL EXPLANATION

Explainability is crucial for enhancing users' trust and acceptance of a machine-learning-based prediction model (Ayoub, Du, *et al.* 2022). Therefore, two tools are employed to interpret the model prediction processes: feature importance from the CatBoost model (Hastie *et al.* 2009) and SHapley Additive exPlanation (SHAP) values from game theory (Lundberg and Lee 2017).

On one hand, feature importance provides a high-level overview of the relative contributions of input features in changing the model's output. A larger importance value indicates a greater potential for changing the prediction output when that feature is altered. The feature importance values sum to 100, enabling direct comparison of the relative contribution of each feature on the model's predictions. For a given feature x^k, its importance is calculated as the sum of the gains (i.e., the reduction of loss) of all splits across the entire dataset (Hastie *et al.* 2009):

$$Feature\_Importance_{x^k} = \sum_{trees, leafs_{x^k}} \left(v_1 - \frac{v_1 \cdot c_1 + v_2 \cdot c_2}{c_1 + c_2} \right)^2 \cdot c_1 + \left(v_2 - \frac{v_1 \cdot c_1 + v_2 \cdot c_2}{c_1 + c_2} \right)^2 \cdot c_2 \tag{4.3}$$

where c_1 and c_2 denote the total weight of objects in the left and right leaves respectively; v_1 and v_2 represent the formula value in the left and right leaves respectively.

On the other hand, SHAP values dive deeper by capturing both the direction and magnitude of each feature's impact on predictions, which offer a more detailed explanation of model behaviors. SHAP values assign an importance value to each feature, indicating its contribution to the prediction. Positive SHAP values denote features that increase the prediction, whereas negative values denote features that decrease the prediction. For a given feature x^k, its SHAP values are calculated as (Shapley *et al.* 1953):

$$SHAP\_Values_{x^k} = \sum_{S \subseteq X \setminus \{x^k\}} \frac{|S|!\,(m - |S| - 1)!}{m!} \left[f\left(S \cup \{x^k\}\right) - f(S) \right] \tag{4.4}$$

where m is the total number of input features; X denotes the set of all input features; $X \setminus \{x^k\}$ refers to removing feature x^k from the set X; S is the set of non-zero feature indices, with the summation covering all subsets of X that do not include feature x^k; and $f\left(S \cup \{x^k\}\right) - f(S)$ signifies the contribution margin of feature x^k.

4.4. RESULTS

4.4.1. PARTICIPANTS

A total of 57 drivers participated in this study, including 33 males and 24 females. Their average age is 38.51 years (SD = 17.23). The relatively balanced gender distribution and broad age variability support the representativeness of the sample by capturing a diverse spectrum of life stages and driving backgrounds. The distribution of individual driver characteristics is illustrated in Figure 4.1, which

further demonstrates diversity across a wide range of relevant attributes. While only a small number of participants self-identified their driving skill as "inexperienced" in the subjective questionnaire, the sample reflects broader diversity in objective indicators such as driving frequency, years of driving experience, and accumulated driving distance. This discrepancy highlights the distinction between perceived and actual driving experience. By including participants with a broad spectrum of characteristics, this study ensures a robust and representative analysis of the factors shaping takeover time (ToT). Additionally, drivers' perceived task demands (pTD) and perceived driver task capabilities (pTC) across nine takeovers are shown in Figure 4.2. The wide variability in these cognitive constructs highlights the diversity in drivers' cognitive styles, even when faced with identical takeover scenarios. This emphasizes the significance of considering driver heterogeneity in drivers' ToT and takeover behaviors.

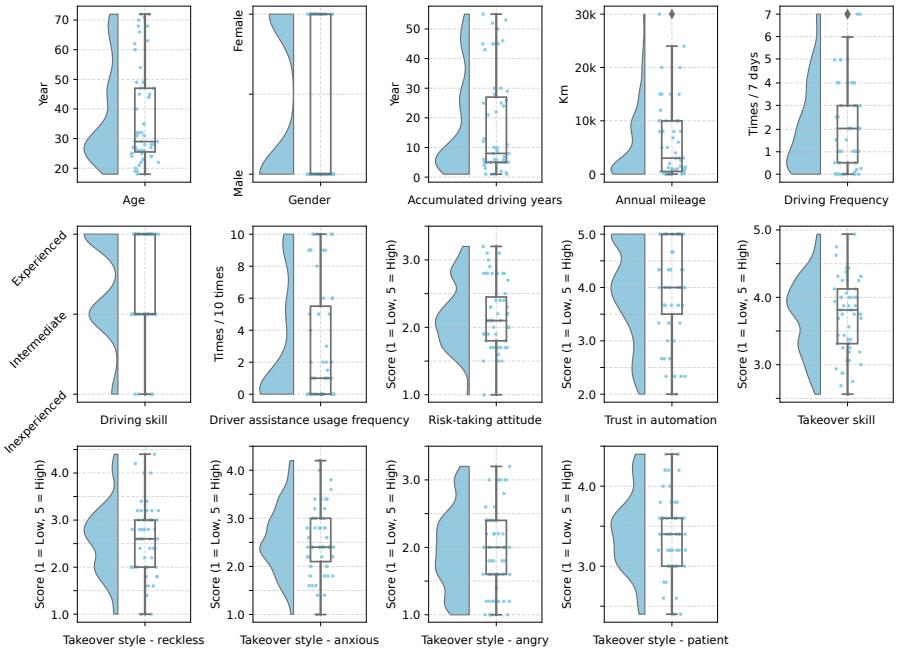


Figure 4.1: The distribution of driver characteristics among participants.

The experiment initially generated a dataset of 513 takeovers. 16 takeovers were excluded, because participants (i) resumed vehicle control before takeover requests, or (ii) neglected to press the button for activating manual inputs. These exclusions are necessary as they can lead to considerable deviations between the measured ToT and the actual ToT. Moreover, 18 takeovers from two participants were removed due to incomplete questionnaire responses. Consequently, the refined dataset, comprising 479 takeovers, is further analyzed.

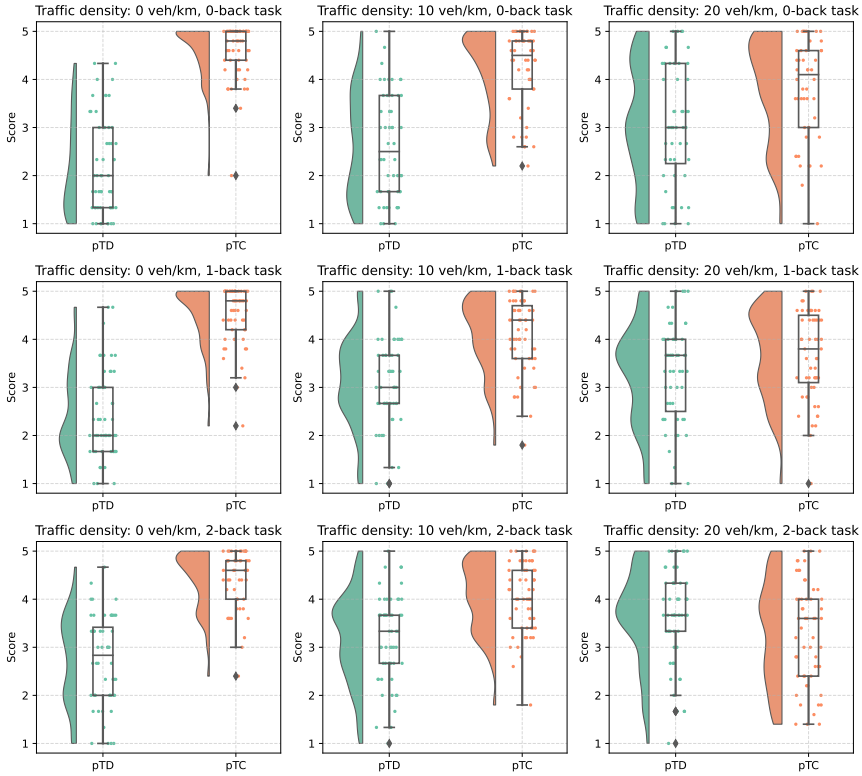


Figure 4.2: Drivers' perceived task demand (pTD) and perceived driver task capability (pTC) across nine takeover scenarios (Score: 1 = low, 5 = high).

4.4.2. TAKEOVER TIME PREDICTION

According to Task-Capability Interface (TCI) theory, drivers adjust their driving behaviors based on the dynamic interactions between their perceived task demand (pTD) and perceived driver task capability (pTC) (Fuller 2011). Our previous research (Liang, Calvert, Nordhoff, Li, *et al.* 2025) found that drivers generally experience longer takeover time (ToT) as their perceived Spare Capacity (pSC, i.e., pTC - pTD) diminishes. On this basis, this study explores the relationship among drivers' ToT, pSC, and multiple driver characteristics.

In this research, we collected 14 characteristics of participants using the questionnaire described in Appendix 1. Variance Inflation Factors (VIF) are computed for these characteristics to identify the potential multicollinearity. The analysis reveals a high correlation between age (VIF: 22.67) and $accu_years$ (VIF: 24.60). Hence, the effect of $accu\_years$ on drivers' ToT is not further examined in this study. The remaining 13 characteristics, along with drivers' pSC, were incorporated into the CatToT$_{dc+sc}$ model for predicting drivers' ToT. The mean importance of each input feature, obtained after 10-fold cross-validation repeated

100 times, is given in Table 4.1.

Table 4.1: Feature Importance from the CatToT$_{dc+sc}$ model.

Feature	**Importance**	**Feature**	**Importance**
pSC	64.82	*age*	1.54
accu_dis	11.39	*takeover_style_anxious*	1.53
takeover_style_angry	4.64	*takeover_skill*	1.16
RTA	3.85	*driving_skill*	0.94
driving_fre	3.23	*takeover_style_reckless*	0.88
trust	2.62	*assist_fre*	0.78
takeover_style_patient	2.09	*gender*	0.53

The experimental results indicate that *pSC* stands out as the most influential feature concerning drivers' ToT, whereas the impact of other features appears limited. This underscores the potential significant influence of drivers' *pSC* on the model learning process. Consequently, an ablation study is conducted to delve deeper into the contributions of *pSC* and driver characteristics to drivers' ToT. To this end, three additional CatBoost-based models are trained: (i) the CatToT$_{dc}$ model, incorporating 13 driver characteristics as inputs; (ii) the CatToT$_{sc}$ model, incorporating only *pSC*; and (iii) the CatToT$_{dc+sc}$ model, incorporating both 13 driver characteristics and *pSC*. To assess model performance, four metrics (namely, RMSE, MAE, R^2, and r) are employed, as detailed in Section 4.3.2. Lower values of RMSE and MAE indicate better predictive accuracy, while higher values of R^2 and r reflect stronger explanatory power and correlation, respectively. The stabilized results following 10-fold cross-validation repeated 100 times are presented in Table 4.2.

Table 4.2: Performance of CatToT$_{dc}$ model, CatToT$_{sc}$ model, and CatToT$_{dc+sc}$ model.

Model	**Inputs**	**RMSE (↓)**	**MAE (↓)**	R^2 **(↑)**	r **(↑)**
CatToT$_{dc}$	13 driver characteristics	1.3030	1.0042	0.0116	0.2000
CatToT$_{sc}$	*pSC*	1.2163	0.9418	0.1315	0.4029
CatToT$_{dc+sc}$	13 driver characteristics + *pSC*	1.2146	0.9376	0.1371	0.4135

These results indicate that the CatToT$_{sc}$ model significantly outperforms the CatToT$_{dc}$ model ($p < 0.01$), reducing RMSE by 6.65% and MAE by 6.21% while increasing R^2 by 1033.62% and r by 101.45%. This demonstrates that *pSC* is a more effective predictor of ToT than driver characteristics alone. Particularly, the significant increases in R^2 and r highlight that pSC not only captures a greater proportion of the variance in ToT but also aligns more closely with actual takeover behaviors, making it a more reliable and interpretable predictor for ToT predictions. Notably, there is no significant difference between the CatToT$_{sc}$ model and the CatToT$_{dc+sc}$ model ($p > 0.05$). This suggests that the addition of 13 driver characteristics does not meaningfully enhance prediction accuracy when pSC is already included.

The above findings give grounds to further explore the relationship between

drivers' pSC and their ToT. As shown in Figure 4.3, a statistically significant negative linear correlation is observed between drivers' average takeover time ($\overline{ToT}$) and perceived spare capacity (pSC) ($r = -0.98, p < 0.01$), except for a slight upward fluctuation when drivers' pSC reaches its highest level. This linear relationship can be effectively represented by the equation (R^2=0.96, RMSE = 0.16):

$$\overline{ToT} = -0.33 * pSC + 3.01 \tag{4.5}$$

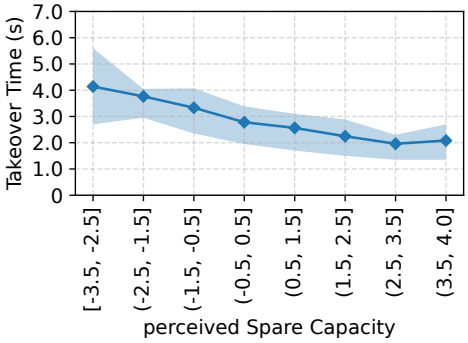


Figure 4.3: Drivers' takeover time across perceived spare capacity (confidence bounds: 25th and 75th percentiles).

This strong linear relationship between $\overline{ToT}$ and pSC indicates that predicting drivers' ToT using pSC without incorporating driver characteristics is feasible and yields reliable predictions. However, previous research has established correlations between drivers' ToT and various characteristics (Chen, Zhao, Li, Li, *et al.* 2023; Gasne *et al.* 2022), such differences with our finding may stem from the influence mechanism of driver characteristics. It is plausible that these characteristics affect how drivers cognitively process the objective takeover scenarios, consequently shaping their pSC, and ultimately impacting ToT. Therefore, it appears that driver characteristics do not directly influence the relationship between pSC and ToT. To delve deeper into this hypothesis, this study investigated the effects of driver characteristics on drivers' pSC across different takeover scenarios in Section 4.4.3.

4.4.3. EFFECTS OF DRIVER CHARACTERISTICS

To examine the influence of diverse driver characteristics on drivers' perceived spare capacity (pSC) under varying traffic densities ($density$) and non-driving-related tasks ($ndrt$), an ablation study is conducted. This approach allows us to isolate the impact of different sets of variables on pSC and understand their relative importance. Specifically, three CatBoost-based models are developed for predicting drivers' pSC: (i) the CatSC$_{dc}$ model, incorporating the full set of 13 driver characteristics as inputs; (ii) the CatSC$_{dn}$ model, incorporating only $density$ and $ndrt$; (iii) the CatSC$_{dc+dn}$ model, incorporating 13 driver characteristics, $density$, and $ndrt$. The use of

these specific models allows for a comprehensive analysis of how both situational and personal attributes influence pSC. Model performance is evaluated using four metrics: RMSE, MAE, R^2, and r. Lower values of RMSE and MAE indicate better predictive accuracy, while higher values of R^2 and r reflect stronger explanatory power and correlation, respectively. The results from 100 iterations of 10-fold cross-validation are presented in Table 4.3.

Table 4.3: Performance of CatSC$_{dc}$ model, CatSC$_{dn}$ model, and CatSC$_{dc+dn}$ model.

Model	**Inputs**	**RMSE (↓)**	**MAE (↓)**	R^2 **(↑)**	r **(↑)**
CatSC$_{dc}$	13 driver characteristics	1.5291	1.2280	0.2013	0.4786
CatSC$_{dn}$	$density$ + $ndrt$	1.5481	1.2654	0.1797	0.4525
CatSC$_{dc+dn}$	13 driver characteristics + $density$ + $ndrt$	1.3321	1.0645	0.3924	0.6647

The comparison of model performance demonstrates that among the three models, the CatSC$_{dc+dn}$ model provides the most accurate predictions of drivers' perceived pSC. Specifically, when comparing with the CatSC$_{dc}$ model, incorporating objective situational factors ($density$ and $ndrt$) results in enhanced performance ($p < 0.01$), reflected in lower RMSE (−13%), lower MAE values (−13%), higher R^2 (+95%), and stronger r (+39%). Similarly, compared to the CatSC$_{dn}$ model, integrating 13 driver characteristics yields improved performance ($p < 0.01$), indicated by lower RMSE (−14%) and MAE values (−16%), higher R^2 (+118%), and stronger r (+47%). This finding emphasizes the impact of both driver characteristics and objective takeover scenarios on drivers' pSC.

From the results in Table 4.3 we can derive that the CatSC$_{dc}$ model slightly outperforms the CatSC$_{dn}$ model ($p < 0.05$), evident in lower RMSE (−1%) and MAE values (−3%), higher R^2 (+12%), and stronger r (+6%). While objective scenario factors contribute to predictive accuracy, the inclusion of driver characteristics alone can yield more precise predictions of drivers' pSC. This finding reveals the importance of considering individual differences in understanding drivers' cognitive constructs, highlighting the potential for more accurate takeover time prediction models. To dive deeper into the influence of these characteristics on drivers' pSC, the average importance of each input feature derived from the CatSC$_{dc+dn}$ model is shown in Table 4.4.

Table 4.4 indicates that the objective situational factor $density$ holds the highest importance in determining drivers' pSC. Following closely are $takeover\_style\_anxious$, $trust$, and the other objective situational factor $ndrt$. Conversely, characteristics such as $gender$, $driving\_skill$, $takeover\_style\_patient$, and $assist\_fre$ exhibit minimal impact on drivers' pSC. It is intuitive that $density$ and $ndrt$ significantly impact drivers' pSC, as these situational factors directly influence the demands placed on drivers during takeover tasks and their capability to effectively resume vehicle control. It is noteworthy that two driver characteristics, namely $takeover\_style\_anxious$ and $trust$, demonstrate greater importance in shaping drivers' pSC compared to $ndrt$. This is a clear indication of the significance of integrating driver characteristics into pSC prediction models, as it suggests that certain driver traits have a more substantial influence on

Table 4.4: Feature importance from the CatSC$_{dc+dn}$ model.

Feature	Importance	Feature	Importance
density	37.33	*driving_fre*	2.54
takeover_style_anxious	18.77	*RTA*	0.99
trust	14.81	*accu_dis*	0.96
ndrt	6.63	*gender*	0.31
takeover_skill	5.88	*driving_skill*	0.22
takeover_style_reckless	5.37	*assist_fre*	0.22
takeover_style_angry	2.89	*takeover_style_patient*	0.20
age	2.87		

drivers' cognitive processes during takeovers than objective situational factors.

To further interpret the determination processes of drivers' *pSC*, the SHAP summary plot of the CatSC$_{dc+dn}$ model is illustrated in Figure 4.4. Each point in the plot represents a SHAP value corresponding to its respective variable instance. As depicted in Figure 4.4, there exists a negative correlation between *density* and drivers' *pSC*. This correlation may stem from the fact that higher traffic density often entails more complex driving environments, necessitating drivers to allocate additional effort to execute a safe takeover of vehicle control, consequently diminishing their *pSC*. Notably, the influence of medium traffic density on *pSC* appears concentrated around zero, indicating a more consistent impact on drivers' perceptions. However, for the highest and lowest traffic densities, the distributions of their influence exhibit right-tailed and left-tailed patterns respectively. This observation suggests that drivers demonstrate more consistent takeover behaviors and responses in moderately busy traffic conditions. However, in extreme traffic density scenarios, other factors (such as takeover styles) could have a more significant impact on drivers' ToT compared to situations with medium traffic density. Another objective situational factor *ndrt* also exhibits a negative correlation with drivers' *pSC*. Specifically, the highest level of *ndrtT* decreases *pSC* by approximately 0.2, while the lowest level increases it by the same amount. Unlike the traffic density, the impact of extreme *ndrt* levels on ToT is more focused, with short tails in the distribution. This suggests that the relatively lower feature importance of *ndrt* (compared with *takeover_style_anxious* and *trust*) does not stem from drivers employing coping strategies to mitigate the impact of *ndrt* based on their individual characteristics. Rather, it implies that drivers may exhibit heightened vigilance and preparedness to resume vehicle control promptly, even in distracting environments.

While the impacts of *density* and *ndrt* on drivers' *pSC* exhibit nearly symmetric distributions, those of *takeover_style_anxious* and *trust* display short-head-long-tail patterns. For example, the impacts of low and medium levels of *takeover_style_anxious* on *pSC* are concentrated, with minimal differences between the two levels. This results in shorter heads in the distributions of the impact of *takeover_style_anxious*, indicating drivers' similar cognitive processing of takeovers. However, the high value of *takeover_style_anxious* exhibits a

spreading impact on drivers' pSC, leading to long tails. This phenomenon may be due to anxious drivers experiencing heightened stress, leading them to potentially overestimate task demands and/or underestimate their capability to different extents, resulting in lower and more varied pSC. Conversely, heightened levels of $trust$ may promote a more relaxed attitude toward takeover scenarios. This relaxed attitude could lead drivers to underestimate task demands and/or overestimate their capability to different extents, resulting in larger and more varied pSC.

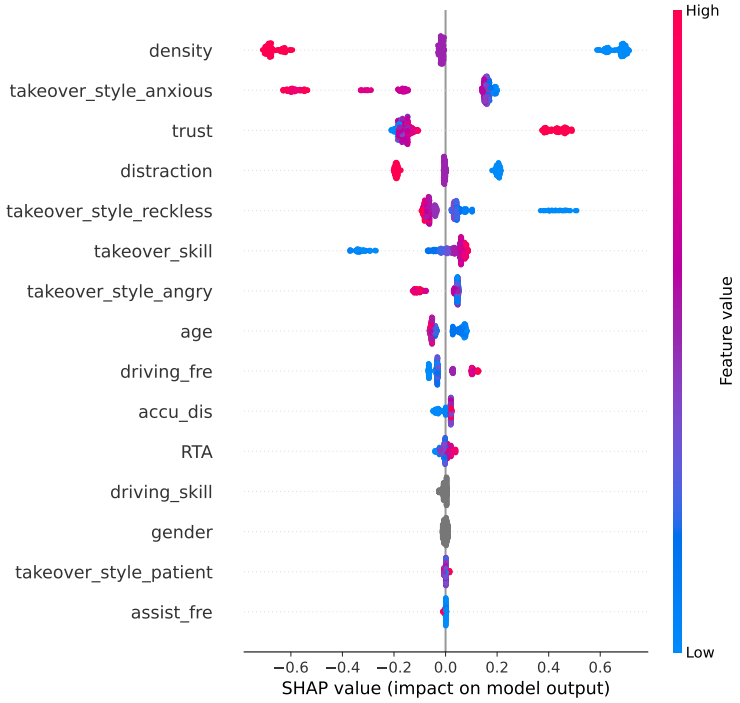


Figure 4.4: Feature contributions in the CatSC$_{dc+dn}$ model.

4.5. DISCUSSION

To develop a reliable and interpretable prediction model for drivers' actual takeover time (ToT), this research focuses on predictive feature selection. For this purpose, we analyze the effects of drivers' perceived Spare Capacity (pSC) and 13 driver characteristics. In this section, we further discuss the input features in ToT predictions (Section 4.5.1), the effects of driver characteristics (Section 4.5.2), and the limitations of the study (Section 4.5.3).

4.5.1. FEATURES IN TAKEOVER TIME PREDICTIONS

Previous studies have made important progress in developing ToT prediction models by incorporating a broad range of takeover-related factors. Building on that foundation, this study emphasizes the importance of feature selection, particularly the role of cognitive constructs. Specifically, we concentrate on drivers' perceived spare capacity (pSC, pTC - pTD), an important cognitive construct that potentially affects drivers' takeover decisions according to TCI theory. Three CatBoost-based ToT prediction models are constructed with different inputs: CatToT$_{dc}$, CatToT$_{sc}$, and CatToT$_{dc+sc}$. We find that predicting drivers' ToT solely through pSC, without considering driver characteristics, proves feasible and yields reliable predictions. This suggests that monitoring cognitive states such as pSC may be more effective for predicting ToT than collecting extensive driver-specific data. This offers a more efficient and generalizable modeling approach across diverse driver populations and takeover contexts. Building on this, we develop three additional CatBoost-based spare capacity prediction models: CatSC$_{dc}$, CatSC$_{dn}$, and CatSC$_{dc+dn}$. Our findings indicate that, apart from objective takeover situations (e.g., traffic density), multiple driver characteristics significantly influence drivers' pSC. It underscores that drivers' cognitive constructs stem from both the influence of objective takeover situations and diverse driver characteristics, making them comprehensive and reliable predictors of ToT.

We infer that the mechanism underlying drivers' ToT is as follows: drivers perceive and interpret objective takeover situations (e.g., traffic density, non-driving related task) differently depending on their individual characteristics (e.g., driving skill, risk-taking attitude). These variations lead to diverse driver cognition, typically indicated by psychophysiological signals (e.g., eye movements, heart rate) and self-reported perceptions (e.g., perceived spare capacity). These cognitive states shape observable driver behavior (e.g., speed adjustments, lane changes), which ultimately contributes to variations in drivers' ToT. Based on this hypothesis, we present the structure of factors influencing ToT in Figure 4.5.

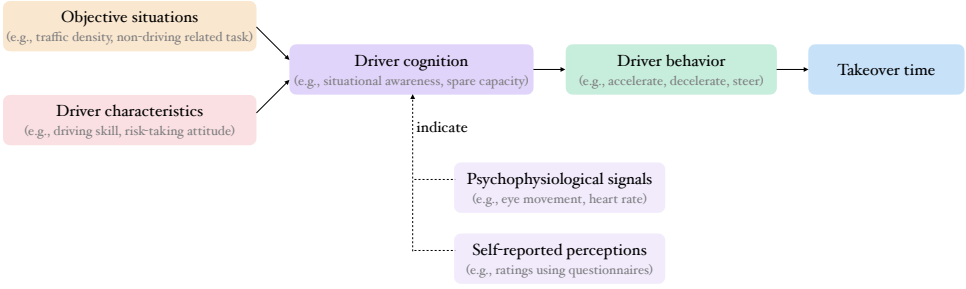


Figure 4.5: Conceptual framework of how driver characteristics and cognition influence takeover time.

This overview of input features offers valuable insights into feature selection for ToT prediction models. It can also aid in selecting psychophysiological, perceptive, and behavioral data for predicting ToT, as these data should align closely

with specific takeover-related cognition, such as perceived spare capacity in this study. By substituting drivers' cognition with psychophysiological, perceptive, and/or behavioral data, the practical validity of the proposed ToT prediction model can be enhanced while maintaining model interpretability. However, further investigation is needed in this regard.

Note that while adding 13 driver characteristics did not significantly improve ToT prediction beyond pSC, these characteristics still hold value. In cases where pSC is difficult to assess or unavailable, static characteristics can provide a baseline for initializing driver models, setting defaults, or serving as fallback inputs. They also offer useful context for interpreting dynamic cognitive data. Rather than being excluded, static driver traits and dynamic cognition can play complementary roles. A hybrid approach may enhance the robustness and personalization of adaptive takeover strategies, particularly in complex or uncertain scenarios.

4.5.2. EFFECTS OF DRIVER CHARACTERISTICS

According to the feature importance (Table 4.4) and SHAP values (Figure 4.4) from the CatSC_{dd+dc} model, we find that in predicting drivers' perceived spare capacity (*pSC*): (i) *density*, *takeover_style_anxious*, and *trust* are the most relevant features, (ii) *ndrt*, *takeover_skill*, and *takeover_style_reckless* are moderately relevant features, (iii) *takeover_style_angry*, *age*, *driving_fre*, *RTA*, and *accu_dis* are less relevant features, and (iv) *gender*, *driving_skill*, *assist_fre*, and *takeover_style_patient* have minimal relevance. The above findings can help designers prioritize the most important factors in the development of CADS, highlight the focus of driver training and education, and inform customized interventions to promote safer and more efficient human-vehicle interactions. Additionally, two observations from the study initially seem counterintuitive, but upon closer inspection, they reflect nuanced insights rather than genuine contradictions:

(i) Although the direct relationship between drivers' general *driving_skill* ratings and their *pSC* is not significant, specific skill-related metrics such as *accu_dic* and *driving_fre* do correlate with pSC. This discrepancy may be attributed to two factors. First, there were few participants who identified themselves as "inexperienced". While the remaining participants were fairly evenly distributed between the "intermediate" and "experienced" groups-suggesting some variation still exists-the limited presence of low-skill self-ratings may have reduced the sensitivity of the general *driving_skill* measure. Second, *accu_dic* and *driving_fre* represent objective, precise indicators of driving ability. This suggests that the observed discrepancy may not be inherently contradictory but rather underscores the potential inaccuracy of self-assessed general driving skills. It highlights the importance of incorporating objective metrics when evaluating driver skills, aligning with suggestions from prior research (Kosuge *et al.* 2021; Sundström 2008).
(ii) Similarly, while the direct relationship between drivers' *RTA* and their *pSC* lacks statistical significance, specific characteristics associated with *RTA*—such as *takeover_style_anxious* and *trust*—show strong correlations with *pSC*. This apparent discrepancy may result from the context-dependent measurement of *RTA* within automated driving scenarios, where drivers may adjust their usual risk

preferences when interacting with CADS. Rather than being contradictory, this finding underscores the phenomenon of behavioral adaptation, where drivers modify their behavior to suit CADS. Such adaptations have been well-documented in existing studies (Soni *et al.* 2022; Varotto *et al.* 2020), emphasizing the importance of understanding how automation influences driver behavior to design effective human-automation interactions that promote both safety and user comfort.

In summary, driver characteristics influence the development of drivers' cognition (such as spare capacity) to varying extents during the transition of control. When measuring these traits, it is essential to use specific questions adjusted appropriately for takeover contexts to ensure the validity and reliability of research findings.

4.5.3. LIMITATIONS

This study is subject to the following limitations: (i) although the final sample size of 57 participants is comparable to those used in similar studies (Liu, Liu, *et al.* 2025; Liu, Wu, *et al.* 2024; Yoon, Lee, and Ji 2021), we acknowledge that a larger sample could further enhance the robustness and generalizability of our findings. A limited sample size may reduce statistical power, particularly in detecting subtle interaction effects or non-linear relationships among multiple influencing factors. Moreover, while the sample includes a range of drivers in terms of years of driving experience, accumulated mileage, and driving frequency, relatively few participants subjectively identified as inexperienced. This discrepancy between objective and perceived experience may influence how self-reported driving competence interacts with perceived spare capacity and takeover time. Future research would benefit from recruiting larger and more diverse participant pools, and from further examining how discrepancies between perceived and actual driving ability shape takeover behavior and cognitive self-assessments. (ii) the experiment was conducted in a simulated environment rather than in real-world driving conditions. While simulators provide controlled environments for experimentation, driver behavior may differ in real-world settings, limiting the generalizability of our findings. Given that this study serves as a foundational step toward optimizing feature selection in takeover time prediction models, future research should evaluate the model's effectiveness under more varied and dynamic conditions. Specifically, our scenarios were structured and non-time-critical, whereas urgent takeovers—such as reacting to sudden hazards or system failures—may involve different cognitive and behavioral dynamics, potentially altering the relationship between perceived spare capacity and actual takeover time. As a result, the current findings may be more applicable to routine or moderately urgent transitions. Future work should test the model in more diverse scenarios, especially those involving real traffic and time-critical demands, to evaluate its robustness and adaptability. (iii) repeated exposure to similar takeover scenarios may lead to faster or more confident responses, potentially inflating performance measures and altering perceived spare capacity. This trial order effect could confound results and limit generalizability to real-world conditions, where takeovers are less predictable and not repeated systematically. To mitigate learning effects in this study, participants completed a 10-minute practice drive (Radhakrishnan *et al.* 2023), and the nine takeover scenarios were arranged using a Latin Square design

to balance order effects across participants (Calvert, Taale, *et al.* 2014). Additionally, takeover requests were randomized between 30 and 60 seconds after automated driving began to reduce predictability within trials (Eriksson and Stanton 2017b). Despite these design features, some residual learning or anticipation effects may still remain and should be considered in future research and experimental designs, particularly in studies involving repeated within-subject measurements. (iv) this study used self-report questionnaires to assess driver cognition, aligning with our aim to capture subjective comfort and cognitive experience during takeovers. We adopted well-established instruments (such as NASA-Task Load Index, Driving Activity Load Index, and Driver Skill Inventory) and carefully adapted them to suit the context of takeover scenarios. While these instruments are widely used and validated in driving research, the reliance on self-report still introduces limitations related to response subjectivity and the lack of continuous data, potentially affecting the reliability of real-time predictions. Future studies could benefit from exploring the integration of psychophysiological data (such as eye movements, heart rates, and EEG), which can serve as real-time, non-intrusive proxies for cognitive load and capacity. Such data has the potential to enhance the practical validity of the proposed takeover time prediction model while maintaining model interpretability, provided that the correlation between these psycho-physiological data and drivers' cognitive constructs is validated. In our future work, we will further explore this relationship to improve model robustness and applicability. Addressing these limitations could further enhance the validity and applicability of the findings to additional driving contexts.

4.6. CONCLUSIONS

This study contributes to improving the reliability and interpretability of takeover time (ToT) prediction models by optimizing predictor selection, enabling the exclusion of redundant predictors—such as extensive driver characteristics—without compromising accuracy. We examine the complex relationship between drivers' ToT, cognitive constructs, and diverse driver characteristics within a driving simulator experiment encompassing nine takeover scenarios. Using CatBoost-based prediction models and a linear regression model, our findings demonstrate that perceived spare capacity (i.e., perceived driver task capability minus perceived task demand) alone serves as a strong predictor of drivers' actual ToT. Notably, incorporating 13 additional driver characteristics does not significantly improve prediction accuracy when perceived spare capacity is already considered. Furthermore, our results reveal that driver characteristics influence ToT indirectly by shaping how drivers cognitively process objective takeover situations. These findings deepen our understanding of drivers' cognitive mechanisms during takeovers and highlight the importance of prioritizing cognition-based predictors over extensive driver characteristics when designing ToT prediction models. We argue that real-time cognitive monitoring, rather than static driver characteristics, may be more effective in predicting ToT and designing adaptive automation strategies. Implementing systems that assess perceived spare capacity dynamically could enable personalized takeover interventions, ensuring drivers receive appropriate support based on their actual

cognitive state.

By refining the selection of predictive features, this study provides a framework for more interpretable and reliable ToT predictions, which can support the development of adaptive takeover assistance systems. Future studies should explore the integration of psycho-physiological and behavioral data—such as eye-tracking or heart rate variability—as additional indicators of cognitive states related to ToT. Besides, the generalizability of these models should be tested across different driving conditions to validate their applicability.

5

TAKEOVER PERFORMANCE: ROLE OF SITUATION AWARENESS AND SPARE CAPACITY

The literature review in Chapter 2 emphasizes that effective control transitions require not only timely reactions, as indicated by drivers' takeover time (studied in Chapter 4), but also the achievement of a certain quality threshold including both objective quality from operational perspective and subjective quality reflecting drivers' personal feelings. This insight motivates this Chapter, which explores the factors influencing takeover performance in multiple dimensions.

This chapter evaluates drivers' takeover performance across three dimensions: response efficiency, user experience, and driving safety. Specially, I employ eXtreme Gradient Boosting (XGBoost) models to investigate the contributions of two critical factors, i.e., Situation Awareness (SA) and Spare Capacity (SC), in predicting various takeover performance metrics by comparing the predictive results to the baseline models that rely solely on basic Driver Characteristics (DC). The results reveal that (i) higher SA enables drivers to respond to takeover requests more quickly, particularly for reflexive responses; and (ii) SC shows a greater overall impact on takeover quality than SA, where higher SC generally leads to enhanced subjective rating scores and objective execution trajectories. These findings provide a comprehensive evaluation of takeover performance and highlight the distinct yet complementary roles of SA and SC in shaping performance components, offering valuable insights for optimizing human-vehicle interactions and enhancing system design in automated driving.

This chapter is based on a journal article (Liang, Kästle, *et al.* 2025):

> Liang, K., Kästle, J. L., Anvari, B., Calvert, S., van Lint, J. (2025). Multidimensional Assessment of Takeover Performance in Conditionally Automated Driving. Under review.

5.1. INTRODUCTION

Automated driving systems have made significant advancements but still face limitations in handling complex and risky driving scenarios. When these systems reach their operational boundaries, they issue a takeover request, prompting drivers to resume manual control of the vehicle within constrained time budgets. Ensuring smooth vehicle control transitions is crucial for avoiding potential hazards and providing a comfortable driving experience.

Control transitions are challenging because they require drivers to timely shift from a state of passive monitoring or non-driving activities to active vehicle control (Hu, Cai, *et al.* 2023; Lu, Happee, *et al.* 2016). This shift is not instantaneous; it demands time and cognitive resources to assess the situation, make decisions, and act. If drivers do not take over vehicle control promptly enough or if their takeover responses are poor in quality, the risks of accidents increase, and the overall user experience deteriorates. Thus, understanding the factors that influence drivers' takeover performance during control transitions and accordingly adopting necessary interventions are essential for enhancing the safety and comfort of conditionally automated driving.

A widely acknowledged factor influencing drivers' takeover performance is Situation Awareness (SA), which reflects how well a driver perceives, understands, and projects the surrounding environment (Endsley 2020; Van Lint and Calvert 2018). Studies by van den Beukel and van der Voort (2013) and Tan and Zhang (2022) demonstrated that drivers with higher SA levels had greater success in executing safe takeover maneuvers. Vlakveld *et al.* (2018) found that drivers' SA was closely related to their hazard perception, suggesting that drivers with better SA are more capable of recognizing potential risks, and consequently, reducing crash rates. McKerral, Pammer, and Gauld (2023) pointed out that improved SA enhanced takeover performance by guiding drivers' responses to takeover requests. Although the positive relationship between SA and takeover performance is well-documented, the concept of "takeover performance" is multifaceted and encompasses various aspects of driver behaviours and responses during control transitions (Li, Wang, Wang, Zeng, Wu, *et al.* 2023). Notably, certain aspects of takeover performance can even conflict: for instance, a shorter takeover time does not always indicate better quality (Wang, Guo, and Rau 2022; Wu, Wu, *et al.* 2022). While a shorter time to resume meaningful human control of the vehicle (Calvert, Johnsen, and George 2024) refers to a more efficient takeover, it may come at the cost of comfort if achieved through abrupt actions, such as hard braking, and can also pose pressure on following vehicles to respond effectively which increases crash risks (Wu, Wu, *et al.* 2022). Furthermore, discrepancies between drivers' subjective evaluations of their takeover quality and objective metrics based on driving trajectory have been observed (Guo *et al.* 2021), though not well studied. These complexities underscore the need for a detailed understanding of how SA affects various takeover performance dimensions.

In addition to SA, this study investigates another critical factor influencing takeover performance: Spare Capacity (SC), derived from Task-Capability Interface (TCI) theory (Fuller 2005). TCI theory suggests that drivers adjust their behaviours based on the dynamic interactions between their perceived task capability (TC) and task

demands (TD) to maintain their perceived safety margin at an acceptable level (Fuller 2005). On this basis, SC is defined as TC minus TD (Fuller 2000), inversely capturing how difficult a scenario is for a driver to manage. As Fuller (2011) noted, drivers with lower SC were more vulnerable to performance errors and the challenges of high-demand situations. In the context of automated driving, Müller *et al.* (2021) used drivers' secondary task performance as an indicator of SC, finding that drivers engaged in high-workload secondary tasks exhibited reduced SC and required longer reaction times. Similarly, our previous work (Liang, Calvert, Nordhoff, and Van Lint 2024) found that drivers with higher SC levels during takeover tasks generally resumed conscious manual control of the vehicle more quickly. We argue that SC has the potential to influence other aspects of takeover performance, especially takeover qualities, but its impacts require further investigation.

This study aims to take a close look at the effects of SA and SC on various aspects of takeover performance. A driving simulator experiment is conducted, where drivers are instructed to take over vehicle control from automation across nine scenarios (three traffic densities $*$ three non-driving related tasks). For each takeover, drivers' SA and SC are measured using both (i) well-established questionnaires (Hart and Staveland 1988; Pauzié 2008; Taylor 2017) that adjusted for takeover scenarios in this study, and (ii) cognition-related eye movement metrics (Deniel and Navarro 2023; Kästle 2024; Liang, Yang, *et al.* 2021; Sharma and Chakraborty 2024) , as detailed in Section 6.3. Meanwhile, takeover performance is systematically evaluated along three dimensions: drivers' reaction times, subjective takeover qualities, and objective takeover qualities. Specially, (i) reaction times refer to the time that drivers take to respond to takeover requests, including the time to first press the driving mode switch button, the time to first redirect visual attention to the road ahead, and the time to resume conscious human control of the vehicle; (ii) subjective takeover qualities refer to drivers' self-evaluation of their takeover experience, including their perceived time sufficiency, risk, and performance satisfaction during control transitions; (iii) objective takeover qualities are assessed using operational data, including minimum time to collision, maximum steering wheel angle, maximum acceleration, and maximum deceleration from the initiation of a takeover request until the driver changes to the left lane to get across of the detected collision. With this framework, we conduct a comprehensive analysis of the effects of drivers' SA and SC on various aspects of takeover performance, which is the main contribution of this study. This study aims to provide valuable insights to readers who are interested in drivers' cognition activities during control transitions and their implications for enhancing human-vehicle interactions for safe and comfortable conditionally automated driving.

5.2. METHOD

5.2.1. DRIVING SIMULATOR EXPERIMENT

The experiment was conducted in a fixed-base, medium-fidelity driving simulator on the campus of Delft University of Technology. Participants were instructed to detach from non-driving related tasks and take over vehicle control from a

simulated Conditionally Automated Driving System (CADS) across nine scenarios (three traffic densities * three non-driving-related tasks). Participants were required to complete a spare capacity survey after each takeover and another post-experiment questionnaire detailing their takeover-related characteristics. Details of the experiment instrumentation and procedures can be found in Chapter 3. The used questionnaires are shown in Section 5.2.2. On this basis, the impacts of Situation Awareness (SA) and Spare Capacity (SC) on drivers' takeover performances (encompassing reaction times and takeover qualities) are investigated by the method in Section 5.2.3.

5.2.2. QUESTIONNAIRES

In this study, two questionnaires are employed to gather data on drivers' characteristics and subjective experiences. The questions in both questionnaires are presented in random order to reduce order effects. Specifically,

(1) Driver Characteristics Questionnaire: assess drivers' characteristics that potentially affect their responses to takeover requests across different scenarios and their corresponding takeover performances. The collected driver characteristics cover the following three aspects:

(i) demographic information: age (age) and gender ($gender$);

(ii) skill-related factors: accumulated driving years ($accu\_years$), accumulated driving distance ($accu\_dis$), driving frequency ($driving\_fre$), driving skill ($driving\_skill$), and takeover skill ($takeover\_skill$); and

(iii) style-related factors: driver assistance usage frequency ($assist\_fre$), risk-taking attitude (RTA), trust in CADS ($trust$), reckless and careless takeover style ($style\_reckless$), anxious takeover style ($style\_anxious$), angry and hostile takeover style ($style\_angry$), and patient and careful takeover style ($style\_patient$).

The utilized questionnaire is developed based on well-established instruments (Lajunen and Summala 1995; Lu, Coster, and De Winter 2017; Ma, Yan, *et al.* 2010; Nordhoff *et al.* 2021, 2023; Taubman-Ben-Ari, Mikulincer, and Gillath 2004). A detailed version of this Driver Characteristics Questionnaire, including all questions, can be found in the Appendix 1.

(2) Driver Experience Questionnaire: assesses drivers' subjective ratings of their takeover experiences. Driver experience in this study covers three aspects:

(i) Situation Awareness (SA): this study measures $SA_{understanding}$ and $SA_{spare\_attention}$ ($SA_{attention\_supply}$ - $SA_{attention\_demand}$) using questions from the three-dimensional version of Situation Awareness Rating Technique (SART) (Taylor 2017). Additionally, two other aspects of SA are assessed based on SART, namely $SA_{arousal}$ (i.e., the driver's level of alertness prior to receiving a takeover request) and $SA_{projection}$ (i.e., the driver's ability to anticipate the steps needed to safely regain vehicle control);

(ii) Spare Capacity (SC): Fuller (2011) defined *SC* as the difference between a driver's task capability (*TC*) and the task demand (*TD*), grounded in TCI theory. In this study, *TC* and *TD* are measured using questions adapted from established literature (Hart and Staveland 1988; Lajunen and Summala 1995; Pauzié 2008; Rosenbloom *et al.* 2010; Zhang, De Winter, *et al.* 2019), tailored for takeover contexts. Specifically, *TC* is assessed across five dimensions, including anticipation capability ($TC_{anticipation}$), reaction capability ($TC_{reaction}$), speed adjustment capability (TC_{speed_adjust}), lane change capability (TC_{lane_change}), and safety capability (TC_{safety}). *TD* is deconstructed into three dimensions, including mental demand (TD_{mental}), visual demand (TD_{visual}), and temporal demand ($TD_{temporal}$). A full description of the questionnaire is available in Appendix 2 from our previous work (Liang, Calvert, Nordhoff, and Van Lint 2024); and

(iii) Subjective Takeover Qualities ($subjQ$): This study gathers drivers' subjective evaluations of their performance for each takeover across three dimensions, namely time sufficiency ($subjQ_{sufficiency}$), perceived risk ($subjQ_{risk}$), and performance satisfaction ($subjQ_{satisfaction}$). Specifically, $subjQ_{sufficiency}$ is measured using a reverse-phrased question, where participants are asked: "To complete the required bypass maneuvers safely and comfortably, how many seconds would you like to adjust the time that you were provided with to take over car control? Please use this sliding scale to indicate the amount of time you want to adjust, from -10 (decrease by 10 seconds) to +10 (increase by 10 seconds)". A higher value reflects a perceived insufficiency in the time provided. All responses are normalized to a scale of [-1, 1]. Regarding $subjQ_{risk}$, participants are asked to respond to the statement, "I was worried about being involved in a traffic accident during the takeover process," indicating their agreement on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Finally, $subjQ_{satisfaction}$ is measured by having participants rate their agreement with the statement: "I was satisfied with my performance in taking over car control," also using a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

An overview of the variables collected from these two questionnaires is provided in Section 5.2.3. These variables offer valuable insights into individual differences and driver cognitions during takeovers, forming the foundation for understanding how these factors affect takeover performance.

5.2.3. DATA ACQUISITION ANA ANALYSIS

The experiment initially produces data from 513 takeovers. After excluding 16 takeovers where participants either took vehicle control before the takeover request or forgot to press the mode switch button, and removing 31 takeovers due to incomplete questionnaires and hardware malfunctions, the final dataset for analysis consists of 466 takeovers.

To understand drivers' operational, visual, and perceptual patterns for taking over vehicle control in conditionally automated driving, this study records data from the

30 seconds preceding the initiation of takeover requests to the successful completion of lane changes in distinct takeover scenarios. The collected data can be classified into three main categories:

(1) operational data, including vehicle positions, driving mode, accelerations, decelerations, steering wheel angles, accelerator pedal positions, braking pedal positions, and timestamps from the driving simulator. On this basis, we calculate five operational metrics as listed in Table 5.1.

Table 5.1: Definitions of drivers' operational metrics based on Gold, Damböck, *et al.* (2013), Hydén (1996), Liang, Calvert, Nordhoff, and Van Lint (2024), and Miller, Sun, *et al.* (2015).

Metrics	Unit	Description	
$t_{buttion}$	s	the interval between the initiation of a takeover request and the moment ...	the driver presses a button to activate manual vehicle control
$t_{steering}$	s		the steering wheel angle exceeds 2 degrees
t_{pedal}	s		the braking/accelerator pedal position surpasses 10%
ToT	s	the shorter time between $t_{steering}$ and t_{pedal}	
TTC	s	the remaining time before a collision occurs if the current course and speed difference remain unchanged	

(2) visual data, including drivers' gaze position, fixation position [1], and the corresponding timestamps from Pupil Invisible eye tracking glasses. To streamline the discussion, this study defines three Areas of Interest (AOIs) (Orquin, Ashby, and Clarke 2016): the forward road, the Human-Machine Interface (HMI, including the text alarm and takeover button), and the mirrors (comprising the left-wing and right-wing mirrors). These AOIs are specified based on the takeover process, because drivers need to detach from the *n*-back task, focus on the road ahead to assess the takeover scenarios, and check the mirrors for lane changes. On this basis, 13 visual metrics are extracted as indicators of drivers' SA, as outlined in Table 5.2. Similarly, another 12 visual metrics are extracted as indicators of drivers' SC, as detailed in Table 5.3. These metrics provide objective measurements of SA and SC.

(3) self-reported data, including drivers' perception of their characteristics, SA, SC, and takeover qualities across various takeover scenarios. These data are collected using the questionnaires detailed in Section 5.2.2, thus presenting subjective measurements of the relevant variables.

To provide an overview of the investigated variables, we summarize the factors that may influence drivers' takeover performance in Table 5.4, which capturing a range of individual characteristics and driver cognition of takeover tasks. Meanwhile, Table 5.5 outlines the key metrics used to evaluate takeover performance in terms of

[1] Samples with gaze velocities below 900 px/s are classified as fixations (Drews and Dierkes 2024).

Table 5.2: Definitions of Situation Awareness (SA)-related visual metrics during the 30 seconds preceding takeover requests (Kästle 2024; Zhou, Yang, and De Winter 2021).

Metrics	Unit	Description
nr_{road}	–	the number of fixations on the forward road
$nr_{rearview}$	–	the number of fixations on the rear-view mirror
$nr_{sideview}$	–	the number of fixations on the left-wing / right-wing mirrors
nr_{HMI}	–	the number of fixations on the text alarm / the takeover button
$nr_{dashboard}$	–	the number of fixations on the dashboard
f_{max}	s	maximum fixation time
f_{mean}	s	mean fixation time
f_{std}	s	standard deviation of fixation time
num_f	–	overall number of fixations
s_{max}	px/s	maximum saccade velocity
s_{mean}	px/s	mean saccade velocity
s_{std}	px/s	standard deviation of saccade velocity
num_s	–	the overall number of saccades

reaction times, subjective takeover qualities, and objective takeover qualities. These metrics serve as critical indicators for assessing how well drivers handle the takeover process from efficiency, safety, and comfort perspectives.

Based on the collected data, this study employs the eXtreme Gradient Boosting (XGBoost) model (Chen and Guestrin 2016) to understand the correlations between drivers' Situation Awareness (SA), Spare Capacity (SC), and diverse aspects of takeover performance. XGBoost has achieved widespread recognition for its success in numerous machine learning competitions (Nielsen 2016) and has been applied in automated driving research to predict takeover time (Ayoub, Du, *et al.* 2022; Chen, Zhao, Li, Gong, *et al.* 2024) and takeover quality (Zhu *et al.* 2023). In this study, XGBoost models are developed to predict various takeover performance metrics based on different input features. The prediction results are evaluated using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) (Antypas *et al.* 2024; Ayoub, Du, *et al.* 2022; Yang, Zheng, *et al.* 2021).

The XGBoost models calculate the mean importance of each input feature through 10-folder cross-validation repeated 100 times, aiding in the identification of key factors influencing various aspects of takeover performance. Further, SHapley Additive exPlanation (SHAP) values (Lundberg and Lee 2017) are employed to explore the identified factors in detail, quantifying their effects on various takeover

Table 5.3: Definitions of Spare Capacity (SC)-related visual metrics for the period between the initiation of takeover requests and the completion of lane changes (Deniel and Navarro 2023; Liang, Yang, *et al.* 2021; Sharma and Chakraborty 2024).

Metrics	Unit	Description	
t_{road}	s	the interval between the initiation of a takeover request and the moment ...	the driver first establishes visual fixation on the forward road
t_{HMI}	s		the driver first establishes visual fixation on the text alarm / the takeover button
t_{mirror}	s		the driver first establishes visual fixation on the left-wing / right-wing mirrors
DUR_{road}	s	the total time duration that ...	the driver fixates on the forward road
DUR_{HMI}	s		the driver fixates on the text alarm / the takeover button
DUR_{mirror}	s		the driver fixates on the left-wing / right-wing mirrors
NO_{road}	–	the number of fixations on ...	the forward road
NO_{HMI}	–		the text alarm / the takeover button
NO_{mirror}	–		the left-wing / right-wing mirrors
AVG_{road}	s	the average duration of each fixation on ...	the forward road
AVG_{HMI}	s		the text alarm / the takeover button
AVG_{mirror}	s		the left-wing / right-wing mirrors

Table 5.4: Overview of studied factors that potentially affect takeover performance.

category	**sub-category**	**variables**
Driver Characteristics (*DC*)	demographics	*age*, *gender*
	skill-related	*accu_years*, *accu_dis*, *driving_fre*, *driving_skill*, *takeover_skill*, *assist_fre*
	style-related	*RTA*, *trust*, *style_reckless*, *style_anxious*, *style_angry*, *style_patient*
Situation Awareness (*SA*)	subjective	$SA_{understanding}$, $SA_{spare\_attetion}$, $SA_{arousal}$, $SA_{projection}$
	objective	nr_{road}, $nr_{rearview}$, $nr_{sideview}$, nr_{centre}, $nr_{dashboard}$, f_{max}, f_{mean}, f_{std}, num_f, s_{max}, s_{mean}, s_{std}, num_s
Spare Capacity (*SC*)	subjective	*TC* (including $TC_{anticipation}$, $TC_{reaction}$, TC_{speed_adjust}, TC_{lane_change}, and TC_{safety}), *TD* (including TD_{mental}, TD_{visual}, and $TD_{temporal}$)
	objective	t_{road}, t_{HMI}, t_{mirror}, PCT_{road}, PCT_{HMI}, PCT_{mirror}, NO_{road}, NO_{HMI}, NO_{mirror}, AVG_{road}, AVG_{HMI}, AVG_{mirror}

performance metrics. Note that the order of features when sorted by SHAP values may differ from the order sorted based on feature importance. This is because (i) SHAP values account for interactions among features, while feature importance

Table 5.5: Metrics for takeover performance (TOR: Takeover Request).

category	metric	unit	description
reaction times	t_{button}	s	time to press the mode switch button to enable manual inputs following a TOR
	t_{road}	s	time to first visually fixate on the road after a TOR
	ToT	s	time to perform the first conscious operational response to a TOR
subjective takeover qualities	$subjQ_{sufficiency}$	–	perceived time sufficiency for a takeover
	$subjQ_{risk}$	–	perceived risk of an accident during a takeover
	$subjQ_{satisfaction}$	–	perceived satisfaction for takeover performance
objective takeover qualities	$objQ_{ttc}$	s	min time to collision from TOR to lane change
	$objQ_{steer}$	rad	max steering wheel angle from TOR to lane change
	$objQ_{acc}$	m/s^2	max acceleration from TOR to lane change
	$objQ_{dec}$	m/s^2	max deceleration from TOR to lane change

only considers the contribution of individual features in isolation; and, (ii) feature importance measures how much a feature contributes to reducing loss, while SHAP values measure both magnitude and direction of a feature's impact. As a result, some features may have high split importance in XGBoost but low overall impact in SHAP rankings. This study employs both methods: feature importance for high-level insights and feature selection, and SHAP values for detailed interpretability and a deeper understanding of feature contributions. Additionally, Bonferroni significance tests are conducted to assess the statistical significance of the observed improvements in model performance and the effects of individual features.

Besides, in Section 5.4, the performance of XGBoost models is compared with two additional machine learning models, namely Random Forest (RF) and Light Gradient Boosting Machine (LightGBM), to strengthen the internal validity of this study. This comparison ensures that the findings are robust and not specific to a single modeling approach. Further, Furthermore, the results of this study are benchmarked against existing literature to establish external validity, demonstrating their alignment with or divergence from prior research in the field.

5.3. RESULTS

5.3.1. PARTICIPANT DISTRIBUTION

A total of 57 drivers participated in this study, with their characteristics summarized in Table 5.6 using descriptive statistics. The data reveals a diverse participant pool encompassing a wide range of demographic backgrounds, driving skills, and driving styles. This diversity allows for a detailed analysis of the factors that may influence takeover performance. In this study, the XGBoost models with those driver characteristics as inputs are considered baseline models because they serve as a reference point for evaluating the contribution of additional factors, such as Situation Awareness (SA) and Spare Capacity (SC), in affecting various components

of takeover performance.

Table 5.6: Descriptive statistics of participants' driver characteristics.

Characteristics	mean	SD	min	max	Characteristics	mean	SD	min	max
age	37.47	16.58	18	72	*takeover_skill*	3.73	0.55	2.56	4.94
gender	0.42	0.50	0	1	*RTA*	2.18	0.49	1	3.2
accu_years	17.04	16.91	1	55	*trust*	3.98	0.88	2	5
accu_dis	5840.91	6936.30	0	30000	*style_reckless*	2.57	0.73	1	4.4
driving_fre	0.30	0.27	0	1	*style_anxious*	2.55	0.69	1	4.2
driving_skill	1.40	0.66	0	2	*style_angry*	1.96	0.60	1	3.2
assist_fre	0.30	0.37	0	1	*style_patient*	3.42	0.49	2.4	4.4

∗ For *gender* : Male = 0; Female = 1.
∗ For *driving_skill*: Inexperienced = 0; Intermediate = 1; Experienced = 2.
∗ Characteristics on the right side of the table (including *takeover_skill*, *RTA*, *trust*, *style_reckless*, *style_anxious*, *style_angry*, and *style_patient*) are assessed on five-point scales ranging from 1 to 5.

5

5.3.2. PREDICTIONS OF REACTION TIMES

This study investigates three reactions times, namely (i) the time to press the mode switch button after receiving a takeover request (t_{button}), (ii) the time to look back on the forward road after receiving a takeover request (t_{road}), and (iii) the time to consciously take over control of the vehicle (ToT). XGBoost-based models are developed for modeling these reaction times using different input combinations: (i) driver characteristics (*DC*), (ii) *DC* combined with Situation Awareness (*SA*), (iii) *DC* combined with Spare Capacity (*SC*), and (iv) *DC* combined with both *SA* and *SC*. The models with different input combinations reveal the relative contributions of *DC*, *SA*, and *SC* in explaining variations in three reaction times. The results for each reaction time are analyzed in the following three subsections.

TIME TO PRESS MODE SWITCH BUTTON

The performance evaluations for t_{button} models are summarized in Table 5.7. Using only driver characteristics (XGBTbutton$_{dc}$) achieves reasonable performance but exhibits the highest RMSE and MAE among the four models, indicating its limitations in fully capturing the variations in t_{button}. Incorporating SA (XGBTbutton$_{dc+sa}$) significantly enhances model performance, with RMSE decreasing by 9.21% and MAE decreasing by 9.91% (both $p_{adjusted} < 0.01$). These performance improvements underscore the critical role of SA in shaping drivers' physical ability to respond promptly to takeover requests, as SA reflects the driver's awareness of the surrounding environment and their readiness to act, making it a pivotal factor in determining t_{button}. Adding SC (XGBTbutton$_{dc+sc}$) leads to minor improvements compared with the baseline model (XGBTbuttondc), with slight reductions in both RMSE (2.79%) and MAE (3.18%). However, these changes are statistically insignificant (both $p_{adjusted} > 0.05$). This suggests that except for basic driver information, adding SC alone does not provide a substantial contribution to explaining the

variations in t_{button}. This may be because SC reflects drivers' available cognitive resources and has a limited influence on their immediate response to pressing a mode switch button for manual intervention following a takeover request. Combining both SA and SC (XGBTbutton$_{dc+sa+sc}$) results in the most accurate representation of t_{button}, with RMSE decreasing by 10.48% and MAE by 10.59% (both $p_{adjusted} < 0.01$) compared to the baseline model (XGBTbutton$_{dc}$). Furthermore, XGBTbutton$_{dc+sa+sc}$ significantly decreases RMSE by 7.92% and MAE by 7.65% compared to XGBTbutton$_{dc+sc}$ ($p_{adjusted} < 0.05$), but shows no significant difference when compared to XGBTbutton$_{dc+sa}$ ($p_{adjusted} = 1.00$). These results suggest that SA plays a more dominant role than SC in explaining the variations in t_{button}. The stronger impact of SA over SC aligns with the intuitive understanding that reflexive responses in takeover scenarios, such as pressing a mode switch button to enable manual intervention, are typically quick and instinctive in nature. These responses are more influenced by the driver's real-time awareness of the situation and readiness to act, rather than by their cognitive load or available mental resources.

Table 5.7: Performance of XGBoost-based t_{button} models.

Model	**Inputs**	**RMSE (↓)**	**MAE (↓)**
XGBTbutton$_{dc}$	DC	0.6848	0.4966
XGBTbutton$_{dc+sa}$	DC + SA	0.6217	0.4474
XGBTbutton$_{dc+sc}$	DC + SC	0.6657	0.4808
XGBTbutton$_{dc+sa+sc}$	DC + SA + SC	0.6130	0.4440

Table 5.8: Feature importance and Bonferroni test results ($p_{adjusted}$) for significant factors of t_{button}.

Feature	**Importance (↑)**	$p_{adjusted}$ **(↓)**	**Feature**	**Importance (↑)**	$p_{adjusted}$ **(↓)**
$SA_{arousal}$	0.2739	1.2234e-43	f_{std}	0.0758	1.6861e-19
nr_{road}	0.1565	3.4159e-23	$nr_{rearview}$	0.0643	3.6289e-06
$SA_{spare\_attention}$	0.1225	2.5558e-21	$takeover\_skill$	0.0635	7.0540e-15
$style\_angry$	0.1043	1.5503e-15	age	0.0441	7.0513e-05
f_{mean}	0.0951	3.3310e-04			

Building on the significant impacts of DC and SA on t_{button}, this study further explores the contributions of individual factors. First, Bonferroni tests are conducted to pinpoint DC- and SA-related factors that significantly influence t_{button}, revealing nine significant factors ($p_{adjusted} < 0.01$). Among them, three factors-$style\_angry$, $takeover\_skill$, and age-are related to DC, while six factors pertain SA, including four objective measurements (nr_{road}, f_{mean}, f_{std}, and $nr_{rearview}$) and two subjective measurements ($SA_{arousal}$ and $SA_{spare\_attention}$). Next, these nine factors are incorporated into the XGBoost model to interpret t_{button}. To ensure stable performance results, 10-folder cross-validation (using 90% of the data for training and 10% for testing) is repeated 100 times. Feature importance and Bonferroni test results ($p_{adjusted}$) for significant factors of t_{button} are summarized in Table 5.8. The

results indicate that SA-related factors play a dominant role, whereas DC-related factors have a smaller yet significant influence. Among all nine factors, $SA\_arousal$ (the driver's level of alertness before receiving a takeover request) emerges as the most critical factor affecting t_{button}, followed by two additional SA-related factors: nr_{road} and $SA_{spare_attention}$. These findings reinforce our earlier conjecture that drivers' immediate responses to takeover requests are driven primarily by their real-time situation awareness and preparedness to act. Finally, the summary plot based on SHAP values is drawn to visualize the quantified correlations between these nine factors and t_{button}. SHAP values indicate how the value of t_{button} changes in response to variations in specific factors. As shown in Figure 5.1, generally, drivers with higher SA (as indicated by higher arousal levels before the takeover request, greater spare attention, more frequent glances at driving-related AOIs such as the road and rearview mirror, and shorter, more stable visual fixation durations), stronger takeover skills, and older age tend to react and press the mode switch button more quickly. Besides, while drivers with a less angry takeover style generally require more t_{button} than those with a moderately angry takeover style, drivers with a more angry takeover style tend to require longer t_{button}, though the extent of this delay varies.

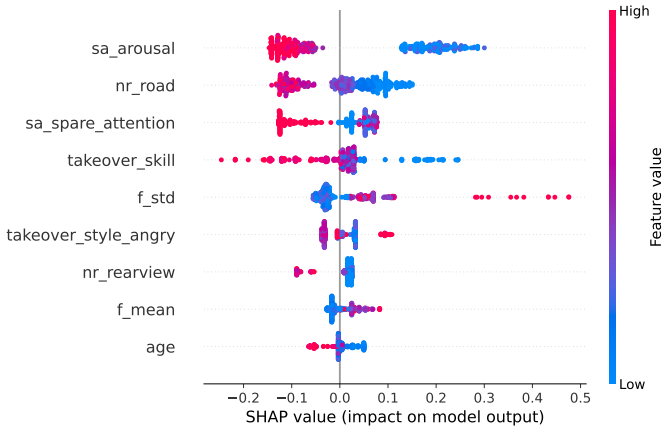


Figure 5.1: Summary plot of significant Driver Characteristics (*DC*)- and Situation Awareness (*SA*)-related factors influencing the time to press the mode switch button (t_{button}).

TIME TO LOOK BACK ON THE ROAD

Table 5.9 presents the results of modeling t_{road}, which represents the time drivers take to reorient their visual attention to the road following a takeover request. The baseline model (XGBTroad$_{dc}$), which relies solely on DC, exhibits the highest RMSE and MAE, suggesting its limitations in adequately capturing the underlying dynamics of t_{road}. Incorporating SA-related factors into the model (XGBTroad$_{dc+sa}$) significantly improves performance ($p_{adjusted} < 0.01$), reducing RMSE by 9.68% and decreasing MAE by 12.81%. These substantial gains highlight the critical role of SA

in determining how promptly drivers respond to a takeover request by reallocating their attention to the forward road. Adding SC-related features (XGBTroad$_{dc+sc}$) to the baseline model does not yield statistically significant changes, as indicated by $p_{adjusted} = 1.00$ for both RMSE and MAE. This suggests that SC, when added alone, does not contribute significantly to improving the model's ability to capture t_{road}. The combined model incorporating both SA and SC features (XGBTroad$_{dc+sa+sc}$) reduces RMSE by 10.05% and decreases MAE by 12.47% ($p_{adjusted} < 0.01$). Notably, there is no significant difference between XGBTroad$_{dc+sa}$ and XGBTroad$_{dc+sa+sc}$ ($p_{adjusted} = 1.00$). This finding suggests that the addition of SC to the combination of DC and SA does not meaningfully enhance the model's ability to capture the variability in t_{road}. These results indicate that SA accounts for a substantial portion of the explainable variation in t_{road}, and the additional contribution of SC remains insignificant. Consistent with the findings from the t_{button} models, the t_{road} results further underscore the dominant role of SA in shaping drivers' immediate, instinctive takeover responses, including pressing the mode switch button and redirecting visual attention back to the road.

Table 5.9: Performance of XGBoost-based t_{road} models.

Model	**Inputs**	**RMSE (↓)**	**MAE (↓)**
XGBTroad$_{dc}$	*DC*	0.6973	0.5332
XGBTroad$_{dc+sa}$	*DC + SA*	0.6298	0.4649
XGBTroad$_{dc+sc}$	*DC + SC*	0.6889	0.5400
XGBTroad$_{dc+sa+sc}$	*DC + SA + SC*	0.6273	0.4667

This study identifies seven significant factors via Bonferroni tests ($p_{adjusted} < 0.01$), including three DC-related factors (*accu_years*, *age*, and *style_angry*), two objective SA-related factors (nr_{road} and $nr_{dashboard}$), and two subjective SA-related factors ($SA_{spare\_attention}$ and $SA_{arousal}$). These seven factors are incorporated into the XGBoost model to interpret t_{road}. A 10-folder cross-validation (using 90% of the data for training and 10% for testing) is repeated 100 times to ensure stable performance results. As shown in Table 5.10, SA-related factors play a dominant role, with objective SA factors being more influential than subjective ones. In particular, nr_{road} stands out as the most influential factor, likely because it directly reflects drivers' visual attention allocation strategies.

Table 5.10: Feature importance and Bonferroni test results ($p_{adjusted}$) of significant factors of t_{road}.

Feature	**Importance (↑)**	$p_{adjusted}$ **(↓)**	**Feature**	**Importance (↑)**	$p_{adjusted}$ **(↓)**
nr_{road}	0.4588	1.8133e-43	*accu_years*	0.0725	9.8633e-15
$nr_{dashboard}$	0.1230	3.2160e-23	*age*	0.0691	5.2440e-11
$SA_{spare\_attention}$	0.1137	9.9628e-22	*style_angry*	0.0690	1.1174e-04
$SA_{arousal}$	0.0940	5.9896e-06			

This study further explores the impact of the identified seven significant DC- and SA-related factors on t_{road}. As illustrated in Figure 5.2, drivers with higher SA (i.e., those who frequently glance at the road and dashboard, and perceive themselves as having greater spare attention and higher arousal levels) generally spend less time returning their gaze to the road after a takeover request. Besides, drivers with a less angry takeover style generally require shorter t_{road}, possibly because angry drivers process their emotions first before taking action which delays their response. Additionally, both high and low levels of $accu\_years$ and age show variations in their correlations with t_{road}. A key distinction between their correlations emerges: the relationship between t_{road} and age appears to follow an inverted U-shape, where middle-aged drivers exhibit the longest t_{road}, while both younger and older drivers react more quickly but with greater variability. In contrast, $accu\_years$ shows a more consistent trend, where it mostly decreases t_{road}, as indicated by negative SHAP values. This suggests that greater driving experience generally leads to quicker visual reorientation, making experienced drivers more efficient in redirecting their attention to the road.

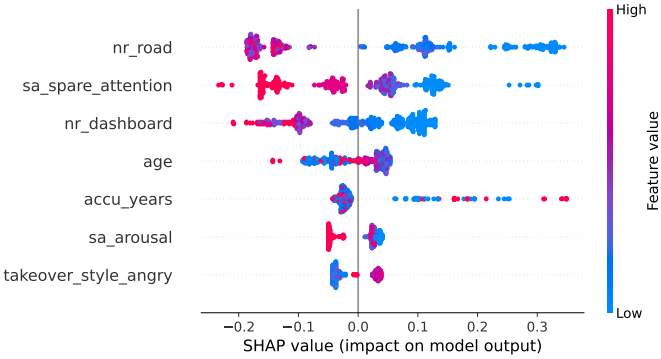


Figure 5.2: Summary plot of significant Driver Characteristics (*DC*)- and Situation Awareness (*SA*)-related factors influencing the time to look back on the road (t_{road}).

TAKEOVER TIME

The performance evaluations of XGBoost-based ToT models are summarized in Table 5.11. Modeling ToT is more challenging compared with t_{button} and t_{road}, as indicated by the relatively higher RMSE and MAE values across all models. Incorporating SA and SC (separately or jointly) significantly improves model accuracy over using DC alone ($p_{adjusted} < 0.05$). Specifically, compared to the baseline model (XGBToT$_{dc}$), incorporating only SA (XGBToT$_{dc+sa}$) reduces RMSE by 5.61% and MAE by 5.52 %. Adding SC alone (XGBToT$_{dc+sc}$) shows a greater improvement over the baseline than SA alone, with RMSE and MAE reductions of 11.80% and 10.55%, respectively. Combining both SA and SC (XGBToT$_{dc+sa+sc}$) provides the best performance, with reductions of 14.01% in RMSE and 12.55% in MAE,

compared to the baseline. These findings highlight that while both SA and SC contribute meaningfully to the model's ability to explain ToT, SC appears to have a more substantial impact. This may be attributed to the more deliberate and resource-intensive nature of decisions required during meaningful engagement with a takeover task. Besides, Bonferroni-corrected tests reveal no significant improvement of XGBToT$_{dc+sa+sc}$ over XGBToT$_{dc+sc}$ ($p_{adjusted} > 0.05$), indicating that the impact of SA becomes negligible when SC is already accounted for. This suggests that SC captures much of the variance in ToT that might otherwise be attributed to SA, highlighting the dominant role of SC in explaining takeover performance.

Table 5.11: Performance of XGBoost-based ToT models.

Model	**Inputs**	**RMSE (↓)**	**MAE (↓)**
XGBToT$_{dc}$	DC	1.3082	1.0068
XGBToT$_{dc+sa}$	DC + SA	1.2348	0.9512
XGBToT$_{dc+sc}$	DC + SC	1.1538	0.9006
XGBToT$_{dc+sa+sc}$	DC + SA + SC	1.1249	0.8804

This study examines the importance of individual DC- and SC-related factors in modeling ToT. Bonferroni tests identify ten significant factors for ToT ($p_{adjusted} < 0.05$) and all of them are related to SC, including three subjective SC measurements and seven objective SC measurements. This underscores the critical role of SC and its sub-components in explaining variability in ToT, while more stable individual differences among drivers (e.g., driving experience and style) may be less impactful on ToT when SC-related factors are already considered. We use these ten SC-related factors as inputs and execute the XGBToT model 100 times, employing 10-folder cross-validation to ensure stable results. Average feature importance and Bonferroni test results ($p_{adjusted}$) of these factors are summarized in Table 5.12. Overall, subjective SC-related factors show greater impacts on ToT than objective SC-related gaze metrics with higher feature importance. Particularly, SC_{TC} emerges as the most influential feature, suggesting that drivers' self-assessed tsak management ability can more accurately explain the time required for drivers to return to the cognitive driving loop.

Table 5.12: Feature importance and Bonferroni test results ($p_{adjusted}$) of significant factors of ToT.

Feature	**Importance (↑)**	$p_{adjusted}$ **(↓)**	**Feature**	**Importance (↑)**	$p_{adjusted}$ **(↓)**
SC_{TC}	0.2553	7.1117e-12	DUR_{HMI}	0.0699	1.4399e-16
SC	0.1634	7.0952e-18	t_{mirror}	0.0688	5.5131e-11
SC_{TD}	0.1079	5.3343e-08	AVG_{mirror}	0.0683	7.0202e-12
t_{HMI}	0.0853	5.7321e-10	AVG_{HMI}	0.0591	3.8123e-22
NO_{mirror}	0.0775	1.0248e-18	AVG_{road}	0.0446	6.4752e-06

This study further explores the impact of the identified ten significant SC-related

factors on ToT. As illustrated in Figure 5.3, drivers who perceive themselves as having lower SC (i.e., those who think the task is more demanding and their capability to handle the task is lower) generally spend more time resuming conscious vehicle control. Besides, gaze interactions with three AOIs (side mirrors, HMI, and the forward road) are important for capturing ToT, while the visual interaction patterns vary across these AOIs. Generally, drivers with longer ToT tend to engage in more extensive side mirror checks, take longer to make their first glance at both the side mirrors and HMI, spend more total time interacting with the HMI, and exhibit longer fixation durations on mirrors and the HMI, while spending less time per fixation on the forward road. These findings highlight the critical role of both self-perceived SC and gaze indicators in understanding and modeling drivers' ToT.

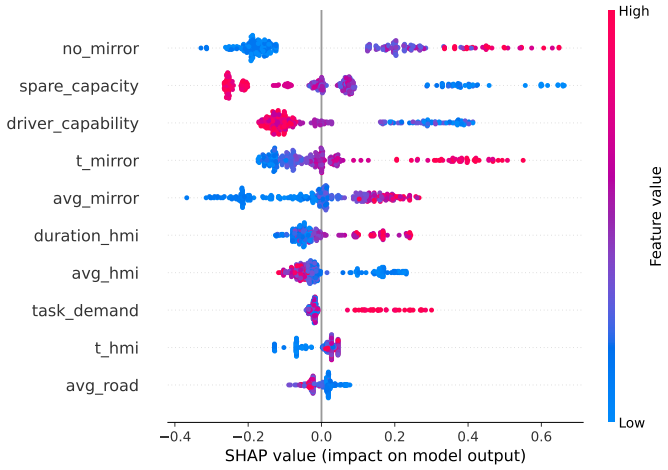


Figure 5.3: Summary plot of significant Spare Capacity (SA)-related factors influencing drivers' takeover time (ToT).

5.3.3. PREDICTIONS OF SUBJECTIVE TAKEOVER QUALITY

In this section, we examine the factors that influence drivers' perceptions of takeover quality. To capture subjective takeover quality, we select three key metrics, measured through a questionnaire: (i) the perceived sufficiency of the time provided for fulfilling the takeover task ($subjQ_{sufficiency}$), (ii) the perceived risk of being involved in an accident during the takeover ($subjQ_{risk}$), and (iii) the perceived satisfaction with their performance during the takeover ($subjQ_{satisfaction}$). XGBoost models with varying input combinations are employed to evaluate the relative contributions of Driver Characteristics (DC), Situation Awareness (SA), and Spare Capacity (SC) in explaining variations in these three metrics. The results for each quality metric are analyzed in detail in the following subsections.

TIME SUFFICIENCY

Table 5.13 presents the performance evaluation of XGBoost-based models for $subjQ_{sufficiency}$ using different input combinations. The baseline model, XGBSQsuff$_{dc}$, which relies solely on DC as inputs, demonstrates strong performance with low RMSE and MAE, indicating a good fit between the actual measurements and predicted values of $subjQ_{sufficiency}$. The addition of SA, SC, and their combination does not significantly improve the model's explanatory power. This is evidenced by the minimal changes in performance metrics and $p_{adjusted} > 0.05$, which suggest no statistically significant differences between the additional models and the baseline. These results imply that SA and SC contribute only minimally, if at all, to explaining $subjQ_{sufficiency}$, with their effects either overlapping with or being negligible relative to DC. This suggests that the perceived time sufficiency in takeover contexts is primarily driven by DC which is relatively stable, rather than situation factors like SA and SC.

Table 5.13: Performance of XGBoost-based $subjQ_{sufficiency}$ models.

Model	**Inputs**	**RMSE (↓)**	**MAE (↓)**
XGBSQsuff$_{dc}$	DC	0.2332	0.1810
XGBSQsuff$_{dc+sa}$	$DC + SA$	0.2325	0.1808
XGBSQsuff$_{dc+sc}$	$DC + SC$	0.2240	0.1712
XGBSQsuff$_{dc+sa+sc}$	$DC + SA + SC$	0.2232	0.1711

On this basis, this study investigates the importance of specific DC-related factors in determining $subjQ_{sufficiency}$. Bonferroni tests identify 12 significant factors ($p_{adjusted} < 0.01$), which are subsequently fed into the XGBoost-based $subjQ_{sufficiency}$ model. Table 5.14 presents the feature importance and Bonferroni-adjusted significance ($p_{adjusted}$) of these factors. Notably, $gender$ emerges as the most influential factor in determining $subjQ_{sufficiency}$, which may stem from a variety of socio-cultural and psychological factors that influence how individuals assess and react to takeover conditions. Such gender disparities in decision-making and attitude formation in automated driving contexts have been consistently documented in previous studies. For example, Teshima, Niitsuma, and Nishimura (2024) found that females generally need less time to finish the perception of takeover tasks than males. Our findings on gender-based differences in perceived time sufficiency offer valuable insights for tailoring time budget strategies to meet the unique needs of each group, potentially enhancing both safety and user experience.

Additionally, we take a closer look at how the significant DC-related factors manifest in drivers' perceptions of time sufficiency. As shown in Figure 5.4, drivers who perceive the provided time budget for takeover tasks as less sufficient tend to be male, older, and more impulsive (e.g., less patient, more reckless, and more prone to risk-taking). They typically have lower trust in conditionally automated driving systems and diminished driving proficiency (e.g., reduced takeover skill, infrequent driving, and shorter accumulated driving distances) despite rating their

Table 5.14: Feature importance and Bonferroni test results ($p_{adjusted}$) of significant factors of $subjQ_{sufficiency}$.

Feature	Importance (↑)	$p_{adjusted}$ (↓)	Feature	Importance (↑)	$p_{adjusted}$ (↓)
gender	0.1820	9.4805e-50	*driving_fre*	0.0733	1.9613e-28
style_patient	0.1062	1.2289e-41	*accu_dis*	0.0681	8.4145e-33
driving_skill	0.0917	1.7749e-19	*style_reckless*	0.0673	1.9803e-12
takeover_skill	0.0906	1.2399e-54	*assist_fre*	0.0615	2.1729e-25
age	0.0799	9.9901e-37	*RTA*	0.0572	1.3316e-19
trust	0.0746	2.6316e-25	*style_angry*	0.0475	2.3371e-03

driving abilities highly. Moreover, they may frequently use driver assistance systems, potentially raising their expectations for automated interventions.

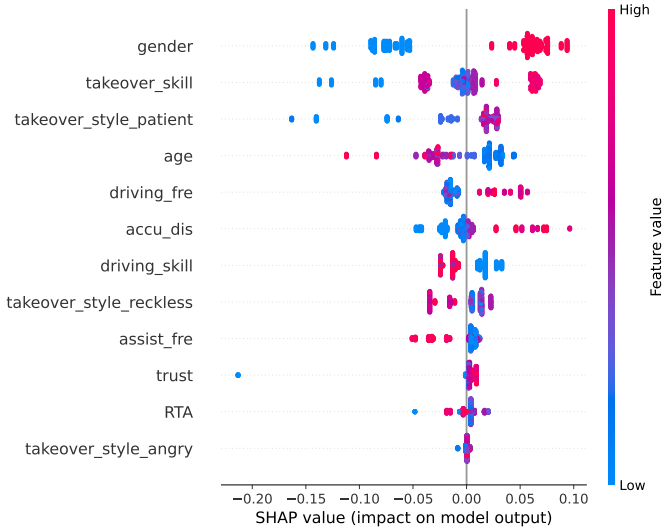


Figure 5.4: Summary plot of significant Driver Characteristics (*DC*)-related factors influencing drivers' perceived time sufficiency ($subjQ_{sufficiency}$).

PERCEIVED RISK

Table 5.15 summarizes the performance of XGBoost-based models in explaining variations in $subjQ_{risk}$ using different input combinations. The baseline model, XGBSQrisk$_{dc}$, shows relatively high RMSE and MAE, reflecting limited explanatory power. Incorporating SA (XGBSQrisk$_{dc+sa}$) leads to substantial improvements, reducing RMSE by 13.03% and MAE by 12.69% compared to the baseline ($p_{adjusted} < 0.01$). Adding SC (XGBSQrisk$_{dc+sc}$) results in greater improvements, with RMSE and MAE decreasing by 25.94% and 25.46%, respectively ($p_{adjusted} < 0.01$). The combined model, XGBSQrisk$_{dc+sa+sc}$, demonstrates the best overall performance among the four models, achieving a 26.26% reduction in RMSE and a 26.04%

reduction in MAE compared to the baseline ($p_{adjusted} < 0.01$). However, its improvement over XGBSQrisk$_{dc+sc}$ is not statistically significant ($p_{adjusted} = 1.00$). The results indicate that the additional explanatory value provided by SA is minimal when SC is already included, suggesting that SA's contribution largely derives from its overlap with SC, while SC plays a more significant role in explaining $subjQ_{risk}$.

Table 5.15: Performance of XGBoost-based $subjQ_{risk}$ models.

Model	**Inputs**	**RMSE (↓)**	**MAE (↓)**
XGBSQrisk$_{dc}$	*DC*	1.1348	0.8931
XGBSQrisk$_{dc+sa}$	*DC + SA*	0.9869	0.7798
XGBSQrisk$_{dc+sc}$	*DC + SC*	0.8404	0.6657
XGBSQrisk$_{dc+sa+sc}$	*DC + SA + SC*	0.8368	0.6605

Table 5.16: Feature importance and Bonferroni test results ($p_{adjusted}$) of significant factors of $subjQ_{risk}$.

Feature	**Importance (↑)**	$p_{adjusted}$ **(↓)**	**Feature**	**Importance (↑)**	$p_{adjusted}$ **(↓)**
SC	0.3021	4.9215e-63	*accu_dis*	0.0360	2.9284e-13
SC_{TC}	0.1812	3.5442e-39	*style_angry*	0.0293	2.8887e-09
trust	0.0672	1.0007e-29	*age*	0.0281	2.9394e-12
takeover_skill	0.0607	4.7243e-22	*assist_fre*	0.0280	1.8195e-10
driving_skill	0.0528	4.3703e-38	*gender*	0.0253	7.1162e-07
style_reckless	0.0482	2.2284e-19	*RTA*	0.0240	4.5956e-05
style_anxious	0.0479	3.6934e-16	*accu_years*	0.0237	9.7020e-07
SC_{TD}	0.0456	2.3842e-16			

This study delves into the importance of specific DC and SC factors in determining $subjQ_{risk}$. Bonferroni tests are conducted to identify the significant determinants of $subjQ_{risk}$, yielding 16 factors (12 DC-related and 4 SC-related) with strong statistical significance ($p_{adjusted} < 0.05$). These significant factors are fed into an XGBSQrisk model, and a 10-folder cross-validation (repeated 100 times) is employed to ensure stable performance results. Table 5.16 presents the feature importance and Bonferroni-adjusted significance for each factor. Among these factor, subjective SC-related factors, particularly drivers' perceived takeover abilities (as reflected in *SC* and SC_{TC}), emerge as dominant contributors. This underscores the central role of self-assessed competence and confidence in shaping risk perception.

To further quantify the relationships between $subjQ_{risk}$ and its 16 significant factors, SHAP values are utilized. A summary plot derived from SHAP values is illustrated in Figure 5.5. The results align with the feature importance findings, confirming that *SC* and SC_{TC} are dominant determinants of $subjQ_{risk}$. Specifically, the higher the drivers' confidence in fulfilling the takeover tasks (i.e., higher values of *SC* and SC_{TC}), the lower their perceived risk. Besides, these two factors are followed by $driving\_skill$ and $takeover\_skil$, which are also competence-related factors. The SHAP values of $driving\_skill$ and $takeover\_skil$ also indicate that

drivers with higher levels of skill tend to perceive lower levels of risk across takeover scenarios, reinforcing the importance of competence in shaping subjective risk perception. Collectively, these findings suggest that drivers' risk assessments are primarily influenced by their perceived competence and confidence in executing takeover tasks, while demographic characteristics and other driver traits provide additional explanatory power.

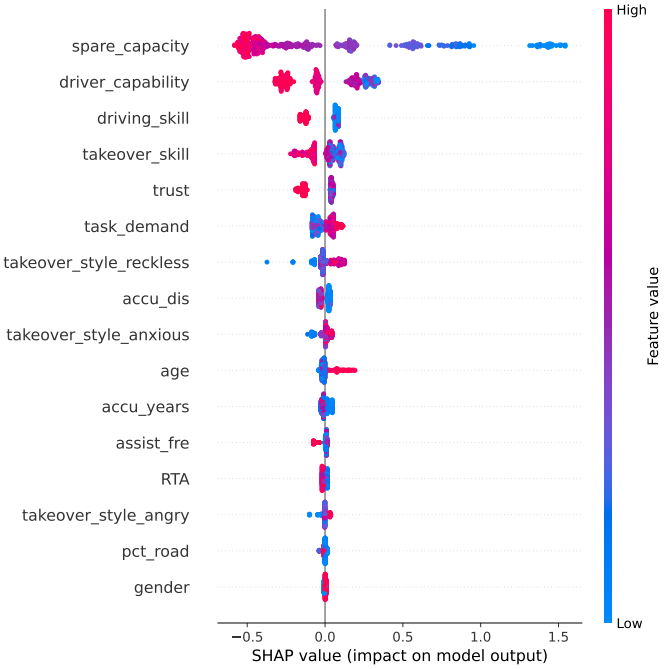


Figure 5.5: Summary plot of significant Driver Characteristics (*DC*)- and Spare Capacity (*SC*)-related factors influencing drivers' perceived risk ($subjQ_{risk}$).

PERFORMANCE SATISFACTION

Table 5.17 summarizes the performance of XGBoost-based models in explaining variations in $subjQ_{satisfaction}$ using different input combinations. The baseline model, XGBSQsatis$_{dc}$, exhibits relatively high RMSE and MAE, indicating limited explanatory capacity. Adding SA (XGBSQsatis$_{dc+sa}$) significantly reduces RMSE by 16.26% and MAE by 16.65% ($p_{adjusted} < 0.01$), highlighting its contribution to explaining satisfaction levels. Incorporating SC (XGBSQsatis$_{dc+sc}$) leads to more substantial improvements, with RMSE and MAE decreasing by 37.10% and 36.21% respectively ($p_{adjusted} < 0.01$), compared to the baseline. Notably, the combined model, XGBSQsatis$_{dc+sa+sc}$, shows no significant improvement over XGBSQsatis$_{dc+sc}$ ($p_{adjusted} = 1.00$), indicating that the additional value provided by SA becomes negligible when SC is included. This also suggests that the

performance improvements observed in XGBSQsatis$_{dc+sa}$ are largely attributable to the shared information between SA and SC. However, SC encompasses more unique and valuable information for explaining $subjQ_{satisfaction}$, extending beyond the commonalities it shares with SA. These findings underscore the critical role of SC in accounting for variations in $subjQ_{satisfaction}$, with SC providing the most substantial explanatory power. While SA contributes to the explanation, its impact does not add meaningful value when SC is already considered.

Table 5.17: Performance of XGBoost-based $subjQ_{satisfaction}$ models.

Model	**Inputs**	**RMSE (↓)**	**MAE (↓)**
XGBSQsatis$_{dc}$	*DC*	1.0436	0.7771
XGBSQsatis$_{dc+sa}$	*DC* + *SA*	0.8739	0.6477
XGBSQsatis$_{dc+sc}$	*DC* + *SC*	0.6564	0.4957
XGBSQsatis$_{dc+sa+sc}$	*DC* + *SA* + *SC*	0.6593	0.4951

This study examines the role of specific DC- and SC-related factors in influencing $subjQ_{satisfaction}$. Using Bonferroni tests, six statistically significant determinants ($p_{adjusted} < 0.05$) are identified, including two DC-related factors ($takeover\_skill$ and RAT) and four SC-related factors (two subjective: SC and SC_{TC}; and two objective: DUR_{mirror} and AVG_{mirror}). These factors were integrated into an XGBSQsatis model, with 10-folder cross-validation repeated 100 times to ensure reliable performance. Table 5.18 displays the feature importance and Bonferroni-adjusted significance. The results demonstrate that SC-related factors contribute more significantly to $subjQ_{satisfaction}$ compared to DC-related factors, with subjective SC factors playing a more prominent role than objective SC factors. Similar to the findings on drivers' risk perception, SC-related factors—particularly drivers' perceived confidence in takeover tasks (SC_{TC} and SC)—emerge as the most dominant determinants of $subjQ_{satisfaction}$. This finding underscores a correlation between drivers' perceived risk and their satisfaction with performance, as drivers are likely to feel dissatisfied with their performance during takeovers if they perceive higher levels of risk. These insights emphasize the importance of enhancing drivers' confidence and mitigating feelings of risk to improve satisfaction during control transitions in conditionally automated driving.

Table 5.18: Feature importance and Bonferroni test results ($p_{adjusted}$) of significant factors of $subjQ_{satisfaction}$.

Feature	**Importance (↑)**	$p_{adjusted}$ **(↓)**	**Feature**	**Importance (↑)**	$p_{adjusted}$ **(↓)**
SC_{TC}	0.5512	7.5965e-74	AVG_{mirror}	0.0792	8.4662e-11
SC	0.1933	4.6711e-21	$takeover\_skill$	0.0592	8.6937e-26
DUR_{mirror}	0.0879	2.8561e-08	RTA	0.0292	1.9477e-02

We employ SHAP values to quantify the contributions of six significant factors to $subjQ_{satisfaction}$. As illustrated in Figure 5.6, drivers who exhibit superficial

mirror-checking behaviour (both in terms of average fixation and total duration) combined with a confident, risk-embracing attitude and high self-perceived takeover skills are more likely to report higher satisfaction with their takeover performance. These findings underscore the potential of mirror-checking metrics as indicators of drivers' confidence in executing takeover tasks, which in turn influences their perception of performance satisfaction. This suggests that future driver assistance systems could utilize such visual cues to evaluate and improve drivers' takeover experiences, ultimately fostering safer and more comfortable control transitions.

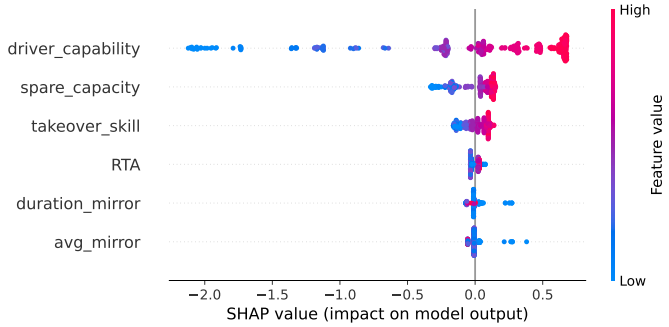


Figure 5.6: Summary plot of significant Driver Characteristics (*DC*)- and Spare Capacity (*SC*)-related factors influencing drivers' perceived performance satisfaction ($subjQ_{satisfaction}$).

5.3.4. PREDICTIONS OF OBJECTIVE TAKEOVER QUALITY

In this section, we examine the factors that influence objective takeover quality indicated by drivers' trajectory data. To capture objective takeover quality, we select four key metrics spanning the period from the initiation of the takeover request to the lane change: (i) the minimum time to collision ($objQ_{ttc}$), (ii) the maximum steering wheel angle ($objQ_{steer}$), (iii) the maximum acceleration ($objQ_{acc}$), and (iv) the maximum deceleration ($objQ_{dec}$). XGBoost models with varying input combinations are employed to evaluate the relative contributions of driver characteristics (DC), situation awareness (SA), and spare capacity (SC) in explaining variations in these four metrics. The results for each quality metric are analyzed in detail in the following subsections.

MINIMUM TIME TO COLLISION

Table 5.19 summarizes the performance of XGBoost-based models in explaining variations in $objQ_{ttc}$ using different input combinations. The results indicate no statistically significant improvements in model performance with the inclusion of SA or SC ($p_{adjusted} = 1.00$) when compared to the baseline model, XGBOQttc$_{dc}$, which relies only on DC. This finding suggests that the addition of SA or SC does not offer substantial explanatory power beyond the baseline model. The contributions

of SA and SC might overlap significantly with the information already contained in DC, leading to negligible improvements when they are added to the model. This conclusion is further supported by the observation that the combined model, XGBOQttc$_{dc+sa+sc}$, performs only slightly better than XGBOQttc$_{dc}$ and does not significantly outperform the baseline model ($p_{adjusted} = 1.00$).

Table 5.19: Performance of XGBoost-based $objQ_{ttc}$ models.

Model	**Inputs**	**RMSE (↓)**	**MAE (↓)**
XGBOQttc$_{dc}$	*DC*	1.0407	0.8175
XGBOQttc$_{dc+sa}$	*DC + SA*	1.0486	0.8212
XGBOQttc$_{dc+sc}$	*DC + SC*	1.0099	0.7979
XGBOQttc$_{dc+sa+sc}$	*DC + SA + SC*	1.0093	0.7980

This study investigates the influence of key DC-related factors on $objQ_{ttc}$ in response to a takeover request. Through Bonferroni-adjusted significance tests, eight significant factors are identified ($p_{adjusted} < 0.01$) and incorporated into an XGBoost-based $objQ_{ttc}$ model to assess their relative contributions. Table 5.20 summarizes the feature importance and Bonferroni-adjusted significance of these factors. Among them, $accu\_dis$ and age are the two most influential factors, suggesting that overall driving experience plays a crucial role in affecting drivers' minimum time to collision in takeover scenarios. These two objective proxies for driving experience outweigh self-reported $takeover\_skill$ in modelling $objQ_{ttc}$, highlighting a key distinction between subjective and objective measures of expertise. This suggests that, for objective performance metrics like $objQ_{ttc}$, objective measures may carry greater predictive power than subjective self-assessments. Beyond experience, takeover styles, including reckless, angry, and anxious tendencies, significantly contribute to $objQ_{ttc}$ estimation, underscoring the impact of behavioural tendencies on takeover responses and collision risk. Notably, we find that the majority of the significant factors influencing $objQ_{ttc}$ are either experience-related or personal preference-related, emphasizing the critical role of accumulated expertise and individual behavioural traits in determining takeover safety.

Table 5.20: Feature importance and Bonferroni test results ($p_{adjusted}$) of significant factors of $objQ_{ttc}$.

Feature	**Importance (↑)**	$p_{adjusted}$ **(↓)**	**Feature**	**Importance (↑)**	$p_{adjusted}$ **(↓)**
$accu\_dis$	0.1727	4.2915e-41	$takeover\_skill$	0.1173	5.2461e-12
age	0.1544	1.3432e-27	$assist\_fre$	0.1124	1.6448e-17
$style\_reckless$	0.1387	2.1205e-12	$style\_anxious$	0.1030	5.0132e-14
$style\_angry$	0.1174	2.3469e-27	$trust$	0.0841	1.3646e-21

We quantify the impact of these eight significant factors on $objQ_{ttc}$ using SHAP values. As shown in Figure 5.7, drivers who exhibit longer minimum time to collision tend to be older, use driver assistance systems less frequently, have a less

anxious takeover style, and demonstrate high trust in conditional driving automation (possibly because they trust the system to alert them in time). Drivers with a more reckless or angry takeover style also exhibit longer $objQ_{ttc}$. This may be because they tend to slow down immediately after a takeover request or take action without fully assessing the situation, leading to extended time margins. Besides, inexperienced drivers (low in $accu\_dis$ and $takeover\_skill$) fall into two distinct groups. Some compensate for their lack of experience by adopting a cautious and conservative takeover strategy, maintaining a shorter $objQ_{ttc}$. Others, however, may struggle with reaction timing, leading to more abrupt takeovers that results in longer $objQ_{ttc}$. These insights not only deepen our understanding of how individual differences influence $objQ_{ttc}$ but also have practical implications for the development of personalized automated driving systems.

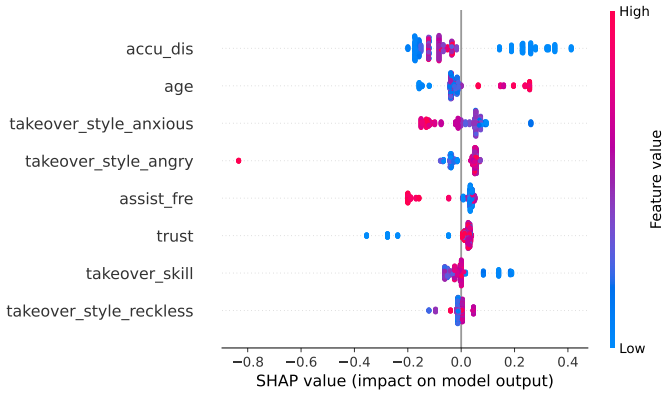


Figure 5.7: Summary plot of significant Driver Characteristics (*DC*)-related factors influencing minimum time to collision ($objQ_{ttc}$).

MAXIMUM STEERING WHEEL ANGLE

Table 5.21 presents the performance of XGBoost-based models in explaining variations in $objQ_{steer}$ using different combinations of input variables. The baseline model, XGBOQsteer$_{dc}$, which relies exclusively on DC, establishes a solid foundation with low RMSE and MAE, demonstrating that DC effectively captures key aspects of drivers' steering behaviour in response to takeover requests. Adding SA alone (XGBOQsteer$_{dc+sa}$) results in minor performance gains, reducing RMSE by 3.44% and MAE by 3.90%, but these improvements are not statistically significant ($p_{adjusted} > 0.05$). This suggests that SA does not provide substantial additional explanatory power when DC is already included. In contrast, incorporating SC (XGBOQsteer$_{dc+sc}$) significantly enhances model performance, reducing RMSE by 10.03% and MAE by 18.25% ($p_{adjusted} < 0.05$). The combined model, XGBOQsteer$_{dc+sa+sc}$, yields performance metrics nearly identical to XGBOQsteer$_{dc+sc}$, indicating that SA adds minimal value when both DC and SC are accounted for. These results emphasize the substantial contributions of both DC

and SC in explaining variations in $objQ_{steer}$, with SC delivering the most significant improvements on top of DC.

Table 5.21: Performance of XGBoost-based $objQ_{steer}$ models.

Model	Inputs	RMSE (↓)	MAE (↓)
XGBOQsteer$_{dc}$	DC	0.3580	0.1874
XGBOQsteer$_{dc+sa}$	DC + SA	0.3457	0.1801
XGBOQsteer$_{dc+sc}$	DC + SC	0.3221	0.1532
XGBOQsteer$_{dc+sa+sc}$	$OQDC$ + SA + SC	0.3253	0.1542

We explore the contributions of DC- and SC-related factors in determining $objQ_{steer}$. Bonferroni tests reveal that seven SC-related factors are statistically significant ($p_{adjusted} < 0.01$), including five objective gaze metrics and two subjective measurements. Table 5.22 summarizes the feature importance of these seven factors after within the XGBoost-based $objQ_{steer}$ model, alongside their corresponding Bonferroni-adjusted significances. Generally, objective gaze metrics—specifically DUR_{mirror} and NO_{mirror}—exhibit greater importance than self-reported SC factors in explaining steering behaviours. Besides, among three primary AOIs (i.e., the forward road, side mirrors, and HMI), drivers' visual attention on side mirrors contributes the most to capturing $objQ_{steer}$, while visual interactions with HMI have a smaller but still significant influence.

The impact of these seven significant factors on $objQ_{steer}$ is illustrated in Figure 5.8. This summary plot reveals that drivers with lower SC generally exhibit larger maximum steering wheel angles when responding to a takeover request to change lane. Specifically, lower SC is not only reflected in the lower self-reported ratings, but also in gaze metrics, including spending more time checking side mirrors and taking onger to make their first glance at the HMI. Besides, we notice there are several long tails in the SHAP distributions, particularly for DUR_{mirror}. These long tails reflect the diversity in driver behaviours, with high or low values of certain features having a more spread impact on $objQ_{steer}$. These findings collectively emphasize the importance of drivers' SC in influencing steering response qualities.

Table 5.22: Feature importance and Bonferroni test results ($p_{adjusted}$) of significant factors of $objQ_{steer}$.

Feature	Importance (↑)	$p_{adjusted}$ (↓)	Feature	Importance (↑)	$p_{adjusted}$ (↓)
DUR_{mirror}	0.3438	2.1701e-08	SC_{TC}	0.1116	5.4067e-07
NO_{mirror}	0.2409	1.6282e-06	t_{HMI}	0.0864	1.3851e-04
SC	0.1315	4.7475e-18	$style\_anxious$	0.0859	8.8415e-07

MAXIMUM ACCELERATION

Table 5.23 presents the performance comparison of XGBoost-based models in explaining variations in $objQ_{acc}$ using different input variable combinations. The

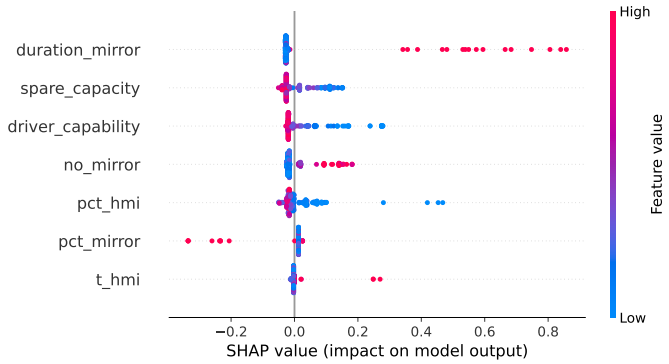


Figure 5.8: Summary plot of significant Spare Capacity (*SC*)-related factors influencing maximum steering wheel angle ($objQ_{steer}$).

baseline model, XGBOQacc$_{dc}$, which includes only DC, achieves the highest RMSE and MAE. Incorporating SA (XGBOQacc$_{dc+sa}$) slightly reduces both RMSE (by 0.73%) and MAE (by 1.79%), but these improvements are not statistically significant ($p_{adjusted} > 0.05$), suggesting that SA contributes minimal unique information beyond DC. In contrast, adding SC (XGBOQacc$_{dc+sc}$) results in substantial performance enhancements, with RMSE reduced by 13.94% and MAE by 17.68%, both statistically significant ($p_{adjusted} < 0.01$). This highlights SC's critical role in capturing additional variation in $objQ_{acc}$. However, the combined model (XGBOQacc$_{dc+sa+sc}$) performs comparably to XGBOQacc$_{dc+sc}$, showing only marginal, non-significant differences ($p_{adjusted} > 0.05$). These findings emphasize SC's pivotal role in enhancing model performance, while the incremental value of SA is minimal when DC and SC are already included.

Table 5.23: Performance of XGBoost-based $objQ_{acc}$ models.

Model	**Inputs**	**RMSE (↓)**	**MAE (↓)**
XGBOQacc$_{dc}$	*DC*	1.6226	1.2291
XGBOQacc$_{dc+sa}$	*DC + SA*	1.6107	1.2071
XGBOQacc$_{dc+sc}$	*DC + SC*	1.3964	1.0118
XGBOQacc$_{dc+sa+sc}$	*DC + SA + SC*	1.4076	1.0224

This study examines the importance of DC- and SC-related factors in modelling drivers' maximum acceleration in response to a takeover request ($objQ_{acc}$). Bonferroni tests identify three DC-related factors and six SC-related factors (including five objective measurements and one subjective measurement) as significant determinants of $objQ_{acc}$ ($p_{adjusted} < 0.05$). These factors are incorporated into an XGBoost model with 10-folder cross-validation repeated 100 times to ensure result stability. The final feature importance rankings and statistical significance levels are summarized in Table 5.24. Overall, SC-related factors are the dominant

determinants of $objQ_{acc}$, while DC-related factors contribute significantly but to a lesser extent. Among SC-related factors, objective gaze metrics are more influential than self-reported SC ratings, emphasizing the value of eye-tracking data in understanding acceleration responses in takeover contexts. Notably, the four most important features—DUR_{mirror}, NO_{mirror}, AVG_{mirror}, and t_{mirror}—suggest that side mirrors are the most critical AOI for modelling $objQ_{acc}$. These findings highlight the role of SC, especially drivers' visual interactions with side mirrors, in explaining drivers' acceleration decisions during takeovers.

Table 5.24: Feature importance and Bonferroni test results ($p_{adjusted}$) of significant factors of $objQ_{acc}$.

Feature	**Importance (↑)**	$p_{adjusted}$ (↓)	**Feature**	**Importance (↑)**	$p_{adjusted}$ (↓)
DUR_{mirror}	0.2363	1.4877e-32	$accu\_years$	0.0608	1.4354e-25
NO_{mirror}	0.2251	9.6136e-14	NO_{road}	0.0486	1.9576e-05
AVG_{mirror}	0.1247	1.6751e-02	$assist\_fre$	0.0436	8.6914e-05
t_{mirror}	0.1206	5.4337e-20	$style\_angry$	0.0377	4.8701e-14
SC	0.1027	2.6390e-37			

We employ SHAP values to quantify the influence of significant factors on $objQ_{acc}$. As shown in the summary plot in Figure 5.9, drivers with lower confidence in fulfilling the takeover task-as indicated by allocating greater visual attention on side mirrors and the forward road, taking longer time to first check side mirrors, and reporting perception of lower spare capacity)-tend to exhibit larger maximum accelerations in response to takeover requests. Additionally, drivers with lower $accu\_years$ and $style\_angry$ show a polarized impact on $objQ_{acc}$, suggesting that their acceleration responses are more variable. Some may exhibit overly cautious behaviours, while others may apply sudden and forceful acceleration. These findings offer valuable insights into understanding drivers' acceleration behaviours in takeover contexts.

MAXIMUM DECELERATION

Table 5.25 presents a comparison of the performance of XGBoost-based models in explaining variations in $objQ_{dec}$ with various input variables. The baseline model, XGBOQdec$_{dc}$, which incorporates only DC, achieves the highest RMSE and MAE, indicating that DC alone may not fully capture the complexity of $objQ_{dec}$. Adding SA (XGBOQdec$_{dc+sa}$) reduces RMSE by 2.61% and MAE by 2.85%, but these improvements are not statistically significant ($p_{adjusted} > 0.05$), indicating limited additional contributions of SA when combined with DC. In contrast, incorporating SC (XGBOQdec$_{dc+sc}$) substantially enhances model performance by reducing RMSE by 13.14% and MAE by 15.78% ($p_{adjusted} < 0.01$) when compared to the baseline model. The combined model (XGBOQdec$dc+sa+sc$) performs almost identically to XGBOQdec$dc+sc$, with no statistically significant differences ($p_{adjusted} > 0.05$). These findings emphasize the crucial contribution of SC in explaining variations in $objQ_{dec}$, while the addition of SA offers only minimal incremental value. The RMSE and MAE values of the $objQ_{dec}$ models are relatively high compared to

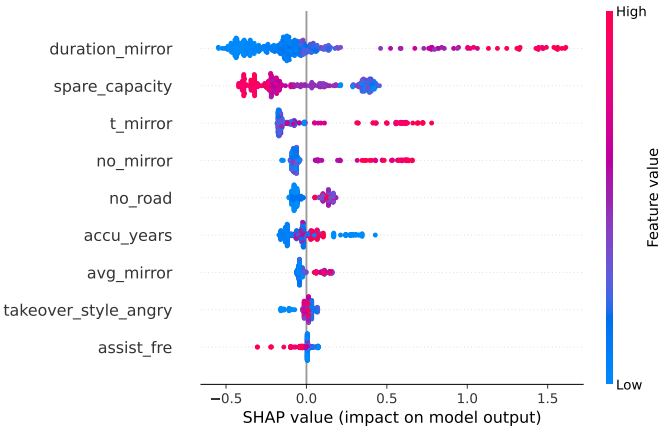


Figure 5.9: Summary plot of significant Driver Characteristics (*DC*)- and Spare Capacity (*SC*)-related factors influencing maximum acceleration ($objQ_{acc}$).

those of the other takeover performance metrics. This suggests that drivers' deceleration responses to a takeover request are less predictable, and there may be additional factors influencing maximum deceleration during takeovers that are not fully captured by the current input variables.

Table 5.25: Performance of XGBoost-based $objQ_{dec}$ models.

Model	**Inputs**	**RMSE (↓)**	**MAE (↓)**
XGBOQdec$_{dc}$	*DC*	3.3894	2.9508
XGBOQdec$_{dc+sa}$	*DC* + *SA*	3.3009	2.8667
XGBOQdec$_{dc+sc}$	*DC* + *SC*	2.9440	2.4852
XGBOQdec$_{dc+sa+sc}$	*DC* + *SA* + *SC*	2.9490	2.4976

This study investigates the feature importance and Bonferroni-adjusted significance results for DC- and SC-related factors influencing drivers' deceleration behaviours in response to takeover requests. The results, as summarized in Table 5.26, identify eight significant factors ($p_{adjusted} < 0.01$), with seven SC-related factors playing a dominant role in modeling $objQ_{dec}$. Specifically, two self-reported SC measurements (i.e., *SC* and SC_{TC}) are the two most influential determinants, followed by two gaze metrics related to side mirrors (i.e., DUR_{mirror} and t_{mirror}). Additionally, $style\_angry$ is the only significant DC-related factor, though it has the smallest importance among these significant factors. These findings underscore the central role of self-reported SC and visual interactions in understanding drivers' deceleration responses, with driving style playing a secondary but notable influence.

We quantify the impact of eight significant factors on $objQ_{dec}$ using SHAP values, as illustrated in Figure 5.10. The summary plot reveals that drivers who exhibit

Table 5.26: Feature importance and Bonferroni test results ($p_{adjusted}$) of significant factors of $objQ_{dec}$.

Feature	Importance (↑)	$p_{adjusted}$ (↓)	Feature	Importance (↑)	$p_{adjusted}$ (↓)
SC	0.2977	2.0528e-35	SC_{TD}	0.0862	9.5316e-10
SC_{TC}	0.2015	7.7216e-16	AVG_{road}	0.0744	1.1295e-08
DUR_{mirror}	0.1052	2.3073e-34	NO_{mirror}	0.0697	1.3810e-15
t_{mirror}	0.0992	1.6802e-28	$style\_angry$	0.0662	1.0259e-12

larger maximum deceleration in response to takeover requests generally perceive themselves as having lower SC (i.e., lower driver capability and/or higher task demand). This reduced SC can also be reflected in their gaze behaviours, as they take longer to first check side mirrors and allocate more visual attention to them (more times and longer total duration). Additionally, drivers with an angry takeover style tend to show greater maximum deceleration, indicating that emotionally reactive individuals are more likely to apply more abrupt and forceful braking maneuvers. Overall, these findings deepen our understanding of drivers' deceleration responses in takeover contexts, revealing how (objective and subjective) SC and takeover styles collectively capture braking behaviours.

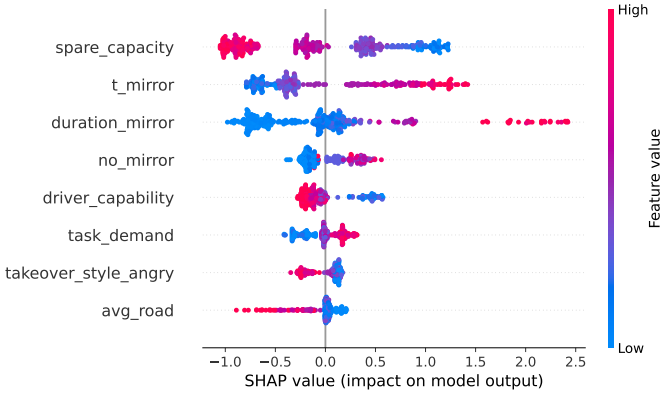


Figure 5.10: Summary plot of significant Spare Capacity (*SC*)-related factors influencing maximum deceleration ($objQ_{dec}$).

5.4. DISCUSSION: COMPARISON WITH RANDOM FOREST AND LIGHTGBM

This study conducts a comprehensive comparison of three machine learning models—Random Forest (RF), Light Gradient Boosting Machine (LightGBM), and eXtreme Gradient Boosting (XGBoost)—across ten performance metrics, using various combinations of input features: Driver Characteristics (DC), Situation Awareness

(SA), and Spare Capacity (SC). RF and LightGBM are selected as complementary models to XGBoost to ensure a robust analysis, as they represent distinct yet widely recognized approaches within the ensemble learning paradigm. Specifically, RF, as a bagging method, is renowned for its robustness and interpretability, effectively mitigating overfitting through random feature selection and averaging across multiple trees. In contrast, LightGBM, a highly efficient gradient-boosting framework, offers a direct comparison to XGBoost due to their shared boosting principles but differing implementations. By including RF and LightGBM, this study aims to verify that the observed patterns in performance metrics such as RMSE and MAE are not driven by specific properties of XGBoost but are generalizable across multiple methodologies.

This study employs 10-folder cross-validation for RF and LightGBM, repeated 100 times to ensure the stability and reliability of the model performance metrics. The RMSE and MAE results are presented in Table 5.27, alongside those obtained from the XGBoost model. By comparing these results, we observe consistent trends in predictive performance across three models for the ten takeover performance metrics when specific features are incorporated. Specifically,

1 **among three reaction times:** drivers' instinctive and immediate responses, such as pressing a mode switch button (t_{button}) and reorienting visual attention to the road (t_{road}), are largely driven by SA. These reflexive actions occur in a short time frame, relying heavily on the driver's perception of the environment and their readiness to act. Reflective responses, such as going back to the conscious driving loop (ToT), involve more deliberate cognitive processes. These responses require drivers to assess the situation, allocate cognitive resources, and execute appropriate actions, which may demand greater integration of SC. This distinction underscores the interplay between rapid, awareness-driven reactions and slower, cognitively mediated processes, offering a deeper understanding of the cognitive mechanisms at play in takeover scenarios.

2 **among three subjective takeover quality metrics:** the baseline model relying solely on DC predominantly explains perceived time sufficiency, indicating that stable traits of drivers play a central role, with minimal additional contributions from SA and SC. In contrast, SC emerges as the most influential factor in explaining subjective perceptions of both risk and satisfaction, demonstrating its critical role in shaping these evaluations. While SA-related features provide supplementary contributions to drivers' perceptions of risk and satisfaction, their additional value is limited when SC is already included in the model. This suggests that the information captured by SC encompasses much of the variance that SA might explain, highlighting the dominant role of SC in understanding subjective evaluations of driving scenarios.

3 **among four objective takeover quality metrics:** for $objQ_{ttc}$, the addition of SA or SC does not provide substantial explanatory power when compared with the baseline model, likely due to overlaps with information already captured by DC. For $objQ_{steer}$, both DC and SC make significant contributions, while

Table 5.27: Model performance comparison for ten performance metrics.

Model output	Model input	Random Forest		LightGBM		XGBoost	
		RMSE (↓)	MAE (↓)	RMSE (↓)	MAE (↓)	RMSE (↓)	MAE (↓)
t_{button}	*DC*	0.6929	0.5018	0.6908	0.5006	0.6848	0.4966
	DC + SA	0.6195	0.4462	0.6292	0.4526	0.6217	0.4474
	DC + SC	0.6808	0.4933	0.6985	0.5017	0.6657	0.4808
	DC + SA + SC	0.6362	0.4531	0.6197	0.4521	0.6130	0.4440
t_{road}	*DC*	0.7143	0.5277	0.7120	0.5264	0.6973	0.5332
	DC + SA	0.6471	0.4725	0.6701	0.4866	0.6298	0.4649
	DC + SC	0.7060	0.5598	0.7349	0.5573	0.6889	0.5400
	DC + SA + SC	0.6469	0.4752	0.6563	0.4812	0.6273	0.4667
ToT	*DC*	1.3555	1.0474	1.3524	1.0445	1.3082	1.0068
	DC + SA	1.2324	0.9588	1.3019	1.0065	1.2348	0.9512
	DC + SC	1.1942	0.9278	1.2135	0.9329	1.1538	0.9006
	DC + SA + SC	1.1833	0.9179	1.1557	0.8871	1.1249	0.8804
$subjQ_{sufficiency}$	*DC*	0.1939	0.1425	0.1936	0.1421	0.2332	0.1810
	DC + SA	0.1875	0.1390	0.1940	0.1469	0.2325	0.1808
	DC + SC	0.2401	0.1818	0.1835	0.1350	0.2240	0.1712
	DC + SA + SC	0.2431	0.1840	0.1857	0.1387	0.2232	0.1711
$subjQ_{risk}$	*DC*	1.1439	0.8418	1.1425	0.8406	1.1348	0.8931
	DC + SA	0.9814	0.7533	0.9937	0.7538	0.9869	0.7798
	DC + SC	0.8540	0.6772	0.7773	0.5724	0.8404	0.6657
	DC + SA + SC	0.8656	0.6861	0.7796	0.5764	0.8368	0.6605
$subjQ_{satisfaction}$	*DC*	1.0809	0.7974	1.0788	0.7948	1.0436	0.7771
	DC + SA	0.8683	0.6356	0.9127	0.6658	0.8739	0.6477
	DC + SC	0.6713	0.4820	0.6919	0.5010	0.6564	0.4957
	DC + SA + SC	0.6732	0.4831	0.6849	0.4951	0.6593	0.4951
$objQ_{ttc}$	*DC*	1.0353	0.8062	1.0337	0.8043	1.0407	0.8175
	DC + SA	1.0177	0.7930	1.0739	0.8378	1.0486	0.8212
	DC + SC	1.0623	0.8459	0.9978	0.7694	1.0099	0.7979
	DC + SA + SC	1.0666	0.8488	1.0006	0.7742	1.0093	0.7980
$objQ_{steer}$	*DC*	0.3781	0.1965	0.3752	0.1952	0.3580	0.1874
	DC + SA	0.3769	0.1959	0.3759	0.2087	0.3457	0.1801
	DC + SC	0.3337	0.1629	0.3382	0.1694	0.3221	0.1532
	DC + SA + SC	0.3342	0.1631	0.3381	0.1698	0.3253	0.1542
$objQ_{acc}$	*DC*	1.6702	1.2345	1.6616	1.2337	1.6226	1.2291
	DC + SA	1.6204	1.2288	1.7325	1.2861	1.6107	1.2071
	DC + SC	1.4761	1.0917	1.4078	1.0132	1.3964	1.0118
	DC + SA + SC	1.4717	1.0887	1.4424	1.0410	1.4076	1.0224
$objQ_{dec}$	*DC*	3.5099	3.0026	3.4981	2.9978	3.3894	2.9508
	DC + SA	3.2757	2.8108	3.4621	2.8659	3.3009	2.8667
	DC + SC	3.0097	2.5845	3.0476	2.4988	2.9440	2.4852
	DC + SA + SC	3.0173	2.5921	2.9949	2.4487	2.9490	2.4976

SA provides minimal additional value when included alongside DC and SC. The results for $objQ_{acc}$ and $objQ_{dec}$ both indicate that while SA provides only marginal improvements over DC, incorporating SC leads to substantial enhancements in model performance, though the performance for $objQ_{dec}$ models are relatively poor. Overall, these results highlight the critical role of DC and SC in explaining variations in objective takeover performance, while the incremental value of SA is limited when DC and SC are included.

In summary, the key finding of this study is that, drivers' reflexive responses to takeover request are largely influenced by their SA, while the quality of takeover performance is largely determined by their SC. The consistency in predictive performance across all three models reinforces the robustness of our findings, suggesting that the observed patterns are not model-specific but reflect underlying relationships in the data. Besides, our finding aligns closely with prior studies. A strong correlation has been observed between drivers' SA and their reflexive reactions to takeover requests. For instance, Zeeb, Buchner, and Schrauf (2015) demonstrated that drivers who were more aware of their surroundings (higher SA) took shorter time to put their hands back on the steering wheel. Clark, McLaughlin, and Feng (2017) found that lower SA led to delays in pressing a takeover button to indicate that drivers wanted to regain vehicle control. However, when it comes to takeover time which requires more cognitive resources than reflexive reactions, the role of SA becomes less straightforward. Jia, Huang, and Du (2024) revealed that higher SA was not always associated with shorter takeover time, especially in complex situations. It is important to note that some studies report a link between improved SA and reduced takeover time, but these investigations often do not differentiate between reflexive reaction time and takeover time, leading to inconsistent conclusions regarding the role of SA. Jia, Huang, and Du (2024) also reported that elevated SA does not necessarily enhance takeover quality, as measured by parameters such as maximum longitudinal and lateral acceleration, minimum time-to-collision, and maximum road deviation. Similarly, Agrawal and Peeta (2021) found that drivers' SA before takeover does not significantly affect takeover quality metrics (e.g., collision risk, intensity of driver response, and trajectory quality), whereas increased mental stress detrimentally impacts these outcomes. Liu, Wu, *et al.* (2024) identified cognitive load as a critical predictor of takeover safety. Collectively, these studies suggest that cognition-related constructs—such as spare capacity and mental load—play a more decisive role in determining takeover quality than SA alone. This convergence of evidence not only reinforces the validity of our findings but also highlights the importance of enhancing both SA and SC to optimize driver performance during vehicle control transitions. These insights carry significant implications for the design of advanced driver-assistance systems, which can leverage these findings to more accurately estimate driver reactions and implement personalized, adaptive alert strategies.

This study is subject to three primary limitations: (i) The experiment was conducted in a simulated environment rather than in real-world driving conditions. While simulators offer controlled settings that facilitate experimentation, driver behaviour may differ in actual driving situations, potentially limiting the generalizability of

our findings; (ii) The analysis primarily examines the impact of individual factors and factor groups on takeover performance. Although SHAP values provide a preliminary insight into the interactions among these factors, we do not fully explore their interplays. A more in-depth investigation, especially into the interplay between situation awareness and spare capacity, could uncover nuanced dynamics within vehicle control transitions; and (iii) This study does not examine the correlation between SA and SC, as the focus is on understanding their distinct roles in influencing different aspects of takeover performance. However, a deeper investigation into the interrelationship between SA and SC and the extent of their unique vs. overlapping contributions could provide further insights into their respective roles in driver behaviour during takeover scenarios. Addressing these limitations could enhance the validity, applicability, and practical relevance of the findings to real-world driving contexts. Such efforts would also help identify more robust strategies for improving the safety and effectiveness of human interactions with automated driving systems.

5.5. CONCLUSIONS

This study conducts a driving simulator experiment and provides a comprehensive investigation of drivers' takeover performance using ten performance metrics categorized into three key aspects: three reaction times, three subjective quality measures, and four objective quality measures. Specifically, we (i) examine the contributions of Situation Awareness (SA) and Spare Capacity (SC) in predicting takeover performance metrics by leveraging XGBoost models, comparing them to a baseline model that included only Driver Characteristics (DC); (ii) analyze the impacts of individual significant factors on various performance metrics using both feature importance from XGBoost for high-level insights and SHAP values from game theory for detailed impacts of input features; and (iii) compare the results from XGBoost models with additional two machine learning models, namely Random Forest and LightGBM for internal validity and compare the findings with existing literature for external validity. The results reveal that higher SA enables drivers to respond to takeover requests more quickly, particularly for reflexive responses, while higher SC generally enhances the quality of takeovers. These findings provide a comprehensive evaluation of takeover performance and reveal the distinct yet complementary roles of SA and SC in shaping various performance aspects, highlighting the importance of designing human-vehicle interactions that align with driver cognitions for improving the safety and comfort of automated driving. Future research should further explore the interaction between SA and SC and validate these insights in real-world automated driving scenarios.

6

ADAPTIVE TIME BUDGETS: ROLE OF TAKEOVER BUFFER

In Chapters 4 and 5, I explored the key factors influencing takeover time and performance, which deepens our understanding of driver cognition during vehicle control transitions. Here in this Chapter, I analyze the relationship between takeover time, time budget, and takeover performance as an integrated sequence, especially focusing on the role of takeover buffer which is the margin between the provided time budget and the required takeover time.

This chapter evaluates the influence of different takeover buffer lengths on safety-related indicators and subjective assessments. Results show that (i) takeover buffers of about 5–6 seconds consistently lead to optimal safety and comfort; and (ii) drivers prefer relatively stable takeover buffers across varying traffic densities and n-back tasks. On this basis, this study introduces an adaptive time budget framework that dynamically allocates transition time by incorporating a predicted takeover time and a preferred takeover buffer (piece-wise function). This can serve as an important first step toward providing drivers with sufficient time to resume vehicle control across diverse scenarios, which in line with the future research recommendations for adaptive time budget strategies proposed in the literature review in Chapter 2.

This chapter is based on a journal publication (Liang, Calvert, and van Lint 2025a):

> Liang, K., Calvert, S., van Lint, J. (2025). Adaptive time budgets for safe and comfortable vehicle control transition in conditionally automated driving. Under review.

6.1. INTRODUCTION

Conditionally automated driving systems issue takeover requests (TORs) in situations that exceed their operational capabilities, requiring drivers to promptly resume manual control and maintain safe vehicle operation. A key factor in ensuring the smoothness of such control transitions is the time budget, i.e., the time offered by automation for control transitions. When the time budget is too short to accommodate the required takeover time (ToT, the time drivers need to regain manual vehicle control after receiving a TOR (ISO 21959:2020 2020)), the risk of accidents increases (Gold, Damböck, *et al.* 2013) as drivers may lack adequate time to perceive, assess, and respond to the situation. Conversely, time budgets that substantially exceed the required ToT may also introduce risks: such TORs can be perceived as false alarms (Huang and Pitts 2022; Skrickij, Šabanovič, and Žuraulis 2020), leading to reduced driver attention and potential dangers, particularly when the out-of-capability situations are not readily perceivable to drivers. Therefore, defining and allocating sufficient time budgets is essential to ensure driving safety and user experience in vehicle control transitions.

Previous research on time budget determination has primarily focused on identifying fixed time budgets for safe driver takeover. A widely cited time budget for drivers to resume vehicle control is 7s (Gold, Damböck, *et al.* 2013), which has been adopted in numerous takeover experiments (Gold, Körber, *et al.* 2016; Jarosch, Bellem, and Bengler 2019; Körber *et al.* 2016; Li, Hou, *et al.* 2021). In on-road applications, Mercedes-Benz, for example, provides drivers with 10s to resume control [1]. However, this fixed-time-budget approach overlooks the substantial variability in the required ToT across drivers and scenarios (Zhang, Ma, Yang, *et al.* 2023; Zhang, Zeng, *et al.* 2021). Favarò, Eurich, and Rizvi (2019) reported 1,143 takeover cases from four vehicle manufacturers and found ToT values ranging from 0.83 s to 3.10 s. Zhang, De Winter, *et al.* (2019) reported ToT values ranging from 0.69 s to 19.79 s across 520 takeovers, with a long right-tailed distribution. These findings highlight the limitations of fixed time budgets in accommodating such variability of ToT, as they may be insufficient for drivers or situations requiring longer ToT or unnecessarily long for others, potentially leading to safety risks and reduced system efficiency in complex traffic scenarios. Determining how to provide sufficient time budgets for different drivers to take over vehicle control smoothly across diverse scenarios remains a key challenge.

Providing adaptive time budgets is a promising approach for addressing the limitations of fixed time allocations by dynamically adjusting the provided time to suffice the required ToT across diverse drivers and driving scenarios (Li, Wang, Wang, Zeng, Li, *et al.* 2021; Liang, Calvert, Nordhoff, Li, *et al.* 2025). One of the practical foundations for determining adaptive time budgets comes from Marberger et al. (2017), which proposed using the difference between the available time budget and the time required for a safe takeover to quantify driver availability (Marberger *et al.* 2017). In our previous review study (Liang, Calvert, and van Lint 2026), a similar concept of "takeover buffer" was defined as the surplus time remaining

[1] https://abcnews.go.com/Business/future-driving-hands-off-eyes-off-mercedes-benz/story?id=103681808

within the provided time budget after subtracting the driver's required ToT. Thus, a sufficient time budget can be determined by adding the predicted ToT required by drivers to the optimal takeover buffer. Among these two components, prior work has predominantly concentrated on predicting ToT (Ayoub, Du, *et al.* 2022; Liu, Liu, *et al.* 2025). However, limited effort has been devoted to determining takeover buffers. Designing appropriately sized takeover buffers tailored to situational demands has not yet been thoroughly investigated (Gold, Happee, and Bengler 2018; Tanshi and Söffker 2022).

This study aims to explore the optimal allocation of takeover buffer by investigating its relationship with takeover time and performance. Specifically, we focus on two main questions:

- How does the takeover buffer affect drivers' response quality and subjective experience across diverse takeover situations?
- What durations of takeover buffer do drivers prefer when their required takeover time varies?

To answer these questions, we conducted a driving simulator experiment where drivers performed takeover maneuvers across nine scenarios (three traffic densities $*$ three non-driving related tasks). With the data collected from the experiment, we conduct a comprehensive analysis of the effects of takeover buffer on various aspects of takeover performance, including (i) subjective driver experience, encompassing performance satisfaction, perceived time sufficiency, and perceived risk; and (ii) objective response quality, encompassing minimum time to collision, maximum deceleration, and maximum steering wheel angle during takeovers. We also investigate drivers' preferred time budget and takeover buffer across various takeover times. Based on the findings, we propose an adaptive time budget strategy that sets the time budget as the predicted takeover time plus a saturated takeover buffer. The findings provide actionable guidance for designing sufficient time budgets that support safe and comfortable takeovers, thereby informing the development of effective control transition strategies in conditionally automated driving.

6.2. RELATED WORK

Research on the takeover buffer and its relationship with takeover time (ToT) and performance is currently underexplored. Li, Hou, *et al.* (2021) introduced a concept similar to the takeover buffer, termed "time to boundary at takeover timing" (TTBT), and analyzed its relationship with crash occurrence using logistic regression. Their results showed that longer TTBT values were linked to a lower probability of crashes. In their following research, Li, Wang, Wang, Zeng, Li, *et al.* (2021) offered participants four TTBT options (3s, 4s, 5s, and 6s). While all takeovers were successfully completed (meeting the minimum safety requirement), the 4-second option emerged as the most preferred. This aligns with Zhang, Zhang, *et al.* (2025), where driver satisfaction showed an inverted U-shape with interval length. A 7s interval was preferred for sufficient situation awareness, good performance, and high satisfaction, while 9s led to more attention toward the non-driving-related task. These results

indicate a potentially consistent optimal takeover buffer that balances safety and driver preference; however, its stability across different takeover times and the factors underlying this consistency remain to be investigated.

From a finer-grained perspective, the takeover buffer consists of two elements: safety buffer and comfort buffer. The *Safety Buffer* represents the temporal margin from when the driver regains conscious control of the vehicle to the point where evasive actions are no longer required to avoid a potential collision. This concept aligns with *Time to Control (TC)*, defined as the time from receiving a takeover request to the moment when no further deceleration is necessary to avoid a hazard (Papadimitriou *et al.* 2024). The safety buffer can thus be calculated as the difference between TC and the ToT, and has been recognized as a key factor in determining adaptive time budgets for successful takeovers (Marberger *et al.* 2017). Specifically, the allocated time budget should exceed the sum of the predicted ToT and the necessary safety buffer (Tanshi and Söffker 2022), thus providing a sufficient margin for safe maneuver execution. Beyond this minimum safety requirement, adding an extra *Comfort Buffer*, i.e., a psychological margin during which no immediate action is required, can enhance user experience by allowing drivers to feel less stressed. This formulation parallels the two-stage takeover request framework, where the first warning serves as a preparatory signal that does not require immediate action (analogous to the comfort buffer), while the second warning prompts drivers to execute actual maneuvers (corresponding to the sum of ToT and safety buffer) (Zhang, Zeng, *et al.* 2021). In the study of Papadimitriou *et al.* (2024), a comfort buffer of 0.9s was used as the minimum threshold, whereas values below 0.9s were considered insufficient. Note that a longer comfort buffer does not necessarily improve driver experience: both Li, Wang, Wang, Zeng, Li, *et al.* (2021) and Zhang, Zhang, *et al.* (2025) found that driver satisfaction exhibits an inverted U-shaped relationship with buffer times. How to allocate optimal takeover buffer while balancing safety and comfort buffers remains underexplored, highlighting the need for empirical studies to guide adaptive time budget design.

To distinguish key temporal metrics associated with the driver takeover process, Figure 6.1 presents these metrics along a typical takeover timeline, clarifying their definitions, interrelationships, and sequential order. This study focuses on the takeover buffer and its subcomponents, examining how they vary with takeover times and influence various takeover performance metrics. The findings can inform the design of adaptive time budgets that meet diverse driver and scenario demands.

6.3. METHOD

6.3.1. DRIVING SIMULATOR EXPERIMENT

The experiment was conducted in a fixed-base, medium-fidelity driving simulator on the campus of Delft University of Technology. Participants were instructed to detach from non-driving related tasks and take over vehicle control from a simulated Conditionally Automated Driving System (CADS) across nine scenarios (three traffic densities * three non-driving-related tasks). After each takeover event, participants take a break and report their subjective feelings of the last takeover, including

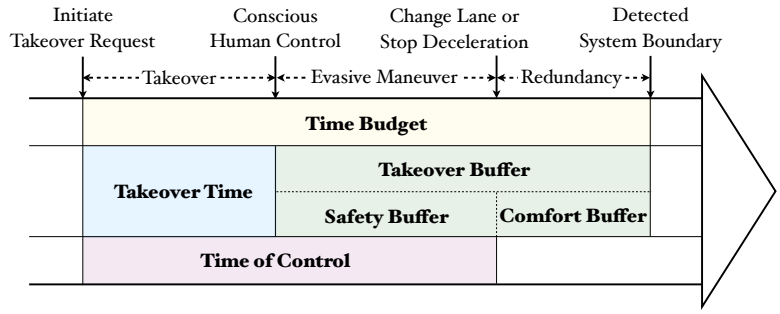


Figure 6.1: Temporal metrics of drivers' takeovers: a timeline-based overview (Segment lengths and boundaries are schematic and may vary with context).

(i) *performance satisfaction*: participants rated their agreement with "I was satisfied with my performance in taking over car control" using a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). (ii) *perceived time sufficiency*: participants responded to: "To complete the required bypass maneuvers safely and comfortably, how much more or less time would you prefer for the takeover?" on a sliding scale from -10 to +10 seconds. Values were normalized to [0, 1], where 0 = Inadequate, 1 = Excessive. (iii) *perceived risk*: participants rated their agreement with "I was worried about being involved in a traffic accident during the takeover process" on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Further details of the experiment instrumentation and procedures can be found in Chapter 3.

6.3.2. DATA ACQUISITION AND ANALYSIS

PARTICIPANT SAMPLE

In total, 57 participants took part in the study. Gender and age distributions are fairly balanced, with 33 males and 24 females, and participants spanning a broad age range (mean = 38.51, SD = 17.23). Their individual traits were assessed using the driver characteristic questionnaire detailed in our previous work (Liang, Calvert, Nordhoff, Li, *et al.* 2025), and summarized through descriptive statistics in Table 6.1. The sample comprises a heterogeneous group in terms of demographic profiles, skill-related attributes, and style-related traits. This diversity enables a comprehensive analysis of the associations between takeover-related intervals and performance outcomes, thereby providing valuable insights for the development of adaptive time budget strategies.

COLLECTED VARIABLES

To explore the optimal takeover buffer for drivers resuming vehicle control from CADS, this study records data from the initiation of takeover requests until drivers successfully change lanes to avoid collisions in distinct scenarios. The collected data can be classified into temporal and performance metrics, as detailed in Table 6.2.

Table 6.1: Descriptive statistics of participants' driver characteristics.

characteristics	mean	SD	min	max
age	37.47	16.58	18	72
gender	0.42	0.50	0	1
accumulated driving years	17.04	16.91	1	55
accumulated driving kilometers	5840.91	6936.30	0	30000
driving frequency	0.30	0.27	0	1
driving skill	1.40	0.66	0	2
driver assistance usage frequency	0.30	0.37	0	1
takeover skill	3.73	0.55	2.56	4.94
risk-taking attitude	2.18	0.49	1	3.2
trust in automation	3.98	0.88	2	5
takeover style - reckless	2.57	0.73	1	4.4
takeover style - anxious	2.55	0.69	1	4.2
takeover style - angry	1.96	0.60	1	3.2
takeover style - patient	3.42	0.49	2.4	4.4

* For gender: Male = 0; Female = 1.
* For driving skill: Inexperienced = 0; Intermediate = 1; Experienced = 2.
* Characteristics on the right side of the table (including takeover skill, risk-taking attitude, trust in automation, takeover style - reckless, takeover style - anxious, takeover style - angry, and takeover style - patient) are assessed on five-point scales ranging from 1 to 5.

DATA ANALYSIS

The statistical analyses are conducted in Python (version 3.11), consisting of four main stages: First, the distributions of (objective and subjective) performance metrics across traffic densities and non-driving-related tasks are visualized using boxplots in Section 6.4.1. This helps to assess the effectiveness of fixed time budgets (7s in this study) across various takeover scenarios. Then, the relationships between takeover buffer levels—including its components, safety buffer and comfort buffer—and various takeover performance metrics are examined in 6.4.2. This analysis aims to determine how buffer allocation influences takeover safety and user comfort. Next, preferred time budgets and preferred takeover buffers are compared across different takeover time levels in Section 6.4.3 to identify the factors driving variations in drivers' temporal preferences. Finally, the findings from the above analyses are integrated into the design of an adaptive time budget framework in Section 6.5.1. Its validity is assessed by comparing the proposed adaptive time budget with the fixed 7s time budget, evaluating which more accurately reflects drivers' preferred temporal allocations. Kruskal–Wallis significance tests followed by Dunn's post-hoc tests are conducted for all four stages, using a significance level of 0.05.

Table 6.2: Overview of collected data.

Category	Metric	Unit	Description
Temporal intervals	Time Budget	s	Time to collision when a Takeover Request (TOR) is issued.
	Takeover Time	s	Time from the TOR to drivers' first conscious operational input.
	Takeover Buffer	s	Remaining time within the time budget after the driver resumes conscious control; calculated as Time Budget - Takeover Time.
	Time to Control	s	Time to complete evasive maneuver, defined as the minimum of the time to lane change and time to stop deceleration (Papadimitriou *et al.* 2024).
	Safety Buffer	s	Time margin for completing necessary intervention (defined as completing deceleration, initiating acceleration, or finishing a lane change in this study), = Time to Control - Takeover Time.
	Comfort Buffer	s	Remaining time within time budget after completing evasive actions for driver experience; = Time Budget - Time to Control.
	Preferred Time Adjustment	s	Participants responded to: "To complete the required bypass maneuvers safely and comfortably, how much more or less time would you prefer for the takeover?" on a sliding scale from -10s to +10s.
	Preferred Time Budget	s	= Time Budget + Preferred Time Adjustment.
	Preferred Takeover Buffer	s	= Preferred Time Budget - Takeover Time
Performance metrics	Performance Satisfaction	–	Participants' agreement with "I was satisfied with my performance in taking over car control" using a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).
	Time Sufficiency	–	Normalize the values of Preferred Time Adjustment to a range of [0, 1], where 0 = Inadequate, 1 = Excessive.
	Perceived Risk	–	Participants' agreement with "I was worried about being involved in a traffic accident during the takeover process" on a five-point scale (1=Strongly Disagree, 5=Strongly Agree).
	Min TTC	s	Minimum time to collision from the TOR to the lane change.
	Max Deceleration	m/s^2	Maximum deceleration between the TOR and the lane change.
	Max Steering Wheel Angle	rad	Maximum steering wheel angle between the TOR and the lane change.

6.4. RESULTS

6.4.1. FIXED TIME BUDGET

To evaluate whether the fixed time budget offers sufficient and consistent support for safe and comfortable takeovers across diverse scenarios, this subsection examines drivers' takeover performance across three traffic densities (0/10/20 vehicle/km) and three n-back tasks ($n = 0, 1, 2$) with a seven-second time budge. Specifically, three objective operational indicators are considered for measuring response quality: minimum Time-To-Collision (TTC), maximum deceleration, and maximum steering wheel angle. Three subjective driver perceptions are also included for capturing user experience: perceived time sufficiency, perceived performance satisfaction, and perceived risk. Distributions of these metrics are illustrated in Figure 6.2. Overall, with a fixed 7-second time budget, traffic density exerts a consistent and strong effect on both subjective experience and objective operations. Higher traffic density is generally associated with (i) worse driver experience, as indicated by reduced sense of time sufficiency ($H = 21.19, p < .001$), lower satisfaction ($H = 40.35, p < .001$), and increased perceived risk ($H = 50.46, p < .001$); and (ii) riskier evasive maneuvers, including shorter minimum TTC ($H = 31.27, p < .001$), greater maximum deceleration ($H = 155.98, p < .001$), and larger maximum steering wheel

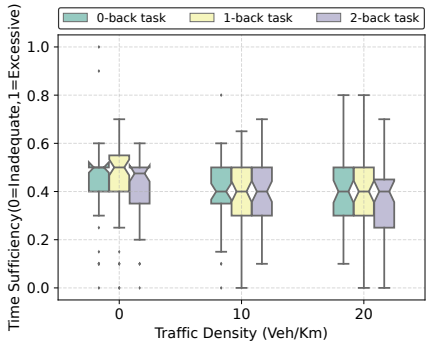
angles ($H = 24.29, p < .001$). In contrast, the n-back task shows more selective effects. It significantly lowers performance satisfaction ($H = 6.59, p = .037$), increases perceived risk ($H = 11.07, p = .004$), and reduces minimum TTC ($H = 18.30, p < .001$). However, it does not significantly alter the perceived time sufficiency ($p = .168$) and the intensity of control inputs, as reflected in maximum deceleration ($p = .147$) and steering angle ($p = .074$). These findings highlight that the effectiveness of a fixed time budget is highly context-dependent, and a uniform 7-second time budget often fails to meet drivers' safety and comfort requirements, especially under complex conditions. They underscore the necessity of adaptive time budgets that adjust to both situational factors and individual needs to ensure safety and user experience.

6.4.2. BUFFER TIME ALLOCATION

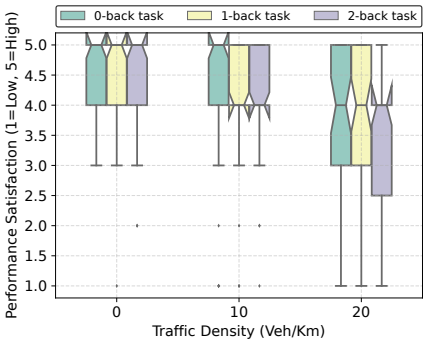
Time budget defines the total time available for drivers to resume conscious manual control once the CADS issues a takeover request. However, completing a takeover within this budget does not necessarily guarantee safety or comfort. A more informative measure is the takeover buffer, which represents the residual time margin remaining after the driver has successfully taken control. The takeover buffer can be decomposed into two complementary components: (i) the safety buffer, which represents the time margin required for driver intervention to ensure collision avoidance, and (ii) the comfort buffer, which provides additional time for drivers to regain control with a positive experience. This section analyzes how variations in takeover buffers, together with their safety and comfort components, relate to both objective performance and subjective evaluations, as illustrated in Figure 6.3. Solid lines indicate metrics where higher values are desirable; dashed lines indicate the opposite.

Generally, the takeover buffer significantly affects all six performance metrics ($p < .001$), as shown in Figure 6.3a. For the subjective measures: (i) performance satisfaction increases sharply from 0 to 1s, stabilizes around 0.75, and reaches a maximum plateau at 5–6s, with larger buffers yielding higher satisfaction than shorter ones ($H = 52.35, p < .001$); (ii) perceived time sufficiency shows a fluctuating upward trend as takeover buffer increases ($H = 26.32, p < .001$), but consistently remains below 0.5, indicating that drivers generally felt the takeover buffer was insufficient and desired more time; (iii) perceived risk decreases gradually with longer takeover buffer ($H = 46.37, p < .001$), reaching near 0 at 5–6s of takeover buffer. For the objective measures: (i) minimum TTC generally increases with longer takeover buffers ($H = 44.61, p < .001$), with no significant differences between the 4–6s conditions ($p > .05$); (ii) maximum deceleration decreases steadily as the takeover buffer increases, showing a consistent downward trend ($H = 82.65, p < .001$); (iii) maximum steering wheel angle is significantly higher for short takeover buffers than for longer ones ($H = 60.42, p < .001$), with no significant differences observed between the 4–6 s conditions ($p > .05$). Overall, longer takeover buffers are associated with better performance, with 5s and 6s buffers producing nearly identical effects.

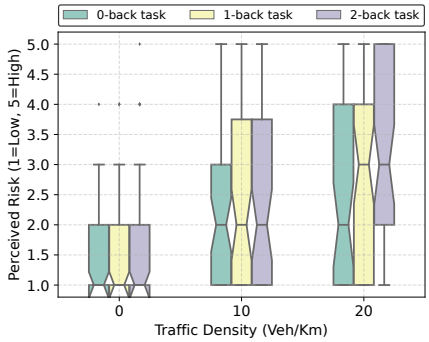
Within the takeover buffer, the safety buffer allows drivers to complete necessary evasive operations after regaining conscious control of the vehicle. Determining an appropriate duration for the safety buffer requires understanding how much time



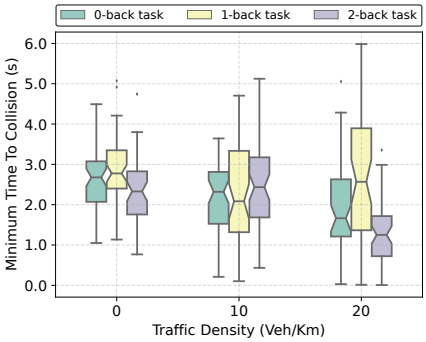
(a) Perceived Time Sufficiency



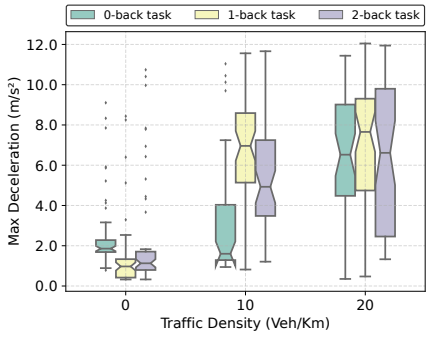
(b) Perceived Performance Satisfaction



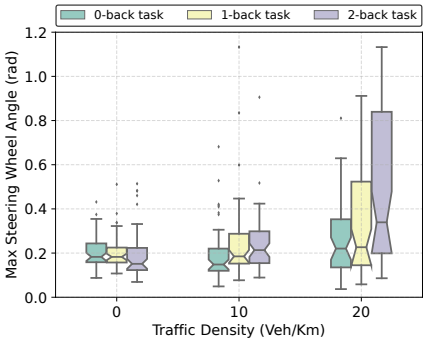
(c) Perceived Risk



(d) Minimum Time To Collision



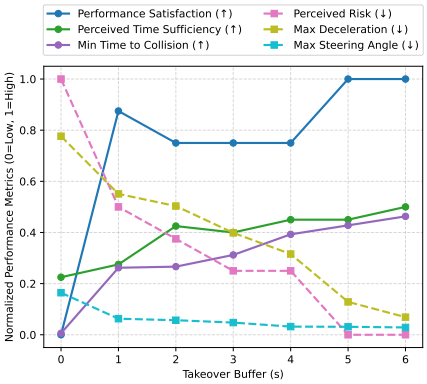
(e) Max Deceleration



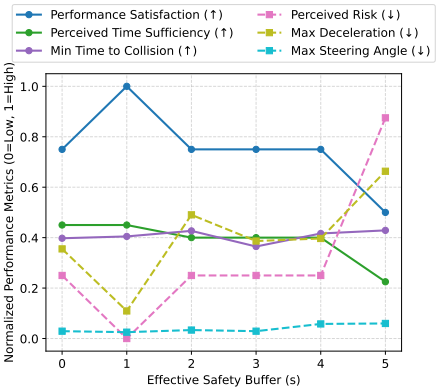
(f) Max Steering Wheel Angle

Figure 6.2: Takeover performance metrics across traffic densities and n-back tasks.

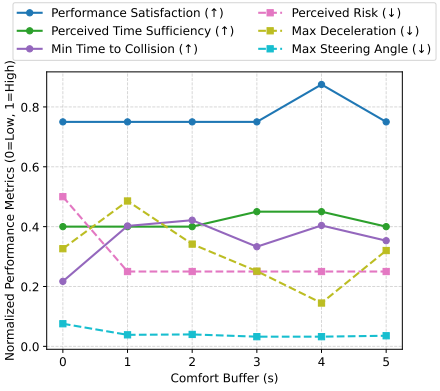
drivers actually need and how this duration affects various takeover performance metrics. In this study, all drivers successfully took over vehicle control without any accidents, satisfying the minimum safety requirements. The interval from when drivers consciously resume control of the vehicle until no further evasive



(a) Takeover buffer



(b) Effective safety buffer



(c) Comfort buffer

Figure 6.3: Effects of different buffer types on performance metrics (↑: higher is better; ↓: lower is better).

maneuvers are performed is defined as the *Effective Safety Buffer*. Intuitively, more challenging takeover scenarios would require drivers to take longer for evasive maneuvers, resulting in larger effective safety buffers. However, Kruskal–Wallis tests indicate that neither traffic density nor engagement in non-driving-related tasks significantly affect the effective safety buffer required by drivers ($p > .05$). Similarly, no significant association is observed with drivers' ToT ($p = .07$). This underlines the need to consider the safety buffer as a robust design parameter, independent of situational variations. The effects of effective safety buffers on six performance metrics are presented in Figure 6.3b. Generally, a longer required safety time for evasive maneuvers is associated with (i) worse subjective experience, reflected by lower performance satisfaction ($H = 24.74, p < .001$), less perceived time sufficiency ($H = 14.49, p = .025$), and higher perceived risk ($H = 32.03, p < .001$); and (ii) more abrupt takeover maneuvers, as indicated by larger maximum deceleration

($H = 18.55, p = .005$)), lager maximum deceleration ($H = 54.04, p < .001$), and greater maximum steering angle ($H = 39.49, p < .001$). Notably, when the effective safety buffer that drivers require is shorter than 1s, drivers' performance is suboptimal, likely due to rushed control or overreactions. This suggests that, in our experimental setting, a safety buffer longer than 1s is necessary to ensure safe and stable takeovers.

Meanwhile, the allocated time budget should not only be sufficient to avoid accidents but also to enable a comfortable takeover experience. Therefore, we introduce the concept of the comfort buffer, which represents an additional, emotionally oriented margin of time that does not require takeover-related cognitive or operational activities. The effects of the comfort buffer on six performance metrics are shown in Figure 6.3c. A significant effect is found for maximum deceleration ($H = 22.893, p < 0.001$,), with a 4-second comfort buffer associated with less abrupt braking during takeovers. No significant effects are observed for the other five performance metrics ($p > 0.05$).

6.4.3. DRIVER-PREFERRED TIME ALLOCATION

In addition to examining the effects of the provided time budget on takeover performance, we also consider drivers' preferences for adjusting time budgets across different scenarios, which is essential for user acceptance and personalized automated driving. Figure 6.4 illustrates drivers' preferred time budgets across different ToT intervals.

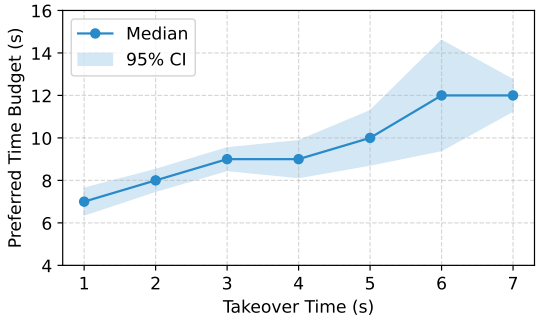


Figure 6.4: Drivers' preferred time budget by takeover time.

Overall, drivers generally prefer time budgets longer than the fixed 7s used in this study. Considering that all takeovers were completed safely, such preferences for longer time budgets therefore represent a desire for reduced stress and smoother transitions, rather than an indication of safety insufficiency. Meanwhile, drivers tend to request longer time budgets when more time is needed to return to the conscious driving loop ($H = 25.57, p < .001$). The relationship between median takeover time ($\overline{ToT}$) and drivers' preferred time budgets (pTB) is well captured by a linear regression model (R^2=0.95, RMSE=0.40):

$$pTB = 0.86 * \overline{ToT} + 6.14 \tag{6.1}$$

This study further examines drivers' preferred takeover buffer across different ToT groups. Although the Kruskal–Wallis test indicates an overall significant difference across ToT groups ($H = 23.35, p < .05$), Dunn's post-hoc comparisons reveals no significant differences within 1-2s groups (median: 6.35s, $p > 0.05$), nor among the 3–7s groups (median: 5.30s, $p > 0.05$). These results suggest that drivers' preferred takeover buffer is largely stable across a wide range of ToTs.

6.5. DISCUSSION

6.5.1. ADAPTIVE TIME BUDGET

This study demonstrates that the sufficiency of fixed time budgets is strongly context-dependent. Results show that a 7-second time budgets can be effective for simple scenarios or skilled drivers with takeover buffer exceeding 5s, but may impair user comfort and operation quality in complex scenarios or for less capable drivers when the takeover buffer falls below 5s. Similar findings have been reported in prior studies. For example, Feldhütter, Ruhl, *et al.* (2019) reported that under a fixed 5s time budget, fatigued drivers exhibited lower takeover quality—characterized by higher decelerations, inappropriate trajectories and initial responses to the TOR, and increased crash risk—compared to alert drivers. Jin *et al.* (2021) found that in both 7s and 10s time budget conditions, higher traffic density led to more abrupt acceleration and deceleration inputs and less stable vehicle trajectories. These findings highlight the necessity of adaptive time budgets that dynamically adjust to both scenario and driver demands, as also suggested by (Li, Wang, Wang, Zeng, Li, *et al.* 2021; Sekadakis *et al.* 2025; Tanshi and Söffker 2022).

To address this need, we propose an adaptive time budget framework composed of two components: the predicted takeover time and the driver's preferred takeover buffer. Compared with the approach proposed by Tanshi and Söffker (2022), which defines the time budget as the sum of takeover time and maneuver response time, our framework incorporates an additional comfort buffer to further enhance user experience. Within this framework, the predicted takeover time reflects how long an individual driver is expected to regain control under a given situation, and can be estimated using prediction models from prior work (e.g., Ayoub, Du, *et al.* (2022) and Liang, Calvert, Nordhoff, Li, *et al.* (2025)). The preferred takeover buffer represents an additional margin of time that should not only exceed a minimum safety threshold to ensure collision avoidance, but also avoid unnecessary extension, as excessively long buffers can reduce attentiveness to takeover requests and impair takeover efficiency (Tanshi and Söffker 2022). By combining these two components, the framework allows the system to dynamically tailor the time budget to drivers' demands under specific situations. These results are relevant to safety and adaptive variation of the time budget for successful takeover.

Regarding the takeover buffer, our results suggest that a minimum threshold of at least one second is necessary to ensure stable and safe takeovers. This is because when the effective safety buffer dropped below one second, drivers often displayed rushed control and overreactions, which were reflected in reduced maneuver smoothness and lower subjective ratings. This lower bound aligns well with Eriksson

and Stanton (2017b), who recommended a following gap of one car length per 16 km/h, translating to approximately 0.9 seconds at 100 km/h, and with Papadimitriou *et al.* (2024), who identified a similar 0.9-second critical threshold. Importantly, however, our analysis also suggests that "longer is not always better." Performance improvements plateau when the takeover buffer exceeds five seconds, with both 5-second and 6-second conditions yielding nearly identical optimal outcomes. This points to a saturation effect, in which additional buffer time provides limited added value. Such diminishing returns have also been observed in (Wan and Wu 2018). Moreover, overly long buffers may even impair driver performance by lowering the perceived urgency and reducing takeover efficiency. This was also pointed out by Li, Huang, *et al.* (2024) as they found that appropriate time pressure can reduce takeover time and improve takeover performance.

An interesting finding of this study is that drivers' preferred takeover buffers remain relatively stable across different takeover time levels. Intuitively, more complex scenarios should increase the demand for larger buffers, yet our results show stable preferences: if drivers resume vehicle control within 3s, there is a large chance that they responded hastily or overreacted, as indicated by drivers' preference for slightly longer buffers (around 6.35s). Beyond this threshold, drivers appeared sufficiently re-engaged with an additional buffer of about 5.30s, showing little inclination for longer buffers to perform evasive maneuvers comfortably and safely. This stability may stem from the uniform evasive task across conditions (a single lane change), making buffer preferences more sensitive to operational complexity than to takeover duration. Another explanation is that buffer preferences are more strongly influenced by stable individual characteristics rather than situational demands. Our prior work (Liang, Kästle, *et al.* 2025), for instance, revealed systematic gender differences in perceived time sufficiency, with females reporting greater sufficiency than males under identical conditions. Similar individual-level factors may shape stable buffer preferences. These considerations underscore that, even though drivers' preferred takeover buffer appears stable, the findings do not diminish the need for adaptive time budgets, since drivers may face evasive maneuvers of varying complexity and individual differences are likely to shape buffer requirements. Even if the preferred buffer itself is stable, combining variable takeover time predictions with this constant buffer can still yield an effective adaptive budget tailored to drivers and contexts.

Accordingly, we conduct a preliminary validation of our proposed adaptive strategy by comparing a fixed 7-second time budget with a piecewise takeover buffer function (6.35s when takeover time $\leq$ 3s, 5.30s otherwise). Results indicate that the adaptive strategy aligns significantly better with drivers' preferred time budgets than the fixed 7-second allocation, with a 13% reduction in MAE and a 16% reduction in RMSE ($p < 0.01$). This suggests that even simple adaptive mechanisms can outperform fixed time budgets. In different takeover scenarios, the saturation value of the optimal buffer may vary depending on the specific demands of the maneuver and the driver. Future research should extend this validation by explicitly modeling operational complexity and driver characteristics, thus refining and optimizing adaptive time budget strategies across a wider range of contexts.

6.5.2. LIMITATION

This study has the following limitations. First, the experiment was conducted in a driving simulator, which, while providing a controlled and repeatable environment, may not fully capture the complexity and unpredictability of naturalistic driving. Real-world validation with a wider variety of evasive maneuvers and more diverse drivers is therefore essential to confirm the generalizability of the findings. Second, we argue that the proposed adaptive time budget framework primarily targets non-time-critical scenarios. Because in time-critical situations, such as sudden cut-ins, the CADS should trigger takeover requests or execute evasive actions immediately, leaving little room for designing a sufficient time budget. This study used a fixed 7-second time budget, which is generally considered as non-time-critical scenarios. However, drivers frequently preferred additional time to regain control safely and comfortably, indicating the need to validate the framework in scenarios with time budgets exceeding 7s. Third, learning effects may have influenced driver behaviors across repeated trials, potentially affecting the time they took to resume conscious vehicle control and their preferences for takeover buffers. To mitigate this, participants completed a 10-minute practice drive, scenarios were counterbalanced via a Latin Square design, and takeover requests were randomized between 30–60s in each session. Nonetheless, residual learning or anticipation effects may persist and should be considered in future studies. Fourth, although we conceptually validated our adaptive framework, participants did not directly experience dynamically adjusted time budgets. Future research should implement adaptive systems that adjust time budgets based on predicted takeover time and driver-preferred buffers. This would enable assessment of how adaptive time budgets affect takeover safety and subjective experience in realistic and interactive scenarios.

6.6. CONCLUSION

This study proposes an adaptive time budget framework as an important first step toward providing drivers with sufficient time to resume vehicle control across diverse scenarios. Specifically, we examine the influence of the takeover buffer on multiple performance metrics and incorporate drivers' time budget preferences into the framework to support both user comfort and driving safety. Results indicate that takeover buffers of five to six seconds consistently yield high and stable levels of performance, suggesting that this range may represent an optimal window for balancing safety and comfort. This also indicates a potential saturation point, where further extending the buffer provides limited additional benefit and, in some cases, may even diminish subjective evaluations such as perceived satisfaction. These findings highlight the importance of considering not only sufficient buffer duration for safety but also the diminishing returns and possible drawbacks of excessively long buffers in time budget design. Within our experimental settings, drivers prefer relatively stable takeover buffers in addition to their required takeover times, regardless of varying traffic densities and n-back tasks. Therefore, the adaptive time budget framework integrates predicted takeover time (pToT, estimated using data-driven models) with a preferred takeover buffer, represented as a piecewise rule:

when the pToT is shorter than three seconds, a buffer of 6.35s is added; when the pToT exceeds three seconds, a buffer of 5.30s is applied. Primary validation shows that the time budgets generated by this framework are better aligned with driver preferences compared with the fixed time budget while ensuring minimum safety requirements.

In summary, this study has three main contributions:

- provides an empirical analysis of the relationship between takeover buffer, takeover time, and multiple dimensions of takeover performance (integrating both objective safety metrics and subjective driver evaluations);
- reveals a consistent preference for takeover buffer across different takeover time conditions, underscoring a stable driver requirement for supplementary time to facilitate safe and comfortable control transitions; and
- proposes an adaptive time budget allocation strategy—predicted takeover time plus a saturated takeover buffer—to accommodate situational demands in conditionally automated driving.

Our findings offer a foundation for designing flexible, human-centered takeover strategies in conditionally automated driving, promoting both safe and comfortable driver–automation interactions. Future research is recommended to (i) investigate how operation complexity and driver characteristics influence preferred takeover buffers, and (ii) experimentally test the adaptive time budget framework in diverse and naturalistic driving environments to confirm its effectiveness and generalizability.

7

CONCLUSION

This final chapter revisits the central research questions, summarizes the key findings of the thesis, and reflects on their broader implications. It consolidates contributions from conceptual explorations, experimental studies, and data-driven modeling efforts, acknowledges limitations, and outlines future research directions to support the development of safer, more human-centered automated driving systems.

7.1. FINDINGS

To address the overarching question—**How to design an adaptive time budget strategy to accommodate drivers' various takeover times, ensuring safe and comfortable vehicle control transitions?**—this thesis explores five sub-questions:

1 **What understanding of takeover time, time budget, and takeover performance can be drawn from existing literature to guide the design of sufficient time budgets (Chapter 2)?**

To answer this question, a systematic review is conducted to investigate the sufficiency of the time budget by examining its determinant (takeover time) and the corresponding result (takeover performance) together. The results show that (i) drivers' takeover time varies significantly due to its complex causal relationships with numerous determinants, making it challenging to understand and model; (ii) fixed time budget is sub-optimal in meeting various takeover demands compared with the adaptive time budget; and (iii) the imbalance between objective and subjective measures of takeover performance may skew studies that treat performance as an optimization goal. Based on these findings, this review proposes frameworks of takeover time determinants and takeover performance measures, as well as introduces a flexible approach to estimating sufficient time budgets by combining predicted takeover time with an appropriate buffer to achieve desired performance outcomes. While this review does not offer a precise formula for calculating sufficient time budgets, the proposed time budget framework (i.e., integrating predicted takeover time with an appropriate buffer) provides a structured method

adaptable to a variety of contexts, offering a foundation for future research on adaptive time budgets for safe and comfortable control transitions.

2 **How do different drivers respond to takeover requests under varying conditions (Chapter 3)?**

To address this research question, Chapter 3 presents a controlled driving simulator experiment. Fifty-seven drivers (33 males, 24 females; mean age: 38.51 ± 17.23) experienced nine distinct takeover scenarios designed to reflect variations in traffic density and engagement in non-driving-related tasks. The experiment captures multimodal data, including driver characteristics, vehicle control operations, self-reported subjective assessments, and physiological responses such as heart rate and eye movements. The results reveal substantial variations in takeover responses, influenced by driver cognition and contextual complexity. This dataset enables in-depth analysis of factors influencing both takeover performance and driver experience. It serves as the empirical foundation for the subsequent analyses in Chapters 4 through 6, which focus on predicting takeover time, evaluating takeover performance, and developing adaptive strategies for determining sufficient time budgets. Researchers and practitioners in human-machine interactions, human factors, and user interface designs can use this dataset to explore effective interaction strategies, personalized in-vehicle systems, and human-centered feature designs.

3 **How can takeover time prediction models be developed to achieve higher interpretability and reliability (Chapter 4)?**

Chapter 4 presents a takeover time (ToT) prediction model with improved interpretability and reliability through optimized predictor selection. The results show that (i) incorporating 13 additional driver characteristics does not significantly improve prediction accuracy when perceived spare capacity (pSC, a cognition-based measure defined as the difference between perceived task capability and task demand) is already considered; and (ii) individual characteristics influence how drivers cognitively process takeover scenarios, and their predictive contribution likely overlaps with pSC. Besides, the linear ToT regression model demonstrates that pSC is a strong standalone predictor of actual ToT. These findings suggest that monitoring cognitive states may be more effective for ToT prediction than extensive profiling of driver characteristics. Consequently, a more targeted feature selection strategy—focusing more on dynamic cognitive indicators—has the potential to enhance the interpretability and reliability of ToT prediction models across diverse drivers and scenarios.

4 **What role does driver cognition play in shaping multidimensional takeover performance (Chapter 5)?**

To address this research question, Chapter 5 systematically examines the influence of Situational Awareness (SA) and Spare Capacity (SC) on various takeover performance aspects, alongside baseline Driver Characteristics (DC). Using XGBoost models and SHAP value analysis across ten performance metrics, the findings reveal that SA and SC play distinct yet complementary

roles in takeover performance. Specifically, SA is more strongly associated with faster responses, particularly reflexive actions, whereas SC has a greater impact on takeover quality, with lower SC levels linked to reduced comfort and more abrupt control inputs. These results, validated through cross-model comparisons (Random Forest and LightGBM) and aligned with existing literature, deepen our understanding of the cognitive underpinnings of driver behavior during control transitions. By disentangling the contributions of SA and SC, this study refines the theoretical modeling of takeover performance, informing the design of human-centered automated driving systems.

5 **How can the relationship among takeover time, time budget, and takeover performance be quantitatively characterized to inform an adaptive time budget strategy (Chapter 6)?**

To address this research question, Chapter 6 quantitatively examines the relationship among takeover time, driver preferred time budget, and takeover performance. The results reveal a critical takeover time threshold around 2 seconds: when drivers resume control in less than 2 seconds, they tend to respond hastily and overreact, leading to poorer performance and a preference for longer buffer time (around 6.35 seconds). However, once takeover time exceeds 2 seconds, the preferred buffer stabilizes around 5.30 seconds regardless of further increases in takeover time, indicating that drivers feel sufficiently re-engaged in the driving task. This suggests a two-stage buffer approach: for instance, if predicted takeover time is $\leq$ 2 seconds, allocate a 6.35-second buffer; if $>$ 2 seconds, a 5.30-second buffer may suffice. While this framework provides a promising basis for adaptive time budget design, the exact buffer values should be further validated in diverse real-world driving contexts to ensure robustness and generalizability.

7.2. OVERALL CONCLUSIONS

The findings of this PhD thesis demonstrate that takeover time is highly variable and influenced by complex cognitive and contextual factors, making fixed time budgets suboptimal. Instead, adaptive strategies that consider dynamic driver states, such as situational awareness and spare capacity, can better accommodate individual differences. The proposed models highlight the strong predictive power of cognition-based measures over static driver characteristics, and reveal how SA and SC shape distinct dimensions of takeover performance. Importantly, the relationship between takeover time and driver-preferred buffer reveals a nonlinear pattern, supporting a two-stage buffer approach for adaptive time budget design. Collectively, these contributions lay a foundation for designing adaptive, human-centered automated driving systems that personalize takeover alerts based on drivers' readiness and task demands. Future work should focus on validating these frameworks in real-world settings and extending them to more diverse populations and driving contexts, ultimately supporting the safe deployment of conditionally automated vehicles in everyday traffic.

This thesis has four main limitations. First, although the sample size of 57 participants is comparable to similar studies, a larger and more diverse sample—particularly including more drivers who self-identify as inexperienced—would improve representativeness and allow for broader generalization. Second, data were collected in a medium-fidelity driving simulator using structured, non-time-critical takeover scenarios. While simulators enable controlled data collection, user behaviour and perception may differ under real-world or high-urgency conditions, warranting caution in interpretation. Third, repeated exposure to similar takeover events within the experiment may introduce learning effects or adaptation, potentially influencing behavioural and subjective measures. Although the scenario order was counterbalanced using Latin Square design and takeover requests were randomized to mitigate predictability, some residual order effects may remain. Lastly, self-reported measures of cognitive state and workload were collected using adapted versions of validated instruments. While these tools offer valuable subjective insights, users should be aware that the adapted forms may require further validation. We recommend considering these limitations when re-using our dataset or interpreting our modeling, analysis, or experimental results.

7.3. RECOMMENDATIONS FOR FUTURE RESEARCH

Based on the findings of Chapter 2-6, we outline six key directions for future research to deepen understanding of sufficient time budget determination in conditionally automated driving, accounting for diverse driver profiles and situational contexts.

1 Develop real-time cognitive state monitoring tools and integrate them into prediction models.

   Future research should focus on developing and validating non-intrusive, privacy-preserving monitoring systems capable of continuously and reliably estimating drivers' cognitive states—such as Situational Awareness and Spare Capacity. These estimations should be integrated into predictive models (e.g., for takeover time or performance) to enhance their accuracy, personalization, and adaptability in dynamic driving contexts.

2 Investigate the evolving sequence of driver states throughout takeovers.

   Future research should investigate how driver state evolves over time to capture the continuous, rather than discrete, nature of driver engagement in conditionally automated driving. A promising direction is to investigate how real-time changes in driver state can inform adaptive interaction strategies. This would allow the system to dynamically adjust alert timing, modality, or support based on moment-to-moment readiness, moving beyond static thresholds or single-point assessments.

3 Extend to diverse driver populations and edge cases.

   Current models should be tested across a wider range of driver populations and takeover scenarios to ensure adaptive systems are inclusive and generalizable.

This includes incorporating older drivers, novice drivers, and individuals with cognitive impairments. Additionally, edge cases—such as extreme fatigue, or rare system failures—should be systematically examined to evaluate the robustness of adaptive time budget strategies under challenging conditions.

4 Validate adaptive time budget frameworks in real-world settings.

Future studies should evaluate the proposed predictive models and two-stage time budget strategy in naturalistic driving environments or high-fidelity simulator scenarios. This will help assess its robustness across real-world driving contexts, identify practical implementation challenges, and guide refinements to ensure that adaptive time budget strategies are effective, reliable, and deployable.

5 Explore takeover performance at mesoscopic or macroscopic levels.

While takeover performance is typically evaluated at the microscopic level—focusing on the ego vehicle and individual driver experience—its impact on broader traffic flow remains underexplored. Understanding how takeover safety and quality affect mesoscopic (group) and macroscopic (network) traffic dynamics is essential for optimizing overall traffic performance and informing policy in conditionally automated driving. This involves modeling how individual driver takeovers affect surrounding road users and overall traffic flow. Coordinated adaptive time budgets across vehicles could help mitigate ripple effects from takeovers, improving traffic safety and efficiency.

6 Ethical and trustworthy automation co-design

As adaptive time budget strategies become more integrated into driving systems, it is crucial to examine their ethical implications—particularly how they shape driver trust, agency, and accountability. Embedding these considerations early in the design process requires collaboration across disciplines, including ethics, law, and interaction design. Co-developing such systems with philosophers, legal scholars, and designers can help ensure that automated driving technologies support meaningful human control and reflect broader societal values.

Together, these six directions provide a foundation for future research aimed at advancing adaptive time budget strategies in conditionally automated driving. They highlight the need to better understand dynamic driver states, expand model inclusivity, validate approaches in real-world contexts, and account for system-wide and ethical implications. Future research that addresses these areas will be instrumental in developing evidence-based, context-aware strategies that promote both safety and comfort in human-automation collaboration.

7.4. RECOMMENDATIONS FOR PRACTICAL IMPLEMENTATION

Build on the empirical findings and conceptual insights from this thesis, the practical recommendations focus on enhancing the design and interaction strategies

of automated vehicles (AVs) to better support users in real-world settings. These recommendations can be translated into actionable guidelines to support the development of more adaptive and user-centered AV systems.

1 Develop Personalized and Adaptive Takeover Systems

Automated vehicles are recommended to integrate personalization modules that adapt interaction strategies based on drivers' cognition, driving history, and situational context. This enables tailored support rather than generic, one-size-fits-all alerts. Incorporating real-time driver state estimation into Human–Machine Interface (HMI) design allows for dynamically triggered takeover requests with buffer times adjusted to prioritize speed or control quality as appropriate. For example, based on the dominant role of spare capacity in capturing drivers' takeover time identified in this thesis, machine learning models can be developed to estimate takeover time using sensor-feasible proxies (such as gaze behaviour and engagement in non-driving-related tasks) captured through driver monitoring systems. The predicted takeover time can then be combined with a calibrated takeover buffer to determine an adaptive time budget, which is used to trigger takeover requests at an appropriate moment and support safe and efficient control transitions. A driver who is predominantly looking at a mobile phone and exhibits low visual attention to the driving scene would therefore be assigned an earlier takeover request than a driver who is already attentive to the road. Such adaptive approaches have the potential to create a more responsive and personalized driving experience.

2 Implement Adaptive Feedback Loops for Takeover Optimization

Automated driving systems are encouraged to incorporate performance-based feedback loops that continuously evaluate takeover performance — considering factors such as driver state and comfort rather than just completion speed. For example, systems can monitor drivers' behaviors and cognitive state after takeovers to assess the interaction effectiveness, and use this information to refine and update its adaptive interaction strategies over time. This iterative approach enables the system to learn from driver responses and personalize support accordingly.

3 Design Cognition-Aware Interfaces to Support Adaptive Takeovers

HMI designs are encouraged to support and enhance drivers' perception, understanding, and projection of the surrounding situation throughout the driving process. This includes offering anticipatory cues, delivering effective multimodal takeover requests, and pacing information appropriately during transitions. Instead of relying solely on static demographic or experience-based profiles, adaptive interaction systems are recommended to prioritize real-time cognitive indicators to improve human–vehicle cooperation.

4 Cognitive-Aware Driver Training Tools

Intelligent driver training simulators and in-vehicle prompts are recommended to go beyond technical instruction. These tools should help users build cognitive self-awareness by understanding how their mental status (such as situational awareness and spare capacity) influence takeover performance. Such training can promote safer, more confident transitions and enhance drivers' trust and acceptance of conditionally automated driving.

5 Support Standardization of Takeover Design and Evaluation

Personalized automated driving offers improved user comfort, but it must be built upon a foundation of standardized frameworks to ensure consistency, reliability, and interoperability across systems. Researchers and developers should collaborate with industry partners and regulatory bodies to support the standardization of takeover request design and performance evaluation. This includes embedding adaptive human-vehicle interaction frameworks that account for drivers' cognitive states into future HMI standards, and encouraging the industry-wide adoption of multidimensional metrics—both objective and subjective—to assess takeover performance consistently across design and regulatory contexts.

Taken together, these practical recommendations offer a pathway toward more adaptive, personalized, and cognitively informed automated vehicle systems. Continued collaboration between researchers, developers, and regulatory bodies will be key to turning these recommendations into impactful, real-world practices that support safer and more effective human–automation cooperation.

APPENDICES

1. DRIVER CHARACTERISTIC QUESTIONNAIRE

This study employs the following questionnaire to assess driver characteristics, drawing from established instruments. The questionnaire collects drivers' background information (Table 1), risk-taking attitudes (Table 2), trust in the conditionally automated driving (Table 3), takeover skills (Table 4), and takeover styles (Table 5).

BACKGROUND INFORMATION

This study employs seven questions to capture drivers' backgrounds as outlined in Table 1. The first two questions collect drivers' demographic information, including *age* and *gender*. The rest five questions measure general driving-related characteristics, namely accumulated driving years (*accu_years*), accumulated driving distance (*accu_dis*), driving frequency (*driving_fre*), driving skill (*driving_skill*), and driver assistance usage frequency (*assist_fre*).

Table 1: Background questions, based on Nordhoff *et al.* (2023) and Lu, Coster, and De Winter (2017).

Latent Variables	Observed Variables
age	What is your age?
gender	What is your gender? [Male; Female; Others]
accu_years	How many years of driving experience do you have?
accu_dis	How many kilometres (approximately) have you driven in the past 12 months?
driving_fre	How many days (on average) have you driven per week in the past 12 months?
driving_skill	How is your general driving skill? Please select the option that best matches your situation. [Inexperienced; Intermediate; Experienced]
assist_fre	How often (out of 10 times) do you use driver assistance functions while driving in the past 12 months?

1.1. RISK-TAKING ATTITUDE

A driver' high risk-taking attitude has previously been observed to strongly correlate with risky driving behaviours (Iversen 2004). Such risk-prone tendencies may become evident in takeover situations, potentially leading to risky takeover behaviours and shorter ToT than those necessary for safe ToC. This study measures drivers' risk-taking attitudes in driving situations using the scale in Table 2. This scale is derived from Ma, Yan, *et al.* (2010), Taubman-Ben-Ari, Mikulincer, and Gillath (2004), and Lajunen and Summala (1995). Participants were instructed to indicate their

agreement with the following statements on a five-point scale (1 = Strongly Disagree, 5 = Strongly Agree). The general risk-taking attitude (RTA) is calculated as:

$$RTA = \frac{\sum_{i=1}^{5}(6 - RTA_i) + \sum_{i=6}^{10} RTA_i}{N} \tag{1}$$

where RTA_1 to RTA_5 represent answers that are negatively related to drivers' RTA, RTA_6 to RTA_{10} represent represent answers that are positively related to drivers' RTA, and N represents the total number of the questions.

Table 2: Scale measuring drivers' risk-taking attitude (RTA), based on Ma, Yan, *et al.* (2010), Taubman-Ben-Ari, Mikulincer, and Gillath (2004), and Lajunen and Summala (1995).

Abbr.	Observed Variables
RTA_1	I follow the traffic rules most of the time [−].
RTA_2	I drive cautiously most of the time [−] .
RTA_3	I am not willing to compete with other drivers in traffic [−].
RTA_4	I try to keep sufficient distances to the cars in front most of the time [−].
RTA_5	I am willing to give up my right of way to other drivers to ensure safety [−].
RTA_6	I enjoy the feeling of pushing a car to its maximum capability limits.
RTA_7	It makes sense to exceed speed limits to get ahead of drivers who drive erratically, slowly, or extremely cautiously.
RTA_8	Engaging in risky driving behaviours does not necessarily mean someone is a bad driver.
RTA_9	It's acceptable to break some traffic rules if they are restrictive.
RTA_{10}	It's acceptable to drive at the moment when traffic lights change from yellow to red.

[−] indicates reversed questions.

1.2. TRUST IN CONDITIONALLY AUTOMATED DRIVING

Drivers' trust in CADS influences their readiness to resume vehicle control when required (Ayoub, Avetisyan, *et al.* 2021), which can, in turn, affect their ToT. To evaluate trust in the context of takeover situations, we selected and adapted three items (Cronbach's alpha = 0.75) from the broader trust scale developed by Nordhoff *et al.* (2021), which was originally designed to capture drivers' trust in partially automated vehicles. The employed three items specifically assessed trust in the system's ability to: (i) maintain safe following distances, (ii) detect hazards it cannot manage, and (iii) issue timely takeover alerts—core functions critical to safe control transitions. Items from the original scale that were unrelated to our setup, such as manual activation, mode awareness, or general engagement, were excluded, as all takeovers were system-initiated, mode status was clearly displayed, and participants were engaged in cognitively demanding n-back tasks. This focused selection helped reduce participant burden while maintaining contextual relevance. Table 3 lists the measurements of drivers' trust in three CADS functions. Participants were instructed to indicate their agreement with the following statements on a five-point scale (1 = Strongly Disagree, 5 = Strongly Agree). Drivers' general trust in CADS ($trust$) is computed as the average of T_1 , T_2, and T_3.

Table 3: Scale measuring drivers' trust in conditionally automated driving, based on Nordhoff *et al.* (2021).

Abbr.	Observed Variables
T_1	I trust the automated car to maintain sufficient distances from the cars around me.
T_2	I trust the automated car to effectively detect the collisions ahead that it can not handle.
T_3	I trust the automated car to alert me to take over car control in time.

1.3. TAKEOVER SKILL

Drivers' takeover skill in various aspects reflects their abilities to assume vehicle control effectively, which can be improved through practice and training. This study develops an inventory to assess drivers' takeover skill ($takeover\_skill$) based on the Driver Skill Inventory (DSI) (Lajunen and Summala 1995). Aligned with the DSI, this takeover skill inventory assesses drivers' perceptual-motor skills (*PMS*) and safety skills (*SS*) (Martinussen, Møller, and Prato 2014), with a specific focus on takeover contexts. Details of the takeover skill inventory are presented in Table 4. Participants were instructed to indicate their agreement with the statements on a five-point scale (1 = Strongly Disagree, 5 = Strongly Agree). Drivers' $takeover\_skill$ is computed as the average of all variables, including PMS_1 to PMS_8 and SS_1 to SS_8.

Table 4: Takeover skill inventory, modified from Driver Skill Inventory (Lajunen and Summala 1995).

Skills	Abbr.	Observed Variables
Perceptual-Motor Skills (*PMS*)	PMS_1	Taking over car control from automation fluently was easy for me.
	PMS_2	Adjusting driving speed was easy for me.
	PMS_3	Controlling the car was easy for me.
	PMS_4	Bypassing the detected collisions ahead was easy for me.
	PMS_5	I realized that I needed to take over car control from automation before the takeover requests.
	PMS_6	I reacted to takeover requests fast.
	PMS_7	I knew the right actions to take in response to the takeover requests.
	PMS_8	I made firm decisions to take over car control from automation.
Safety Skills (*SS*)	SS_1	I followed the traffic rules while taking over car control from automation.
	SS_2	I was cautious while taking over car control from automation.
	SS_3	I paid attention to the cars around me in automated mode.
	SS_4	I paid attention to the cars around me while taking over car control.
	SS_5	Keeping sufficient distances from the cars ahead was easy for me.
	SS_6	Merging into the adjacent lane was easy for me.
	SS_7	Braking effectively (i.e., not too hard nor too soft) was easy for me.
	SS_8	I did not cause risks to myself and the cars around me.

1.4. TAKEOVER STYLE

To evaluate drivers' takeover styles, this study adapts the Multidimensional Driving Style Inventory (MDSI) (Taubman-Ben-Ari, Mikulincer, and Gillath 2004) for takeover

contexts. A takeover style inventory is formulated based on the four-factor structure of the MDSI, categorizing drivers' characteristic takeover behaviours into: (i) reckless and careless (*takeover_style_reckless*); (ii) anxious (*takeover_style_anxious*); (iii) angry and hostile (*takeover_style_angry*); and (iv) patient and careful (*takeover_style_patient*). The specifics of the takeover style inventory are presented in Table 5. Participants were instructed to indicate their agreement with the statements on a five-point scale (1 = Strongly Disagree, 5 = Strongly Agree). For *takeover_style_reckless*, *takeover_style_anxious*, and *takeover_style_angry*, each is computed as the average of five observed variables in the same subcategory. For *takeover_style_patient*, it is calculated as the average of $\sum_{i=1}^{4} PC_i + (6 - PC_5)$, as PC_5 is measured via a reversed question.

Table 5: Takeover style inventory, modified from the Multidimensional Driving Style Inventory (Taubman-Ben-Ari, Mikulincer, and Gillath 2004).

Styles	**Observed Variables**
reckless	I misjudged the speed of the cars passing me when I was taking over car control. I forgot to switch on the turn indicator before changing lanes. I nearly crashed due to misjudging my distances from other cars. I engaged in mind wandering from time to time when I was driving the car manually. I tried to move into the left lane as soon as possible.
anxious	I felt nervous when I was taking over car control. Taking over car control frustrated me. It worried me when taking over car control after engaged in the n-back task. I drove at or below the speed limit when I was taking over car control. I used muscle relaxation techniques (such as taking deep breaths).
angry	I swore at the automation when it asked me to take over car control. I wanted to blow my horn or "flash" the car in front as a way of expressing frustrations. I enjoyed the excitement of taking risks when I was taking over car control. I took chances to merge into the adjacent lane. I removed at least one hand from the steering wheel when I was driving the car manually.
patient	I waited for a proper gap to change lanes. I based my takeover behaviours on the motto "better safe than sorry". I took over car control from automation cautiously. I shifted my focus from the game to taking over car control before the takeover requests. I had to slam on the brake to avoid collisions [−].

[−] indicates reversed items.

2. SPARE CAPACITY SURVEY

This study assesses drivers' perceived spare capacity (pSC) using a survey composed of items measuring perceived takeover task demand (pTD) and perceived task capability (pTC). These questions were presented randomly to reduce order effects. Participants were asked to indicate their agreement with the scale statements on a five-point scale (1 = Strongly Disagree, 5 = Strongly Agree).

PERCEIVED TASK DEMAND FOR TAKEOVERS

Drivers' pTD for takeovers is deconstructed into their perceived mental demand (pTD_{mental}), visual demand (pTD_{visual}), and temporal demand ($pTD_{temporal}$) for takeover contexts. Accordingly, three scales for measuring drivers' pTD are developed based on NASA Task Load Index (NASA-TLX) (Hart and Staveland 1988) and Driving Activity Load Index (DALI) (Pauzié 2008), as listed in Table 6.

Table 6: Scales measuring perceived task demand for takeovers.

Demands	Observed Variable	Reference
Mental	Taking over car control in this situation was mentally demanding.	Hart and Staveland (1988); Pauzié (2008)
Visual	Taking over car control in this situation was visually demanding.	
Temporal	The time left for me to take over car control was short.	

PERCEIVED DRIVER CAPABILITY FOR TAKEOVERS

This study extends the scales in Rosenbloom *et al.* (2010) and deconstructs drivers' pDC for takeovers into five distinct dimensions based on the Driver Skill Inventory (DSI) (Lajunen and Summala 1995; Martinussen, Møller, and Prato 2014). As shown in Table 7, drivers' pDC is measured from their perceived anticipation capability ($pDC_{anticipation}$), reaction capability ($pDC_{reaction}$), speed adjustment capability (pDC_{speed_adjust}), lane change capability (pDC_{lane_change}), and safety capability (pDC_{safety}). This is because the takeover manoeuvres in this study encompass anticipating the takeover situation, resuming motor readiness in response to takeover requests, adjusting driving speed to suit the takeover situation, changing lanes to bypass the detected collision ahead, and keeping sufficient distances from surrounding vehicles (Zhang, De Winter, *et al.* 2019). The developed scales are employed to measure drivers' pDC when they have made decisions for takeover manoeuvres, i.e., when they start to take over vehicle control.

Table 7: Scales measuring perceived driver capability for takeovers.

Capabilities	Observed Variable		Reference
Anticipation	When I started to take over car control, ...	I anticipated what would happen next in this situation.	Lajunen and Summala (1995), Rosenbloom *et al.* (2010), and Zhang, De Winter, *et al.* (2019)
Reaction		I responded to the takeover request promptly.	
Speed adjust		I could adjust speed effectively in this situation.	
Lane change		I could change lanes fluently in this situation.	
Safety		I could maintain sufficient distance from the cars around me in this situation.	

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SUMMARY

Conditionally automated driving systems rely on drivers to act as safety backups when automation encounters conditions beyond its operational limits. These so-called control transitions require drivers to resume manual control within a limited time budget, which places critical demands on their perception, decision-making, and execution. Providing time budgets that can suffice diverse driver needs and situational demands is therefore essential for ensuring both the takeover safety and driver comfort. This thesis addresses this challenge by systematically investigating how drivers respond to takeover requests, how takeover time can be predicted, how takeover performance can be evaluated, and how adaptive time budget strategies can be designed.

The thesis consists of five core chapters that collectively contribute to an adaptive framework for providing sufficient time budgets.

Chapter 2: Systematic Review of the Takeover Sequence

The significant variability in drivers' takeover time (the time needed to regain control) poses challenges in balancing time budgets to avoid being too short (compromising safety and comfort) or too long (reducing driver alertness). The thesis begins with a systematic review of the takeover sequence, including takeover time, time budget, and takeover performance. Specifically, it synthesizes causal factors influencing takeover time using a task-capability interface model; reviews studies on fixed and adaptive time budgets and introduces the concept of the "takeover buffer" as a key metric relating allocated time budget to required takeover time; develops a second taxonomy of takeover performance measures, encompassing objective and subjective indicators; hypothesizes a qualitative relationship among takeover time, time budget, and performance; and outlines six directions for future adaptive time budget research.

Chapter 2 positions the thesis within the broader discourse and establishes the need for research that links takeover time prediction, multidimensional performance assessment, and adaptive time budget strategies. Structuring the takeover sequence clarifies trade-offs in time budget design. Adaptive approaches that estimate takeover time and allocate an appropriate takeover buffer to achieve targeted performance show promise yet warrant further investigation.

Chapter 3: Driving Simulator Experiment

Chapter 3 presents the empirical foundation of the thesis: a controlled driving simulator experiment designed to collect comprehensive data on driver takeover behavior. The experiment exposed participants to nine takeover scenarios under varying traffic densities and non-driving-related tasks, requiring them to resume control promptly within a seven-second time budget. The collected data integrates five structured data streams: (i) driver characteristics, such as demographics, driving experience, risk-taking attitude, and takeover style; (ii) scenario information, including three traffic densities and three non-driving-related tasks; (iii) vehicle operational data from the driving simulator, such

as speed, acceleration, and steering wheel angle; (iv) scenario experience data, such as situational awareness and spare capacity for each scenario assessed via questionnaires; (v) psycho-physiological signals, including heart rate and eye-tracking data.

The combination of behavioral, physiological, and subjective data allowed for a detailed exploration of the mechanisms underlying takeover processes. The dataset provides the empirical foundation for predictive modeling, multidimensional performance assessment, and adaptive time budget strategies in subsequent chapters.

Chapter 4: Predicting Takeover Time

Building on the empirical data, Chapter 4 investigates the prediction of takeover time, a critical step for designing adaptive time budgets, as it is essential to first understand how much time drivers require. This Chapter addresses enduring challenges in reliability and interpretability of takeover time prediction models by optimizing predictor selection. The relationship between takeover time, driver characteristics, and perceived Spare Capacity (pSC, a cognitive construct from Task-Capability Interface theory) is examined using Category Boosting models. Results show that (i) incorporating 13 additional driver characteristics does not significantly improve prediction accuracy when pSC is already considered; and (ii) individual characteristics influence how drivers cognitively process takeover scenarios, and their predictive contribution likely overlaps with pSC. These findings suggest that monitoring cognitive states may be more effective for takeover time prediction than extensive profiling of driver characteristics.

By carefully selecting meaningful, human-interpretable features, the models provide not only accurate estimates of takeover time but also insights into the underlying cognitive and behavioral mechanisms. These findings underscore the feasibility of predicting individual drivers' takeover times and address the methodological challenge of balancing predictive performance with interpretability.

Chapter 5: Multidimensional Assessment of Takeover Performance

Takeover time captures the speed of response and it does not necessarily correlate with drivers' response quality. To ensure safe and comfortable control transitions, it is essential to develop a deep understanding of the key factors influencing various takeover performance aspects. This Chapter evaluates drivers' takeover performance across three dimensions: response efficiency, user experience, and driving safety— using a driving simulator experiment. EXtreme Gradient Boosting (XGBoost) models are used to investigate the contributions of two critical factors, i.e., Situational Awareness (SA) and Spare Capacity (SC), in predicting various takeover performance metrics by comparing the predictive results to the baseline models that rely solely on basic Driver Characteristics (DC). The results reveal that (i) higher SA enables drivers to respond to takeover requests more quickly, particularly for reflexive responses; and (ii) SC shows a greater overall impact on takeover quality than SA, where higher SC generally leads to enhanced subjective rating scores and objective execution trajectories. These findings highlight the distinct yet complementary roles of SA and SC in shaping performance components, offering insights for optimizing human-vehicle interactions and enhancing automated driving system design.

By disentangling different performance dimensions, Chapter 5 contributes to a deeper understanding of the factors shaping takeover behaviours and highlights the importance of designing systems that balance efficiency, safety, and comfort.

Chapter 6: Adaptive Time Budget

Chapter 6 integrates insights from the previous chapters to address the central challenge of determining sufficient time budgets across diverse drivers and scenarios. It focuses in particular on the takeover buffer, i.e., the extra time available after drivers consciously resume control to complete evasive maneuvers. The influence of different takeover buffer lengths on safety-related indicators (minimum time-to-collision, maximum deceleration, and steering wheel angle) and subjective assessments (perceived time sufficiency, perceived risk, and performance satisfaction) is evaluated. Results show that (i) takeover buffers of about 5–6 seconds consistently lead to optimal safety and comfort; and (ii) drivers prefer relatively stable takeover buffers across varying traffic densities and n-back tasks. On these bases, this study introduces an adaptive time budget framework that dynamically allocates transition time by incorporating a predicted takeover time and a preferred takeover buffer (piece-wise function).

This Chapter shows how predicted takeover time can be combined with performance targets to dynamically adjust time budgets. This can serve as an important first step toward providing drivers with sufficient time to resume vehicle control across diverse scenarios, which needs to be validated in more diverse and real-world driving contexts. By aligning the provided time budget with driver needs under specific circumstances, the adaptive framework can improve reliability of control transitions, facilitate human-centered automated driving, reduce crash risk, and maintain overall traffic efficiency.

Overview

By combining systematic review, empirical experimentation, predictive modeling, multidimensional assessment, and integrative analysis, this thesis provides an adaptive framework for designing sufficient time budgets. It bridges the gap between human factors research and automated driving system design, contributing to safe and more comfortable human-vehicle interactions during control transitions.

Looking forward, the thesis identifies several avenues for future research and practical implementation. For future research, these include: developing real-time cognitive state monitoring tools and integrating them into prediction models; investigating the evolving sequence of driver states throughout takeovers; extending studies to diverse driver populations and edge cases; validating adaptive time budget frameworks in real-world settings; exploring takeover performance at mesoscopic and macroscopic levels; and co-designing ethical and trustworthy automation. For future practical implementation, avenues include: developing personalized and adaptive takeover systems; implementing adaptive feedback loops for takeover optimization; designing cognition-aware interfaces to support adaptive takeovers; creating cognitive-aware driver training tools; and supporting the standardization of takeover design and evaluation. By addressing these directions, future work can further advance the design of automated systems that are both safe and human-centered.

SAMENVATTING

Conditioneel geautomatiseerde rijsystemen vertrouwen op bestuurders om als veiligheidsreserve op te treden wanneer de automatisering omstandigheden tegenkomt die buiten de operationele grenzen vallen. Deze zogenoemde controletransities vereisen dat bestuurders binnen een beperkte tijdsmarge de manuele controle hervatten, wat kritische eisen stelt aan hun waarneming, besluitvorming en uitvoering. Het voorzien van tijdsmarges die kunnen voldoen aan diverse bestuurdersbehoeften en situationele omstandigheden is daarom essentieel voor zowel de veiligheid als het comfort tijdens de overgang. Dit proefschrift richt zich op deze uitdaging door systematisch te onderzoeken hoe bestuurders reageren op overnameverzoeken, hoe overnametijd kan worden voorspeld, hoe overnameprestaties kunnen worden geëvalueerd en hoe adaptieve strategieën voor tijdsmarges kunnen worden ontworpen.

Het proefschrift bestaat uit vijf kernhoofdstukken die gezamenlijk bijdragen aan een adaptief raamwerk voor het bieden van voldoende tijdsmarges.

Hoofdstuk 2: Systematische review van de overnamesequentie

De aanzienlijke variabiliteit in de overnametijd van bestuurders (de tijd die nodig is om de controle te herwinnen) vormt uitdagingen bij het balanceren van tijdsmarges om te voorkomen dat deze te kort zijn (wat de veiligheid en het comfort kan aantasten) of te lang (wat kan leiden tot verminderde alertheid van de bestuurder). Het proefschrift begint met een systematische review van de overnamesequentie, inclusief overnametijd, tijdsmarge en overnameprestaties. Specifiek synthetiseert het causale factoren die de overnametijd beïnvloeden aan de hand van een taak-capaciteitsinterfacemodel; bespreekt het studies over vaste en adaptieve tijdsmarges en introduceert het het concept van de “overnamebuffer” als een belangrijke maatstaf die de toegewezen tijdsmarge relateert aan de vereiste overnametijd; ontwikkelt het een tweede taxonomie van prestatiemaatstaven voor overname, die zowel objectieve als subjectieve indicatoren omvat; formuleert het een kwalitatieve relatie tussen overnametijd, tijdsmarge en prestatie; en schetst het zes richtingen voor toekomstig onderzoek naar adaptieve tijdsmarges.

Hoofdstuk 2 positioneert het proefschrift binnen de bredere wetenschappelijke discussie en benadrukt de noodzaak van onderzoek dat overnametijdvoorspelling, multidimensionale prestatie-evaluatie en adaptieve strategieën voor tijdsmarges met elkaar verbindt. Het structureren van de overnamesequentie verduidelijkt de afwegingen in het ontwerp van tijdsmarges. Adaptieve benaderingen die de overnametijd schatten en een passende overnamebuffer toekennen om beoogde prestatieniveaus te bereiken, laten potentie zien maar vereisen verdere ontwikkeling.

Hoofdstuk 3: Rijsimulator-experiment

Hoofdstuk 3 presenteert de empirische basis van het proefschrift: een gecontroleerd rijsimulator-experiment dat is ontworpen om uitgebreide gegevens te verzamelen over het overnamegedrag van bestuurders. De deelnemers werden blootgesteld aan negen

overnamescenario's met variërende verkeersdichtheden en taken die niet aan het rijden gerelateerd waren, waarbij zij binnen een tijdsmarge van zeven seconden de controle moesten hervatten. De verzamelde gegevens omvatten vijf gestructureerde datastromen: (i) bestuurderskenmerken zoals demografie, rijervaring, risicohouding en overnamestijl; (ii) scenario-informatie, waaronder drie verkeersdichtheden en drie niet-rijgebonden taken; (iii) operationele voertuigdata uit de simulator, zoals snelheid, acceleratie en stuurhoek; (iv) scenario-ervaringsdata zoals situationeel bewustzijn en resterende capaciteit, gemeten via vragenlijsten; (v) psychofysiologische signalen, waaronder hartslag en oogbewegingsgegevens.

De combinatie van gedrags-, fysiologische en subjectieve gegevens maakte een gedetailleerde analyse van de mechanismen die ten grondslag liggen aan het overnameproces mogelijk. Deze dataset vormt de empirische basis voor voorspellende modellering, multidimensionale prestatie-evaluatie en adaptieve tijdsmarges in de volgende hoofdstukken.

Hoofdstuk 4: Voorspelling van overnametijd

Op basis van de empirische gegevens onderzoekt Hoofdstuk 4 de voorspelling van overnametijd, een cruciale stap voor het ontwerpen van adaptieve tijdsmarges. Dit hoofdstuk behandelt aanhoudende uitdagingen met betrekking tot betrouwbaarheid en interpreteerbaarheid van voorspellingsmodellen door de selectie van voorspellers te optimaliseren. De relatie tussen overnametijd, bestuurderskenmerken en waargenomen Resterende Capaciteit (pSC, een cognitief construct uit de taak-capaciteitsinterfacetheorie) wordt onderzocht met behulp van Category Boosting-modellen. De resultaten tonen aan dat (i) het toevoegen van 13 extra bestuurderskenmerken de voorspellingsnauwkeurigheid niet significant verbetert wanneer pSC al is opgenomen; en (ii) individuele kenmerken invloed hebben op hoe bestuurders overnamescenario's cognitief verwerken, waarbij hun voorspellingsbijdrage waarschijnlijk overlapt met pSC. Deze bevindingen suggereren dat het monitoren van cognitieve toestanden effectiever kan zijn voor het voorspellen van overnametijd dan uitgebreide profilering van bestuurderskenmerken.

Door betekenisvolle en interpreteerbare variabelen te selecteren, bieden de modellen niet alleen nauwkeurige schattingen, maar ook inzicht in de onderliggende cognitieve en gedragsprocessen.

Hoofdstuk 5: Multidimensionale evaluatie van overnameprestaties

Overnametijd geeft de snelheid van reactie weer, maar correleert niet noodzakelijk met de kwaliteit van de reactie. Om veilige en comfortabele transities te waarborgen, is het noodzakelijk om de factoren die verschillende aspecten van overnameprestaties beïnvloeden, diepgaand te begrijpen. Dit hoofdstuk beoordeelt de overnameprestaties van bestuurders over drie dimensies: reactiedoeltreffendheid, gebruikerservaring en verkeersveiligheid. EXtreme Gradient Boosting (XGBoost)-modellen worden gebruikt om de bijdragen van twee cruciale factoren, namelijk Situationeel Bewustzijn (SA) en Resterende Capaciteit (SC), te onderzoeken door voorspellingsresultaten te vergelijken met basismodellen die uitsluitend vertrouwen op basisbestuurderskenmerken (DC). De resultaten tonen dat (i) hoger SA bestuurders in staat stelt sneller op overnameverzoeken te reageren, met name bij reflexmatige reacties; en (ii) SC een grotere algehele invloed heeft op de kwaliteit van de overname dan SA, waarbij hogere SC leidt tot betere subjec-

tieve beoordelingen en stabielere voertuigbeheersing.

Door verschillende prestatiecomponenten te onderscheiden, draagt Hoofdstuk 5 bij aan een beter begrip van de factoren die overnamegedrag vormgeven en benadrukt het belang van systemen die efficiëntie, veiligheid en comfort in balans brengen.

Hoofdstuk 6: Adaptieve tijdsmarge

Hoofdstuk 6 integreert inzichten uit de voorgaande hoofdstukken om de centrale uitdaging van het bepalen van voldoende tijdsmarges voor diverse bestuurders en scenario's aan te pakken. De focus ligt op de overnamebuffer, d.w.z. de extra tijd die beschikbaar is nadat de bestuurder bewust de controle hervat om ontwijkende manoeuvres uit te voeren. De invloed van verschillende buffergroottes op veiligheidsindicatoren (minimale time-to-collision, maximale remvertraging en stuurhoek) en subjectieve beoordelingen (waargenomen tijdsadequaatheid, waargenomen risico en prestatie tevredenheid) wordt geëvalueerd. Resultaten tonen aan dat (i) overnamebuffers van ongeveer 5–6 seconden consequent leiden tot gunstige veiligheids- en comfortuitkomsten; en (ii) bestuurders de voorkeur geven aan relatief stabiele buffers bij verschillende verkeersdichtheden en n-back taken. Op basis hiervan introduceert dit hoofdstuk een adaptief tijdsmargekader dat de toegewezen overgangstijd dynamisch afstemt door een voorspelde overnametijd te combineren met een gewenste buffer (stukgewijze functie).

Dit hoofdstuk laat zien hoe voorspelde overnametijd kan worden gecombineerd met prestatiedoelen om tijdsmarges dynamisch bij te stellen. Door tijdsmarges af te stemmen op bestuurderbehoeften onder specifieke omstandigheden kan dit kader de betrouwbaarheid van overgangen verbeteren, mensgerichte automatisering ondersteunen, het ongevalsrisico verminderen en de verkeersdoorstroming bevorderen.

Overzicht

Door systematische literatuurstudie, empirisch experiment, voorspellende modellering, multidimensionale prestatiemeting en geïntegreerde analyse te combineren, biedt dit proefschrift een adaptief kader voor het ontwerpen van voldoende tijdsmarges. Het slaat een brug tussen onderzoek naar menselijke factoren en het ontwerp van geautomatiseerde rijsystemen, met als doel veilige en comfortabele mens-voertuiginteracties tijdens controleresovergangen.

Voor toekomstig onderzoek worden verschillende richtingen voorgesteld, waaronder: het ontwikkelen van realtime monitoring van cognitieve toestanden en integratie in voorspellingsmodellen; het onderzoeken van de evolutie van bestuurdersstaten tijdens overname; uitbreiding naar diverse bestuurderspopulaties en randgevallen; validatie in praktijksituaties; het bestuderen van overnameprestaties op meso- en macroschaal; en het gezamenlijk ontwerpen van betrouwbare en verantwoorde automatisering. Voor praktische implementatie omvatten mogelijke stappen: het ontwikkelen van gepersonaliseerde en adaptieve overnamesystemen; het implementeren van adaptieve feedbackloops; het ontwerpen van cognitie-geïnformeerde interfaces; het creëren van trainingsmiddelen die gericht zijn op cognitieve capaciteiten; en het ondersteunen van standaardisatie in overnameontwerp en evaluatie.

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LIST OF PUBLICATIONS

JOURNAL ARTICLES

1. Kexin Liang, Simeon C Calvert, and JWC van Lint (2026). "Towards Safe and Comfortable Vehicle Control Transitions: A Systematic Review of Takeover Time, Time Budget, and Takeover Outcomes". In: *Human Factors*, In press

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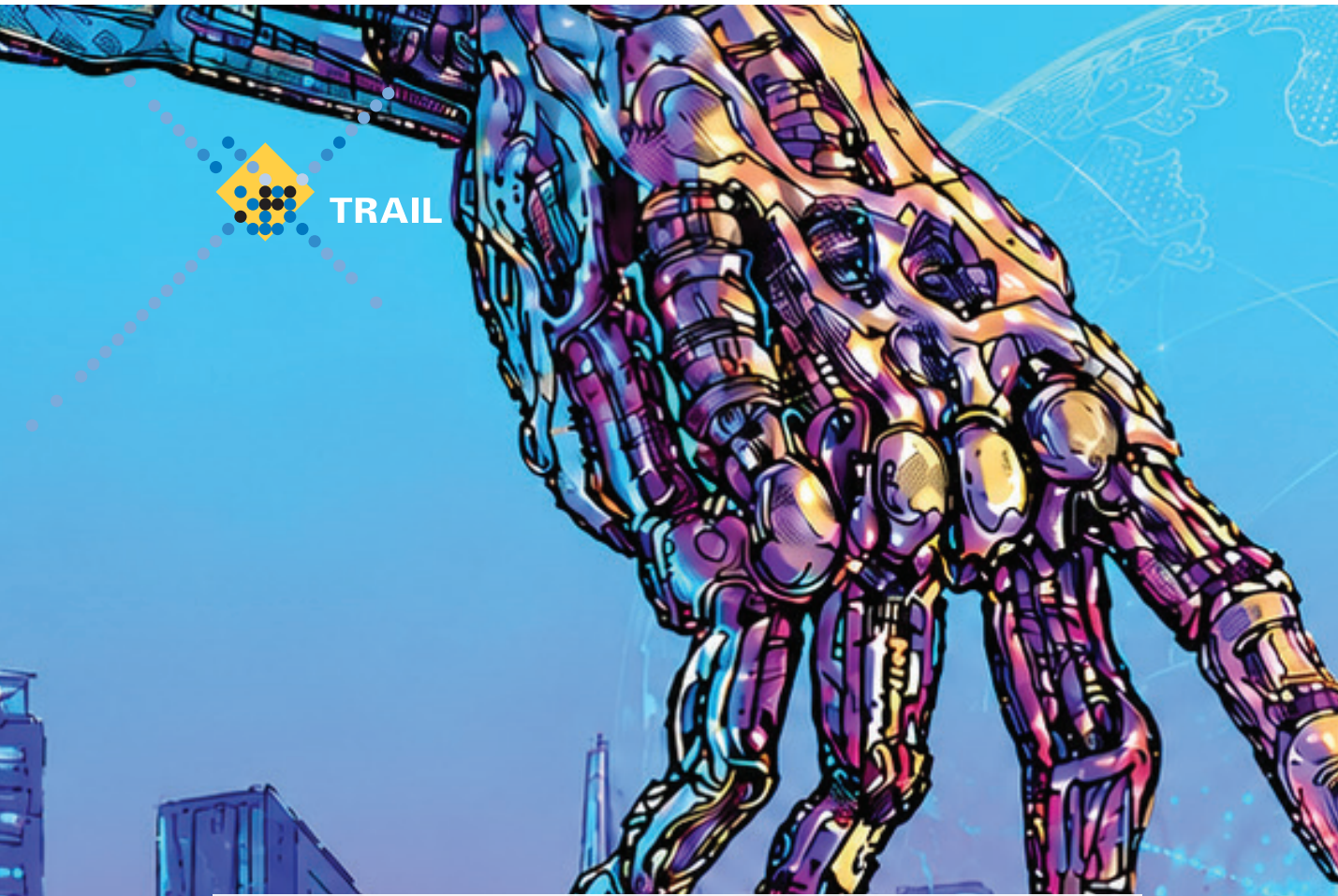

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Summary

Conditionally automated driving requires drivers to resume control within limited time budgets when system limits are reached. Ensuring sufficient time budgets for diverse drivers and situations is critical for driving safety and user comfort. This thesis systematically reviews studies on the takeover sequence, predicts takeover time, evaluates performance across multiple dimensions, and develops adaptive time budgets. Such adaptive time budgets can enhance takeover reliability, reducing risk, and improving driving experience.

About the Author

Kexin Liang is a PhD researcher at TU Delft, focusing on adaptive takeover time budgets in conditionally automated driving. She is passionate about interdisciplinary research that bridges human factors, human–computer interaction, user experience, automated driving, and driver behavior modeling.

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