Designing Human-Machine Interaction for Trustworthy Automated Vehicles

Kim, S.

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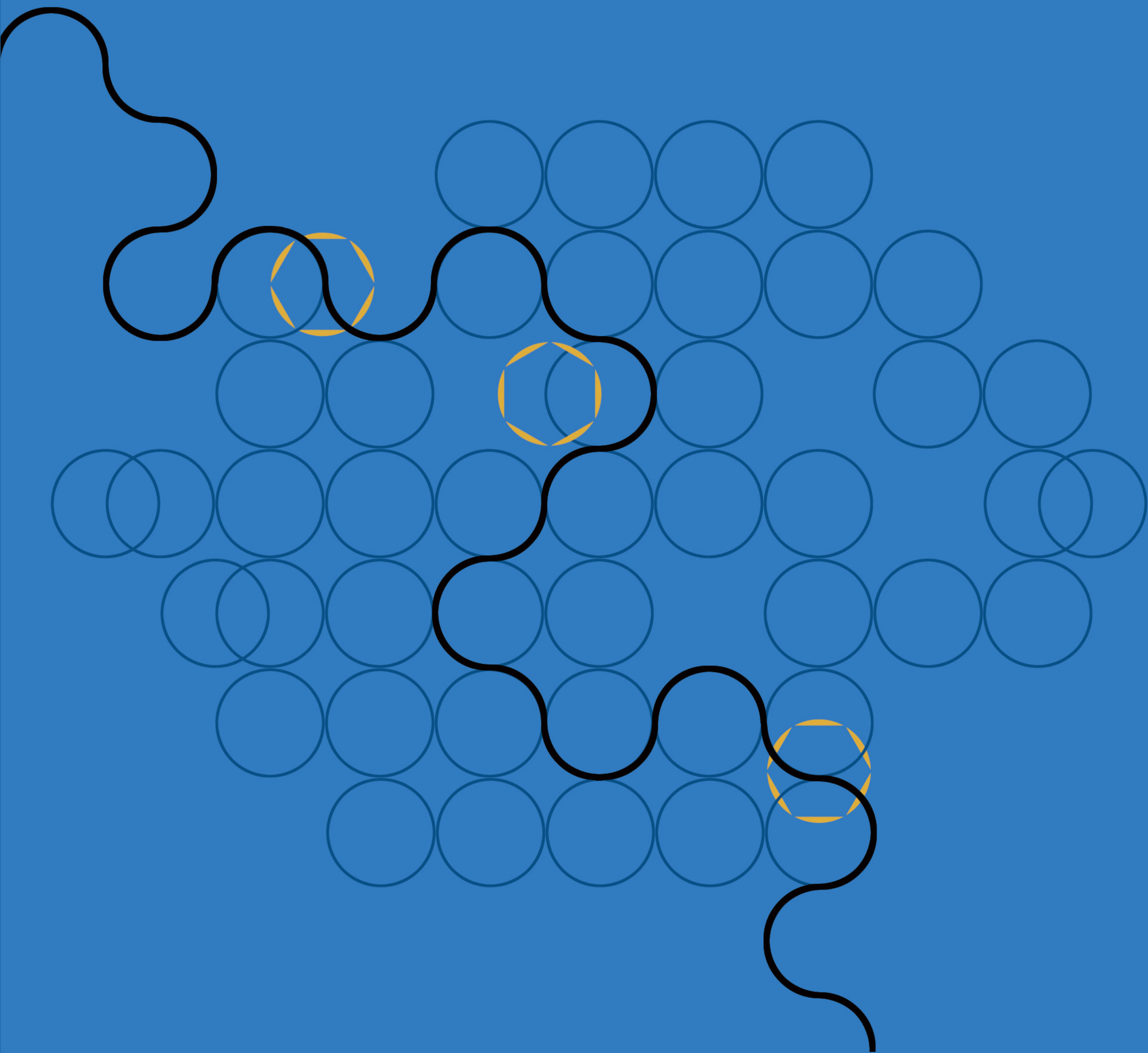

Soyeon Kim

DESIGNING HUMAN-MACHINE INTERACTION FOR TRUSTWORTHY AUTOMATED VEHICLES

Designing Human-Machine Interaction for Trustworthy Automated Vehicles

DISSERTATION

for the purpose of obtaining the degree of doctor
at Delft University of Technology,
by the authority of the Rector Magnificus, Prof.dr.ir. T.H.J.J. van der Hagen,
chair of the Board for Doctorates,
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by

Sou-youn KIM

Master of Science in Industrial and Systems Engineering,
KAIST (Korea Advanced Institute of Science and Technology), Republic of Korea,
born in Seoul, Republic of Korea

This dissertation has been approved by the promotors.

Composition of the doctoral committee:

Rector Magnificus	chairperson
Prof. dr. ir. R. Happee	Delft University of Technology, promotor
Dr. R. Van Egmond	Delft University of Technology, promotor
E.D. van Grondelle MBA	Delft University of Technology, external advisor

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HADRIAN
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As it is now and ever shall be

Contents

Preface

My journey in the automotive field commenced with the entry into Hyundai Motor in 2017. During the onboarding training, I was presented with a vision: by 2024, we would enter the phase of a commercial automated vehicle, where drivers could be hands-off at the steering wheel and perform other activities. Reflecting on it now, I believe this vision to be both partially accurate and partially inaccurate. Technologically, we are making strides in the development of automated driving, with several automakers having introduced conditionally automated vehicles in the market. However, a slight delay in technological advancement has brought to the forefront the significance of considering humans. Even in automated driving scenarios, humans are inside the vehicle, engaging with it, and human factors dynamically come into play in real time. Humans' reactions can vary from overtrust to heightened perception of risks, and their acceptance of new technologies may be uncertain. Therefore, it has become evident that we need to refocus on a human-centred approach. In 2020, I returned to academia, bringing my practical experience seamlessly into my research. Within the HADRIAN project funded by EU Horizon 2020, I had a valuable chance to collaborate with international colleagues to design state-of-the-art interactions for automated vehicles, taking a holistic perspective. Throughout the doctoral journey, I endeavoured to address the questions and challenges arising from the interaction between drivers and automated vehicles. I believe that my research will make a modest contribution to the design of trustworthy automated vehicles, ensuring safety and delivering experiences that go beyond the car.

Summary

Automated vehicles are anticipated to not only improve safety and comfort but also redefine the nature of driver-vehicle interactions. With these advancements, drivers in automated vehicles share the monitoring and supervising role with the system, creating a unique human-machine team. In this relation, beyond technical excellence, it is important for drivers to comprehend and trust the system for its effective and safe utilisation. Trust evolves during interactions, influenced by the system's performance, emphasising the significance of provided information and interaction format. Design features of driving automation, particularly user interfaces, impact trust and shape perceptions of system performance, forming a crucial element for human-machine interaction.

This dissertation addresses three critical research gaps. First, an understanding of driver-vehicle interaction is crucial for designing effective interfaces. Current studies lack a clear comprehension of interactions during driving and transitions in complex systems, emphasising the need for an integrated view that considers various contexts and levels of driving automation. In this dissertation, I address this gap by investigating how drivers perceive complex interactions and identifying necessary interactions for drivers. Second, interactions extend beyond isolated take-over events, forming a sequence of interconnected behaviours that shape the overall driving experience. While take-over situations are undeniably critical, they represent just one facet of a broader continuum of scenarios. In-depth research on interactions during automated driving, where the human driver transitions between passive monitoring and active engagement, is lacking. Therefore, I explore the interactions in various situations, including automated driving and mode transitions in automated vehicles. Third, my research emphasises the design phase of user interfaces, beyond the conventional focus on identifying the effects of interfaces on drivers in specific scenarios. It stresses the importance of considering interface design comprehensively, incorporating factors such as cognitive load, situational awareness, and driver experience. Specifically, I look into the design of soundscapes to guide the driver back to control in take-over situations, creating a novel transition experience while prioritising safety.

Aligned with the goal of designing human-machine interaction for trustworthy automated vehicles, the research objectives are delineated into two objectives and six studies. The first objective aims to understand the driver-automated vehicle interaction, focusing on identifying the effects of interfaces, investigating human-machine interaction, and understanding drivers' mode transition logic. The second objective aims to contribute to the development of interaction design guidelines, designing and evaluating user interfaces and developing an approach to soundscape design in automated vehicles. Finally, I consolidate the findings, discuss the research's contribution, and provide an outlook on future work in the evolving landscape of automated vehicle technology.

Six studies employing diverse methods yield following results. A literature review and an on-road study unveil that the interaction between the driver and the automated vehicle through user interfaces significantly influences drivers' performance and trust. Specifically, the literature review indicates that this interaction during automated driving has an impact extending from take-over situations to overall performance. The on-road study, using a vehicle with multiple levels of driving automation, reveals mode confusion related to mode transitions. Further exploration of driver's understanding of mode transition logic, through an online survey demonstrates that, despite the driver performing certain interventions related to driving functions, there is no dominant mental representation of mode-transition logic under specific scenarios. Simulator experiments in partial and conditional automated driving scenarios illustrate that providing automation information during driving enhances the driver's trust and acceptance. In particular, delivering the manoeuvre of driving automation to the driver through auditory modality is effective in enhancing trust and acceptance. The proposed soundscape design for take-over requests and spatial sound delivering manoeuvre information while automated driving showcases the potential of sound design to elevate the driver's experience beyond a simple beep.

Throughout this dissertation, I investigate interactions in automated vehicles, addressing interaction challenges and designing and evaluating user interfaces. By conducting a literature review, on-road observations, interviews, online surveys, and simulator experiments, it navigates the complexities of trust, acceptance, and overall user experience. The contributions extend to understanding driver trust, performance, and the impact of system complexities on human-machine interaction, enriching the field with empirical evidence and practical guidelines for interaction design.

요약

자동화된 차량은 안전과 편의성을 향상시키는 것뿐만 아니라 운전자와 차량 간 상호작용의 본질을 재정의할 것으로 예상됩니다. 이러한 발전으로 인해 자동화된 차량의 운전자는 시스템과 모니터링 및 감독 역할을 공유함으로써 인간-기계 팀을 형성하게 됩니다. 이 관계에서 기술적 우수성 이상으로 운전자가 시스템을 이해하고 신뢰하는 것이 중요합니다. 신뢰는 상호작용 중에 발전되며, 시스템의 성능에 영향을 받으며 제공된 정보와 상호작용 형식의 중요성을 강조합니다. 특히 운전 자동화의 디자인 기능, 특히 사용자 인터페이스는 신뢰를 높이고 시스템 성능에 대한 인식을 형성하여 인간-기계 상호작용의 중요한 요소가 됩니다.

이 논문은 세 가지 중요한 연구 공백에 대한 대응을 다룹니다. 첫째, 효과적인 인터페이스를 디자인하기 위해 운전자-차량 상호작용의 이해는 중요합니다. 현재의 연구들은 운전 중의 상호작용 및 복잡한 시스템에서의 전환을 명확히 이해하지 못하고 있으며, 다양한 맥락과 운전 자동화의 수준을 고려하는 통합된 관점이 필요함을 강조합니다. 이 논문에서는 운전자가 복잡한 상호작용을 어떻게 인식하고 필요한 상호작용을 파악하는지 조사함으로써 이 공백을 다룹니다. 둘째, 상호작용은 고립된 전환 이벤트를 넘어서는데, 이는 전반적인 운전 경험을 형성하는 연결된 행동의 일부를 형성합니다. 전환 이벤트는 의심할 여지없이 중요하지만, 이것은 더 광범위한 시나리오의 한 가지 측면일 뿐입니다. 자동화 운전 중 운전자가 수동 모니터링과 활성 참여로 전환하는 과정에서의 상호작용에 대한 심층적인 연구가 부족합니다. 따라서 이 논문에서는 자동화 운전 및 자동화된 차량에서의 모드 전환 상황을 포함한 다양한 상황에서의 상호작용을 탐색합니다. 셋째, 이 연구는 특정 시나리오에서 인터페이스의 영향을 확인하는 것 이상으로 사용자 인터페이스의 설계 단계에 중점을 둡니다. 이것은 인터페이스 디자인을 종합적으로 고려하는 것의 중요성을 강조하며, 인지적 부하, 상황 인식 및 운전자 경험과 같은 요소를 포함합니다. 구체적으로, 이 논문에서는 타이밍 요청에 대한 소리 환경의 디자인을 다루어 안전을 우선시하는 동시에 운전자의 경험을 혁신적으로 개선합니다.

신뢰할 수 있는 자동화된 차량을 위한 인간-기계 상호작용을 디자인하는 목적에 부합하게, 이 논문은 두 가지 목표와 여섯 가지 연구로 나누어집니다. 첫째 목표는 운전자-자동화된 차량 상호작용을 이해하고, 인터페이스의 영향을 파악하고, 인간-기계 상호작용을 조사하며, 운전자의 모드 전환 논리를 이해하는 것입니다. 둘째 목표는 상호작용 설계 지침의 개발에 기여하는 것으로, 사용자 인터페이스를 디자인하고 평가하며, 자동화된 차량에서의 사운드 디자인에 대한 접근법을 개발하는 것입니다. 마지막으로, 이 연구 결과를 종합하고 연구의 기여를 논의하며, 자동화된 차량 기술의 발전하는 환경에서의 미래 연구에 대한 전망을 제공합니다.

다양한 방법을 사용한 여섯 가지 연구는 다음과 같은 결과를 내놓습니다. 문헌 고찰 및 도로에서의 연구는 사용자 인터페이스를 통한 운전자와 자동화된 차량 간의 상호작용이 운전자의 성능과 신뢰에 중요한 영향을 미친다는 것을 밝혀냅니다. 특히 문헌 고찰은 자동화 운전 중 이러한 상호작용이 타이밍 이벤트에서부터 전체적인 성능까지 영향을 미친다는 것을 보여줍니다. 다수의 운전 자동화 수준을 갖춘 차량을 사용한 도로 연구는 모드 전환과 관련된 모드 혼란을 보여줍니다. 운전자의 모드 전환 논리에 대한 온라인 설문조사를 통해 특정 시나리오에서도 운전자가 특정 시나리오에서 주행 기능과 관련된 특정 개입을 하지만, 지배적인 정신적 표현은 없다는 것을 보여줍니다. 부분 및 조건부 자동 운전 시나리오에서의 시뮬레이터 실험은 주행 중 자동화 정보를 제공함으로써 운전자의 신뢰와 수용성을 높입니다. 특히 주행 자동화의 조작을 운전자에게 사운드로 제공함으로써 신뢰와 수용성을 향상시킵니다. 전환 요청에 대한 사운드 디자인 및 자동화된 주행 중의 공간 음향을 통해 주행 상태를 안전하게 안내하는 제안된 사운드 디자인은 단순한 경보 이상의 운전자의 경험을 향상시킵니다.

이 논문을 통해 자동화된 차량에서의 상호작용을 조사하고 상호작용에 대한 도전에 대응하며 사용자 인터페이스를 디자인하고 평가합니다. 문헌 고찰, 도로 관찰, 인터뷰, 온라인 설문 조사 및 시뮬레이터 실험을 통해 신뢰, 수용성 및 전반적인 사용자 경험의 복잡성을 탐색합니다. 이 논문은 운전자 신뢰, 성능 및 시스템 복잡성이 인간-기계 상호작용에 미치는 영향을 이해하는 데까지 이어지며, 실질적인 지침을 위한 경험적 증거와 실용적 지침을 풍부하는데 기여합니다.

CHAPTER

1

Introduction

1.1 Research Context

Automated vehicle technology has been gradually developing, with the promise to increase safety and comfort for drivers (Litman, 2017; Milakis et al., 2017). While altering the way they interact with their vehicles, such as engaging in other activities (Krueger et al., 2016). Compared to conventional vehicles, drivers share the monitoring and supervising role with the system in automated vehicles (Hancock & Kajaks, 2020), resulting in a unique partnership between drivers and automated vehicles as a human-machine team. This new role of vehicles embodies the collaborative relationship between humans and machines, characterised by their shared pursuit of a common goal set by humans themselves (Ibrahim et al., 2022).

Excellent system performance resulting in actual safety may be sufficient from a technical point of view. However, it is important for drivers to understand and trust the system for it to be accepted and appropriately used (Korber et al., 2018; van der Laan et al., 1997). Trust plays a vital role in user acceptance and user experience for automated systems (Choi & Ji, 2015; Cysneiros et al., 2018; Detjen et al., 2021; Ghazizadeh et al., 2012; Hoff & Bashir, 2015; Wilson et al., 2020). However, sometimes, the introduction of automation undeservedly or insufficiently conveys trust (Norman, 2009). Overtrust may lead to misuse or unintended use, potentially causing various or even fatal accidents (O'Kane, 2020). Conversely, undertrust may result in a low acceptance or even an abandonment of the new technology (Lee & Seppelt, 2012). To ensure the safe operation of automated vehicles, a driver should fully understand and trust the system's actual capabilities (Lee & See, 2004). When the actual capabilities and performance of the system evoke an appropriate level of trust, i.e. the calibrated level of trust, drivers show an appropriate usage (Muir, 1987).

Trust is formed through learning, disposition, and situations (Hoff & Bashir, 2015). The result of learning through interaction is also reflected in a change in trust. Specifically, the information and interaction format (modality) influence the understanding of automation performance, ultimately shaping trust (Lee & See, 2004). Designing interaction should adopt a holistic perspective, considering multiple design features rather than individual elements. These design features, when integrated holistically, impact trust directly or indirectly by influencing various human factors. Consequently, the success of human-machine collaboration hinges on effective human-machine interaction. User interfaces serve as the primary communication channel (Carsten & Martens, 2019), such as sound or visual display, for effective collaboration between humans and automation. Through user interfaces, humans can convey their intentions, preferences, and expectations to autonomous systems while machines provide feedback, updates, and relevant information (Mills & Swain, 2002). This interaction fosters the development of shared understanding, shared goals, and, ultimately, shared trust between humans and machines (Mathis, 2020).

While previous studies have explored various human factors, such as acceptance and trust in automated vehicles, a comprehensive investigation into the interactions during various technologies in vehicle automation is in ongoing development, and despite technical perfection, issues with vehicle usage may arise. Rather than attributing this degradation to human error, it should be regarded as a design error (Stanton & Baber, 2002). This perspective emphasises that designing interaction in automated vehicles needs to adapt drivers' behaviour, ensuring effective performance (Banks et al., 2018).

1.2 Research Gaps

Previous human factors research in automated vehicles has primarily focused on take-over situations and evaluating the impact of interfaces, yet interactions encompass a broader spectrum that influences the overall driving experience and safety. Thus, the need to comprehensively explore and understand interactions is evident, calling for research that delves into this intricate area. Therefore, further research is required to address the following three research gaps.

Understanding driver-vehicle interaction

The foundation for designing appropriate interaction lies in the understanding of drivers' behaviour in and interaction. Comparing new interfaces with existing ones without a clear comprehension has limitations. Automated vehicles present a novel and radical environment that drivers have rarely experienced; thus, access to incremental design through the existing car user interface is limited. Studies have investigated the behaviours and evaluated the impact of automated driving on human factors such as trust, situation awareness, and workload. However, research to comprehend interactions remains insufficient. Moreover, understanding interactions in automated vehicles requires an integrated view of various contexts. Automated vehicles have multiple levels of driving automation, and interactions do not only occur within a single stage. For example, drivers in a conditionally automated vehicle experience driving at a lower level of automation and transition between different automation levels. Therefore, investigating how drivers perceive complex interactions and identifying necessary interactions for drivers is needed. This research gap will be addressed in Chapter 3 and Chapter 4.

More than a single take-over request

Interactions do not happen in an isolated single event but rather as a sequence of interconnected behaviours that influence the overall experience. While the take-over is an undeniably critical situation in automated vehicles, it represents only one facet of a broader continuum of scenarios. It is important to examine interactions during automated driving, where the human driver may transition between passive monitoring and active engagement with the driving process. Interactions during driving have been shown to affect situational awareness, experience, and trust. In-depth research is also needed on mode transitions. From a safety perspective, interfaces for take-over requests and driver behaviours have been studied, but there is a lack of research on how the driver understands mode transitions and the driver's experience. Beyond take-over requests, it is necessary to delve into the multifaceted landscape of interactions that transpire during various phases of using automated vehicles. This research gap will be addressed in Chapter 2, Chapter 5, and Chapter 6.

Holistic Interaction Design
Previous studies on user interfaces have utilised visual and audio modalities to identify the impact of information related to automation state or transition warnings during takeovers or automated driving situations. Additionally, the impacts of modalities were specifically examined in terms of evaluating workload or urgency. However, there was little attention to the design phase and evaluate the impact of various factors. The first is the interaction of information and modality. While the impact of individual requirements for each information and modality has been explored, the synergy between the two—specific information working optimally with a particular modality—remains underexplored. Additionally, the importance of the design phase has been underestimated. In previous studies, the auditory modality has been focused on its role in drawing attention, which is effective but at the same time causes driver irritation. Designing sound should consider how users perceive the context information through sounds or what experiences could be delivered (Özcan & Egmond, 2008). Furthermore, there is a notable absence of research on the soundscape effect beyond the traditional beep used in previous studies. Lastly, interactions should be designed holistically, considering the understanding of the autonomous driving situation, including cognitive load, situational awareness, and factors influencing the driver experience. These research gaps will be covered in Chapter 6 and Chapter 7.

1.3 Research Objectives

To design human-machine interaction for trustworthy automated vehicles, this doctoral thesis aims to achieve the following research objectives:

Objective 1. Understand the driver-automated vehicle interaction.
Objective 2. Contribute towards the development of interaction design guidelines.

For ease of navigation, this dissertation is divided into 8 chapters. Chapters 2 to 4 correspond to Objective 1. Chapters 5 to 7 correspond to Objective 2. Finally, Chapter 8 reviews the findings and provides an outlook on future work. Note that I used various methods which are appropriate to conduct each study. Various methods are used to conduct each study. The literature review, on-road observation, and interviews contribute to understanding driver-automated vehicle interactions in the overall driving scenario. Additionally, for exploring interactions in specific scenarios, such as understanding mode logic, an online survey was employed to access and collect responses from many individuals. To develop interaction design guidelines, the designed interface was evaluated through a simulator driving experiment. The overview of the dissertation is given in Figure 1.1.

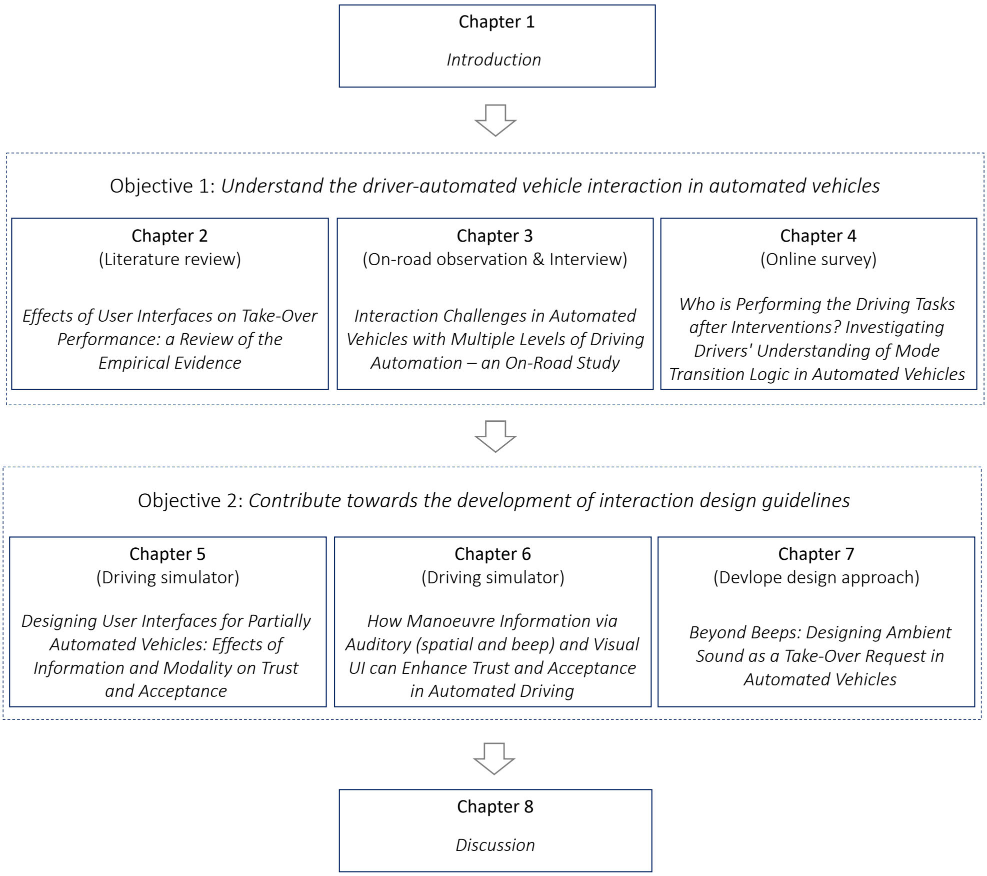

Figure 1.1 Structure of the thesis

In Chapter 2, the effect of user interfaces on drivers is identified through a literature review. The primary criterion considered is how the user interface (UI) affected take-over performance in highly automated vehicles. UI factors related to automated vehicles are classified during this study. While most studies support the positive effects of UI as improving acceptance and trust, several show no significant benefits. Moreover, UI affects drivers' performance and trust not only in take-over situations but also during automated driving. These insights guide the design of experiments in Chapter 5 and Chapter 6.

Chapter 3 explores the interaction between drivers and automated vehicles using an on-road study. The increasing availability of SAE Level 3 automated vehicles in the automotive industry highlights the need to craft effective driver-vehicle interactions. Sixteen participants drove a Wizard of Oz vehicle with varying automation levels (SAE Level 1, 2, and 3) and had a post-driving interview. Use errors related to mode transition and awareness were observed. This study provides insights for designing user interfaces in automated vehicles, aiming to enhance mode awareness and trust. In addition, the study discusses the limitation of interaction design impact.

Chapter 4 investigates drivers' understanding of mode transition logic in partial and conditional driving automation through an online survey. As automation functionalities become more complex, discrepancies arise between how drivers understand an automated vehicle and how it operates. The survey, administered to 838 respondents, focused on their understanding of control responsibilities in partial and conditional driving automation, considering interventions like brake pedal, steering wheel, gas pedal control, and take-over requests. Results indicated that while drivers associated specific interventions with driving functions, they lacked a dominant mental model for mode transition logic in certain scenarios, and their mental models did not align with actual mode transitions. Additionally, a mismatch between the actual logic of commercial partially automated vehicles and drivers' expectations of control responsibilities from the survey. This study fills a research gap by examining drivers' understanding and expectations of mode transition during interactions with automated vehicles.

In Chapter 5, user interfaces designed to enhance trust were evaluated in partial automated driving situations using a driving simulator. Trust and perceived safety play key roles in accepting automated vehicles, which is achievable by providing users with clear automation information for safe vehicle operation. Four interfaces with different complexities were designed, varying in the type of automation information (surrounding vs. surrounding and manoeuvre) and modality (visual vs. visual and auditory). Results show that all interfaces, and specifically manoeuvre information via auditory modality, increase the driver's trust, perceived safety, and acceptance. The benefits of the UIs were consistent over events. However, in the most critical events, drivers did not feel entirely safe and did not trust the automation completely. The study recommends designing UIs for partially automated vehicles that combine visual and auditory cues for surrounding and manoeuvre information to enhance user trust and acceptance.

Chapter 6 designs innovative auditory user interfaces using the spatial sound of driving automation manoeuvre movement to increase trust and acceptance in conditional driving automation and evaluates their effectiveness using a driving simulator. In conditional driving automation, drivers may take their eyes off the road but will still need to be ready to take control. The study shows how novel spatial sounds could offer intuitive automation cues compared to traditional alerts, a visual interface, and a baseline without cues. The study underscores the importance of designing user interfaces and considering user experience in usage scenarios in automated driving.

In Chapter 7, a new approach to soundscape design in automated vehicles is suggested. Traditionally, the design of take-over requests in automated vehicles focuses mainly on safety and reaction time. The study explores how take-over requests can be designed to provide a broader user experience while prioritising safety. The proposed designs involve soundscape using driving noise to alert the driver in scheduled take-over situations. This study aims to address the design approach to guide the driver back to control, creating a novel transition experience while ensuring safety.

Chapter 8 reflects the research and discusses the contribution and further research. I outline a transformative vision for future automated vehicles based on three key findings. These insights contribute to a future where vehicles actively collaborate with drivers, employing natural signals and systemic redesigns for enhanced trust and acceptance in automated driving scenarios.

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CHAPTER

2

Effects of User Interfaces on Take-Over Performance: A Review of the Empirical Evidence

This chapter has been published in the following research article:
Kim, S., van Egmond, R., & Happee, R. (2021). Effects of User Interfaces on Take-Over Performance: A Review of the Empirical Evidence. Information, 12, 162

Abstract

In automated driving, the user interface plays an essential role in guiding transitions between automated and manual driving. This literature review identified 25 studies that explicitly studied the effectiveness of user interfaces in automated driving. Our main selection criterion was how the UI affected take-over performance in higher automation levels, allowing drivers to take their eyes off the road (SAE3 and SAE4). We categorised user interface (UI) factors from an automated vehicle-related information perspective. Short take-over times are consistently associated with take-over requests (TOR) initiated by the auditory modality with high urgency levels. On the other hand, take-over requests directly displayed on non-driving related task devices and augmented reality do not affect take-over time. Additional explanations of take-over situations, surrounding and vehicle information while driving, and take-over guiding information were found to improve situational awareness. Hence, we conclude that advanced user interfaces can enhance the safety and acceptance of automated driving. Most studies showed positive effects of advanced UI, but quite some studies show no significant benefits. A few studies show negative effects of advanced UI, which may be associated with information overload. The occurrence of positive and negative results of similar UI concepts in different studies highlights the need for systematic UI testing across driving conditions and driver characteristics. Our findings propose future UI studies of automated vehicles focusing on trust calibration and enhancing situation awareness in various scenarios.

* The American English used in the original paper was modified to British English to maintain consistency within the thesis.

2.1 Introduction

Cars and other road vehicles see increasing levels of support and automation. The majority of current and near-future automated vehicles (AVs) will still need a capable driver on-board who can take control of the vehicle when manual driving is preferred or in driving conditions not supported by the automation. This requires information provided by the user interface (UI) to prepare drivers and guide the transitions between automated and manual driving.

Driving automation systems are classified by the American Society of Automotive Engineers (SAE) (SAEInternational, 2021) into six levels, from level 0 (no driving automation) to level 5 (full driving automation),. Level 1 automates longitudinal control (advanced cruise control) or lateral control (lane-keeping assist). Level 2 simultaneously automates longitudinal and lateral control. However, drivers are always required to monitor Level 2 automation. In Levels 3 to 5, drivers may take their eyes off the road creating the opportunity to engage in non-driving related tasks (NDRT). In Level 3, drivers need to be ready to resume manual control in reaction to take-over requests (TOR) issued by the automation (Gold et al., 2016). Such TOR can be issued when the vehicle leaves the operational design domain (ODD) of the automation. Level 4 may issue TOR but will resort to a minimal risk control strategy if drivers do not take back control. Level 5 automation is fully capable of driving under all conditions.

The take-over process comprises several time-consuming stages: perception of TOR stimuli using drivers' sensory system, interruption of the NDRT, drivers' motoric readiness, rebuilding of situation awareness (SA) and cognitive state meeting the demands of manual driving (Jarosch et al., 2019; Naujoks et al., 2018). Drivers should take-over within the time budget, which is the time from TOR to the automation system limit. The time needed for a safe transition of control depends on the complexity of the driving scenario and has been estimated to be at least 10 seconds (Merat et al., 2014). The take-over is an essential situation where drivers return from a passive driving or monitoring role to an active driving role. During the transition, the driver and the vehicle have critical interactions from a safety perspective. In automated mode, drivers can perform NDRTs or relax, leading to a lower level of situation awareness and alertness. A widely-accepted definition of situation awareness is provided by Endsley as "the perception of environmental elements and events with respect to time or space, the comprehension of meaning, and the projection of states in the near future" (Endsley & 1995b). Studies have shown that the rapid transition from a low level of alertness and situational awareness to active vehicle control can lead to poor performance in safety critical situations (Mok et al., 2015). Therefore, a properly designed user interface is needed to inform and guide the driver before and during take-over.

A wide range of experimental studies has addressed take-over performance, and several reviews and meta-studies have summarised findings (Eriksson et al., 2017; Jarosch et al., 2019; McDonald et al., 2019; Mirnig et al., 2017; Weaver et al., 2020; Zhang et al., 2019). However, there is no review yet that interprets TOR studies in terms of holistic user experience in the transition of control. Hence, this paper reviews empirical studies that identify the effect of UI on take-over performance. Zhang et al. (2019) and Weaver et al. (2020) performed meta-analyses, and McDonald et al. (2019) provided an empirical review. Zhang et al. (2019) reviewed the effect of time budget, modality, and urgency on only take-over time in Level 2 and 3 driving. Weaver et al. (2020) reviewed the effect of time budget, NDRT, and information support on take-over time and quality at Level 3. McDonald et al. (2019) analysed the impact of secondary task, modality, TOR presence, driving environment, automation level, and driver factor of experimental studies on take-over time and quality during Levels 2, 3, and 4 driving. Further papers reviewed factors such as time budget (Eriksson et al., 2017) and NDRT (Jarosch et al., 2019). One study categorised interface studies (Mirnig et al., 2017) but did not quantify the benefits of various UI concepts.

Our study uniquely quantifies the effect of UI with Level 3 or 4 automation. In particular we reviewed the effectiveness of an advanced UI informing the users of automation status and operation and guiding the user during TOR. Where most take-over studies employed simple signals with basic sounds, light signals and icons, our review addresses the benefits of advanced UI using contextual message, language-based sound, graphical displays and augmented reality in heads up displays. We categorised UI factors from an AV-related information perspective based on driving situation and information type (Figure 2.1) In addition, we reviewed empirical studies to identify their impact on take-over performance. Finally, we conclude with a comprehensive interpretation of the UI effects in the empirical studies and provide recommendations for UI design and evaluation.

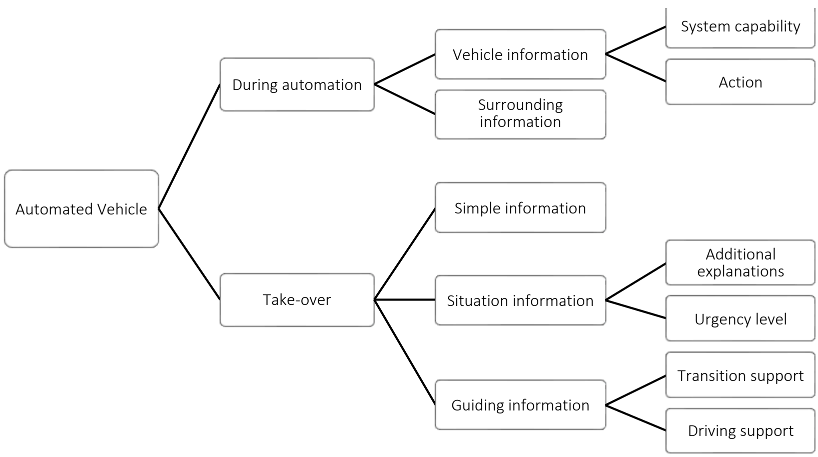


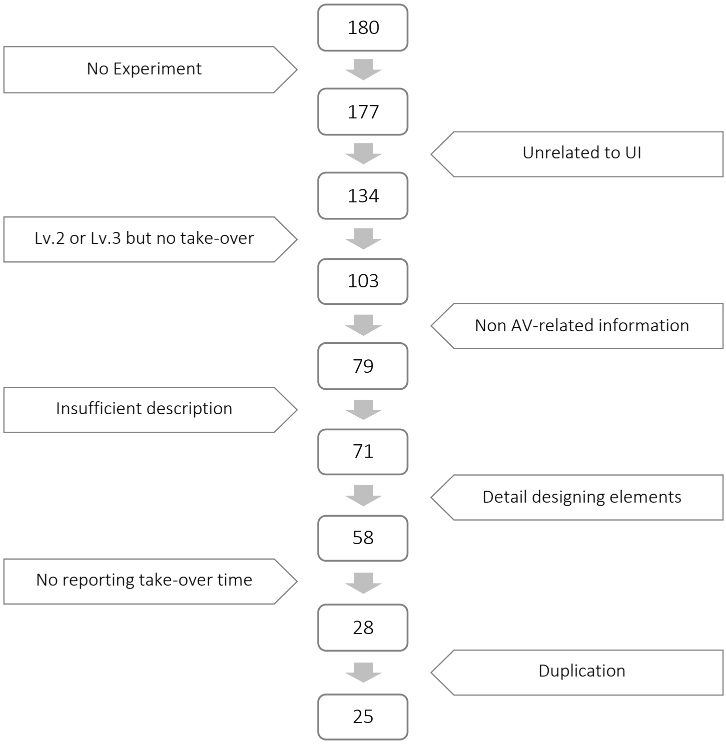
Figure 2.1. UI categorisation from an AV information perspective

2.2 Materials and Methods

We conducted a literature search on publications from 2013 through 2020 evaluating user interfaces in take-over situations. We were looking for papers that met detailed criteria covering ‘interfaces’ affecting ‘transition performance’ in ‘automated vehicles’. To reduce to full scanning papers, we searched directly or found relevant papers from a few papers that met our criteria. Searches were performed using Google Scholar and ScienceDirect (Elsevier), selecting keywords, titles and abstracts. In Google Scholar, ‘cited by’ was also used. In addition, we scanned the reference lists of selected papers. We used the following keywords: ‘take-over’, ‘take-over request’, ‘TOR,’ or ‘transition of control’ combined with user interfaces and automated vehicles. The review included only published journals and conference proceedings.

For selection, studies had to meet the following criteria:
• The study covers SAE level 3 or higher (i.e., conditionally automatic driving, highly automated driving).
• The study includes transitions of control from automated mode to manual mode.
• The study includes experiments with human participants in a real vehicle or a driving simulator.
• The study includes a change in the user interface that carries the TOR, such that the effectiveness of the UI can be quantified.
• The study includes objective data on take-over time after take-over requests (where available, we also analysed take-over quality relevant for safety, and we analysed subjective data relevant for UI acceptance).

Thousands of papers met criteria 1-3, but criteria 4 and 5 were highly restrictive resulting in 180 papers selected for further review (Figure 2.2). Reviewing the full text, 155 papers were removed for the following reasons: no experiment (3 papers), unrelated to UI (43 papers), only level 2 (16 papers), level 3 but no take-over (11 papers) or for mode recognition between level 3 and other levels (4 papers), no AV-related information in the UI (i.e., tutoring, general warning) (24 papers), insufficient description of experimental conditions (8 papers), focus on detail designing elements rather than providing contents itself (i.e., seating pattern, auditory type, message sentence) (13 papers), no take-over time (30 papers). Three remaining papers were excluded as duplications, considering that the same author made similar experimental designs on the same interface element. So, in the end, twenty-five papers met our criteria (Table 2.2). These remaining studies were only performed in driving simulators, and not in real vehicles.



Figures 2.2 Selection process of twenty-five papers

We systematically classified the experimental conditions and findings, including effect direction, size and statistical significance. Conditions were classified regarding driver characteristics, experimental set-up, automation system, user interface, and transition scenario. Transition performance was classified by take-over time and quality (Table 2.1). The take-over time is measured from the TOR start to measurable driver reactions and the take-over quality measures how well the transition is performed and implies potential driver danger (Kerschbaum et al., 2014). We also classified subjective measures of driver trust and driver attention, and objective measures of situation awareness (e.g., awareness of other vehicles).

Table 2.1 Constructs and their definitions of the two categories take-over time and take-over quality defining take-over performance

Category	Definition
Take-over time*	
First gaze time	Driver redirects gaze to the forward road
Hands-on time	Driver has hands on the steering wheel
Press button time	Driver presses a specific button
Intervention time	Driver initiates the driving action such as pressing the brake pedal or turning the steering wheel >2 degree
Driving task time	Driver finishes a driving task such as a lane change
Take-over quality	
Time to collision	Minimum time towards a forward hazard (minimum distance divided by relative speed)
Lane positioning	Vehicle lateral movement deviation after TOR (Standard deviation of lane position)
Lateral position change	Maximum lateral acceleration / Steering wheel angle
Longitudinal position change	Maximum longitudinal acceleration/Average deceleration

*Note. * Take-over time was measured from the start of the TOR*

Information presented by UI was classified in terms of when, how and what, according to Figure 2.1. Regarding timing (when), we discriminate information preceding the TOR, the actual TOR signal and guiding information following the first TOR signal. We do not focus on the time budget between TOR and the system limit, as this has been well addressed in other reviews (Gold et al., 2013; Zhang et al., 2019).

2.3 Results

We analysed twenty-five papers (Table 2.2) that addressed the driver's performance and the user interface (UI) role in transitions of control. The papers addressed the following single or multiple aspects of user interfaces: Ten papers studied the effect of the information channel on the take-over requests (TOR) channels via visual, auditory, or tactile modality, including two papers that studied TOR on the device used by the driver in non-driving related tasks (NDRT) (Simple information); two papers investigated benefits of an explanatory message following an abstract auditory TOR (Situation information – Additional explanations); two papers studied benefits of TOR signals with different levels of urgency (Situation information - Urgency level); four papers presented vehicle information such as system capability and vehicle's action (Vehicle information – Vehicle action/system capability); three papers studied surrounding information during automated driving (Surrounding information); eight papers provided driver transition guiding information, including four papers using AR (Guiding information). In the twenty-five papers, twenty-seven results of UI variations were described in terms of take-over time. When there were two different types of take-over time results, if one type was significantly reduced and the other non-significantly reduced, we counted this as a positive result.

The twenty-seven results include seventeen cases where the reaction time decreased significantly; three cases where the reaction time was increased significantly, and eight cases with non-significant effects. In the three cases with increased reaction time, a visual text or icon was added to an auditory-only TOR in two cases, and one case added augmented reality to a tactile-only TOR. Five studies evaluated the effects of UI on situation awareness; four studies provided vehicle and surrounding information during automated driving; one study presented TOR via different channels. Channels are types of communication that are basically human senses, and each of the different independent single channels is called a modality (Karray et al., 2008). All five studies showed that advanced UI helped drivers be aware of the driving situation, where effects were significant in four out of five studies. The selected papers evaluate UI, including auditory, visual and tactile modalities. Auditory is the key TOR modality and was present in at least one condition in twenty-one papers. Tactile is used in ten papers and visual in twenty papers, where visual was in a heads-up display (HUD), instrument panel, mid-console display or NDRT.

Information complexity varied from single beeps to complex contextual information shown in HUD, including augmented reality (AR). We divided the UI into simple signals' and 'complex signals' according to the information type. Simple signals present alarms, while complex signals provide contextual information and guidance.

Table 2.2 UI Category and take-over performance reported in literatures

No.	Study	N	NDRT	UI Category	Dependent factor
1	*(Borojeni et al., 2016)*	21	Tablet 1-back task	Guiding- Driving support	Intervention time
2	*(Cohen-Lazry et al., 2017)*	16	Game	Surrounding, Vehicle- Action	Intervention time
3	*(Cohen-Lazry et al., 2019)*	27	Game	Guiding – Driving support	Intervention time
4	*(Eriksson et al., 2019)*	25	Game (tablet)	Guiding – Driving support (AR)	First gaze time, Hands-on time, Intervention time, Driving task time
5	*(Forster et al., 2017)*	17	Reading a magazine	Situation – Additional explanations	Frist gaze time, Hands-on time, Press button time
6	*(Helldin et al., 2013)*	57	Read paper of eat sweets	Vehicle – System capability	Intervention time
7	*(Köhn et al., 2019)*	53	Passive task (Watching) Active task (Little man task)	Surrounding	Intervention time
8	*(Kunze et al., 2019)*	34	Searching (tablet)	Vehicle – System capability	Intervention time, Lateral position change, Longitudinal position change

9	*(Langlois & Soualmi, 2016)*	26	Video Game	Guiding – Driving support (AR)	Hands-on time, Press button time, Intervention time, Lateral position change Longitudinal position change
10	*(Lindemann et al., 2019)*	18	Game (tablet)	Guiding – Driving support (AR)	Intervention time, Lane positioning, Lateral position change
11	*(Lorenz et al., 2014)*	46	Surrogate Reference Task (Center console)	Guiding – Driving support (AR)	First gaze time, Hands-on time Intervention time, Lane positioning Lateral position change, Longitudinal position change
12	*(Melcher et al., 2015)*	44	Game (smart phone)	Simple information	Intervention time
13	*(Naujoks et al., 2014)*	16	Reading magazines	Simple information	Hands-on time, Lane positioning, Lateral position change
14	*(S. M. Petermeijer et al., 2017)*	18	N-back task	Simple information	Hands-on time, Intervention time, Driving task time, Lane positioning, Lateral position change
15	*(S. Petermeijer et al., 2017)*	101	Reading / Calling/ Watching	Simple information	First gaze time, Intervention time, Driving task time, Lane positioning, Lateral position change
16	*(Politis et al., 2015)*	21	Game (tablet)	Simple information, Situation – Urgency level	Press button time, Lane positioning
17	*(Razin et al., 2018)*	30	-	Simple information	Intervention time
18	*(Roche & Brandenburg, 2018)*	52	Game (tablet)	Situation – Urgency level	Intervention time
19	*(Roche et al., 2019)*	40	Game (tablet)	Simple information	Intervention time, Time to collision Lane positioning, Lateral position change
20	*(Telpaz et al., 2015)*	26	Texting	Guiding – Driving support	Intervention time, Driving task time
21	*(van den Beukel et al., 2016)*	37	Watching, Reading	Simple information Situation – Additional explanations	Intervention time, Time to collision
22	*(White et al., 2019)*	49	Chosen activities	Vehicle – System capability, Guiding – Transition support	Intervention time, Lane positioning
23	*(Wintersberger et al., 2018)*	18	Texting	Simple information	Intervention time, Time to collision
24	*(Yang et al., 2018)*	50	Smart phone	Surrounding Vehicle – Action	Intervention time, Time to collision, Lane positioning Lateral position change, Longitudinal position change
25	*(S. H. Yoon et al., 2019)*	20	No-task/Calling / Smart phone / Video watching	Simple information	Hands-on time, Press button time

2.3.1 TOR Channel & Simple signals

At SAE Level 3, one of the key design issues is which modality is used for TOR (Seppelt et al., 2016). Seven studies investigated the effects of a single modality or multiple modalities (Table 2.3). Three papers studied modality effects on reaction time (S. Petermeijer et al., 2017; Politis et al., 2015; S. H. Yoon et al., 2019); two papers investigated the effects of using both auditory and tactile signals to complement the visual modality (Naujoks et al., 2014; Razin et al., 2018); two papers identified the effects of adding visual and tactile signals to the auditory modality (Roche et al., 2019; van den Beukel et al., 2016). Modality-related studies show the following trends. First, TOR only presented as a visual signal yielded the longest take-over time. Auditory signals are effective to decrease the reaction time. Finally, multi-modal TORs do not necessarily lead to faster reaction times. Take-over time and significant differences in the modality-related studies are shown in Table 2.3.

Table 2.3 Take-over time of Modality studies (times are given in seconds)

Study	NDRT	Dependent factor	Visual (V)	Auditory (A)	Tactile (T)	A+V	A+T	T+V	A+T+V	Significant difference
(S. Petermeijer et al., 2017)	Reading / Calling/ Watching	First gaze time	1,94	1,57	1,44					A<V / T<V
		Intervention time	2,29	1,54	1,47					A <V / T <V
(Politis et al., 2015)	Tablet Game	Mean Press button time	6,91	2,24	2,85	2,12	2,32	2,37	2,21	A,AT,AV,TV,ATV<T<V
(S. H. Yoon et al., 2019)	Watching	Hands on time	1,84	1,61	1,64	1,3	1,3	1,54	1,26	A,T,AV,AT,VT,AVT < V
		Press button time	2,42	2,23	2,18	1,97	2,05	1,88	1,95	A,AV,AT,VT,AVT < V
(Naujoks et al., 2014)	Reading	Hands on time	6,19			2,29				AV < V
(Razin et al., 2018)	-	Intervention time	9,46			3,84			5,64	No mention but seems like
(Roche et al., 2019)	Tablet game	Intervention time		3,24		4,61				A < AV
(van den Beukel et al., 2016)	Watching / Reading	Intervention time		4,32		4,88 (Visual : icon)			5,31 (Visual : light)	A < AV

Several studies (Naujoks et al., 2014; S. Petermeijer et al., 2017; Politis et al., 2015; Razin et al., 2018; S. H. Yoon et al., 2019) concluded that visual-only TOR should be avoided for safety, given that TOR with visual-only signals yielded the longest take-over time. In Politis et al. (2015), visual-only TOR was more than 4 seconds slower than single tactile and auditory.

Lane positioning was also poor with visual-only TOR (Naujoks et al., 2014; Politis et al., 2015). When adding auditory signals to visual-only TOR, take-over time was reduced by more than 50% from 6.19 seconds to 2.29 seconds and 9.46 seconds to 3.84 seconds, respectively in Naujoks et al. (2014) and Razin et al. (2018). In Naujoks et al. (2014), participants were reading magazines. Whereas, in Razin et al. (2018), it is not mentioned what participants were doing during automated driving. On the other hand, adding visual signals to auditory TOR made the take-over time significantly longer in two studies (Roche et al., 2019; van den Beukel et al., 2016). However, no significant difference in take-over time was found in other single modality and multi-modality comparisons (S. Petermeijer et al., 2017; S. H. Yoon et al., 2019) and combining all three modalities did not always yield the fastest take-over time (Razin et al., 2018; van den Beukel et al., 2016).

In Level 3 or 4 automated driving, drivers will not always monitor the driving task but will perform NDRT such as reading, texting or gaming on smartphones or integrated information system. Several studies integrated TOR messages in NDRT devices. However, UI that presented visual TOR to NDRT devices did not significantly affect the take-over time when auditory TOR were also presented (Melcher et al., 2015; Wintersberger et al., 2018). In Melcher et al. (2015) when the TOR was presented only through instrument panel and audio, the reaction time was 3.78 seconds, and it decreased to 3.44 seconds with TOR provided on a smartphone but this improvement was not-significant. However, the driver's subjective trust increased when providing TOR to NDRT (Wintersberger et al., 2018). It can be beneficial to provide TOR using modalities not used in the NDRT. However, no significant benefits were found in terms of take-over time (S. Petermeijer et al., 2017; S. H. Yoon et al., 2019).

Tactile TORs have the advantage of delivering stimuli to channels which are unused in monitoring automation or NDRT. Tactile TOR studies focused on seating vibration rather than steering wheel or pedal vibration since the higher the automation level, the lower the driver's steering wheel and pedal usage (S. Petermeijer et al., 2017; S. M. Petermeijer et al., 2017; Telpaz, 2015). Tactile TOR yield similar reaction times as auditory TOR (S. Petermeijer et al., 2017; S. H. Yoon et al., 2019). However, in some combinations with other modalities, adding seating tactile stimuli results in an insignificant effect or counter-productive effects (Razin et al., 2018; van den Beukel et al., 2016).

Modality directly affects the initial reaction time, such as hands-on time or first gaze time. However, the effects of modality on reaction time decrease in the later stages of transitions and when more time budget is available (S. Petermeijer et al., 2017).

The above results review simple signals and their effectiveness to elicit timely initial reactions. Advanced UI can further support the driver, as detailed below.

2.3.2 Complex Signals & Contextual Information

Drivers receive information not provided in conventional vehicles when sharing the driving role with the AV. Based on information presented in previous studies, we categorise UI information in AV in Figure 2.1 and Table 2.4. The information delivered during automated driving includes vehicle and surrounding information. Vehicle information provides feedback for drivers to be aware of the mode and their own vehicle's technical status. Surrounding status information helps drivers notice the traffic state and road hazards. This information help drivers stay 'in the loop' even during automation. Therefore, it eventually affects the transition response time and quality.

Table 2.4 Example information types in advanced UI

When	Information	Example	Related Study
Automated driving	Vehicle system capability	- Display the sensor detection accuracy level	*(Helldin et al., 2013) (Kunze et al., 2019) (White et al., 2019)*
	Vehicle action	- Alert "Increasing speed to 130km/h" - Display intended lane change direction	*(Cohen-Lazry et al., 2017) (Yang et al., 2018)*
	Surrounding	- Display the surrounding view or hazards - Alert "Vehicle approaching from behind"	*(Cohen-Lazry et al., 2017; Köhn et al., 2019) (Yang et al., 2018)*
With TOR	Additional explanations	- Alert "Unclear lane ahead, please take over soon" - Display 'Steering wheel holding' symbol with TOR - Display a danger point motivating the TOR in AR	*(Forster et al., 2017) (van den Beukel et al., 2016)* *(Eriksson et al., 2019; Langlois & Soualmi, 2016; Lindemann et al., 2019; Lorenz et al., 2014)*
	Urgency level	- High urgency : Alert "Danger! Collision Imminent, You have control!" - Low urgency : Alert "Notice! Toll ahead, Want to take over?"	*(Politis et al., 2015) (Roche & Brandenburg, 2018)*
	Transition support	- Display "Check for hazards" message	*(White et al., 2019)*
Right after TOR	Driving support	- Directional steering light indicating lane change direction - Display lane to be changed in AR	*(Borojeni et al., 2016) (Telpaz et al., 2015)* *(Eriksson et al., 2019; Langlois & Soualmi, 2016; Lindemann et al., 2019; Lorenz et al., 2014)*

Vehicle system capability

Awareness of the system capability is essential for drivers to gain understanding of the current situation (McGuirl et al., 2006). Since Level 2 systems require drivers to resume instant control, it is an important design problem to provide sufficient feedback to prevent overtrust in the automation (Seppelt et al., 2016). In Level 3 automation, drivers are not expected to monitor the driving environment but should respond when the vehicle requests a transition of control. Therefore, sufficient system feedback is required to enable drivers to recognise the automation status for safe driving.

In previous work, the automation system's state was presented with seven levels of capability (Helldin et al., 2013), or the level of uncertainty was indicated as a heart-beat animation with a numerical display (Kunze et al., 2019). In addition, another study system sensing capabilities and external hazards were presented on a centre console tablet using icons of different colours (White et al., 2019). Take-over times were reduced significantly (Helldin et al., 2013; White et al., 2019) or reduced but not significantly (Kunze et al., 2019) when automation system states were provided. System feedback improves driver readiness, which supports uncertainty information for transition readiness (Ekman et al., 2015). Interestingly, displaying system capability reduced the subjective trust that drivers perceived using the system when visibility range was short because of snow or fog (Helldin et al., 2013). It seems to be a series of processes in which system feedback affects trust and trust affects driver behaviour.

Vehicle action

Cohen-Lazry et al. (2017) communicated vehicle's actions and information on the perception of surrounding vehicles on a gaming device. The difference in TOR reaction time was not significant when action and/or perception information was provided. When vehicle action information was provided, the glance ratio (the number of glances made in reaction to the information relative to the number of total information) was only about two out of ten. With surrounding vehicle information, the glance ratio was about eight out of ten. Since drivers expect the vehicle to drive autonomously until the vehicle requests take-over at Level 3, vehicle action information seems to not very effective in attracting the driver's attention.

Surrounding

Drivers can identify the surrounding status by windows, mirrors, cameras, and sensors. However, since the situation awareness decreases during automated driving, it can be beneficial to inform drivers of surrounding information using additional stimuli. When watching a movie was interrupted showing the driving forward scene every 30 seconds, the driver's take-over time was shortened, and situation awareness was significantly increased (Köhn et al., 2019). On the other hand, when surrounding road information such as approaching vehicles was provided, the road glance ratio was increased, but take-over time was not affected (Cohen-Lazry et al., 2017). The author interpreted that the information assisted the perception, which is the first stage in rebuilding situation awareness, but did not support the comprehension and projection stage. Furthermore, the demonstrated benefits may be simply related to the interruption of NDRT which directly encourages the driver to redirect attention towards the road. In Yang et al. (2018), the vehicle's intention (vehicle action) and detected potential hazard (surrounding) were displayed using ambient light. The effect of each information type was not studied separately. The number of road glances increased, but the mean glance duration was not affected. However, trust was increased. Take-over time was also reduced, although not statistically significant.

TOR additional explanations

TOR generally provide simple warning signals, such as beeps or lights, but can also include additional information. For example, speech explaining what to do after a warning signal has been referred to as a header sound (Heydra et al., 2014). Visual displays can provide similar textual information or icons. Drivers' reactions were changed when TOR was presented with the explanation of the take-over situation. Comparing auditory beeping TOR to adding speech explanation, there was no significant difference in the first gaze reaction time, but speech explanations reduced hands-on time. Explanations also significantly improved subjective satisfaction and usefulness (Forster et al., 2017). On the other hand, when a single auditory TOR was accompanied by a visual explanation holding the steering wheel, the take-over time was longer (van den Beukel et al., 2016). The author interpreted this as an increased processing time for the additional TOR information. Such an increased take-over time can be detrimental in time-critical situations but can also signify better rebuilding of situation awareness and preparation for the transition of control.

Urgency level

High urgency TOR can reduce reaction time but there may be side effects such as cognitive load and decreased response accuracy. TOR's urgency level can also be included in the header sound if appropriately designed. Providing different speech wording and tactile stimuli at different levels of urgency reduces take-over time (Politis et al., 2015). However, the number of take-over reactions to TOR was reduced, with drivers failing to take back to control occasionally, and lateral deviation after transition was increased. It was found that the effects of TOR urgency level on take-over time were not significant when drivers perceived a high risk of a situation. When the time budget was 7 seconds, the take-over time was faster at the high urgency level TOR. However, the TOR urgency level's effect on drivers' reaction time was insignificant when the time budget was 3 seconds. Also, the satisfaction level was better with the long time budget (Roche & Brandenburg, 2018).

Guiding information

Guiding information includes transition support and driving support. Transition support suggests safe transition behaviour. When drivers received a message to check for hazards during the transition, it did not affect the take-over time but led drivers to check the road risk using mirrors (White et al., 2019). Driving support information helps to elicit desired manual driving behaviour immediately after the transition. With an auditory TOR, the steering wheel control time was faster when the desired steering direction to change lanes was indicated by ambient lighting than with steering wheel illumination without directional information (Borojeni et al., 2016). Similarly, when using directional seat vibration TOR to guide lane change direction, steering-wheel control time was shortened compared to non-directional TOR. Also, the lane change direction accuracy was increased (Cohen-Lazry et al., 2019). In addition, lane change time was reduced by seat vibration, indicating the approaching vehicle's direction. This also increased the percentage of road safety checks by mirrors (Telpaz et al., 2015).

AR – Situation & Guiding information

Head-up displays (HUD) support drivers to keep an eye on the road by displaying information on the windshield. With HUD, the vehicle provides visual aids and annotations necessary to carry out the driving task. Augmented reality (AR) extends the three-dimensional world by matching the drivers' real-world with information displayed on the windshield. Therefore, it allows information that is helpful for object detection, analysis, and reaction mapped to the real context depending on the drivers' situation (Pauzie & 2015). During the transition, AR provides additional explanations of situations and guiding information that supports manual driving. It helps drivers rebuild situational awareness and perform safe driving. Intervention time showed no significant difference between with and without AR (Eriksson et al., 2019; Langlois & Soualmi, 2016; Lindemann et al., 2019; Lorenz et al., 2014). With auditory TOR (Langlois & Soualmi, 2016; Lindemann et al., 2019; Lorenz et al., 2014) or seating tactile TOR (Eriksson et al., 2019), adding AR visual information does not seem to affect the initial reaction. However, although the factors used to evaluate the take-over performance vary from study to study, AR visual information affected the driving behaviour after the transition (Eriksson et al., 2019; Langlois & Soualmi, 2016; Lindemann et al., 2019; Lorenz et al., 2014). The information provided in the AR of each paper is shown in Table 2.5. 'Present the danger' indicates the road's risk factors that made the transition. 'Guide the manual driving' is information that helps manual driving, such as carpet trajectory or arrow direction.

Table 2.5 AR information

	AR UI	Present the danger	Guide the manual driving
(Lorenz et al., 2014)	AR Red	O	-
	AR Gree	-	O (Carpet trajectory)
(Langlois & Soualmi, 2016)	AR	-	O (Arrow direction)
(Eriksson et al., 2019)	Sphere condition	O	-
	Carpet condition	-	O (Available road)
	Arrow condition	-	O (Arrow direction)
(Lindemann et al., 2019)	AR	O	O (Carpet trajectory)

Lorenz et al. (2014) used AR red, highlighting a red corridor showing a risk location, and AR green representing a green road surface where lane changes should be made. As a result of the reaction type, 80% of the AR absence participants only controlled the steering wheel during the transition, while approximately 50% of AR red and AR green participants used both the steering wheel and the braking pedal. In other words, drivers using AR performed safer transitions than without AR. According to this study, the framed information affects the take-over behaviour differently when providing AR. 25% of participants stopped using brakes and did not change lanes in AR red, while there were no participants who stopped using only brakes in AR green. Besides, no AR red participants checked the corridor beside the vehicle during lane change. All AR green drivers drove around the obstacle with very similar tracks along the recommended corridor. It seems drivers regard 'AR red' as a warning and 'AR green' as a recommendation where AR green has a positive effect on the transition, such as safe lane changes and similar road trajectories.

Langlois and Soualmi (2016) provided situation and guiding information as AR in scenarios of lane changes on highways or exits and analysed the take-over quality with longitudinal control and distance to the manoeuvre limit point. With AR, participants adapted well to the slow traffic of the destination lane, resulting in less sharp longitudinal control compared to the control group. The distance to the manoeuvre limit point with AR was also significantly longer than without AR, except for one scenario with a distance limitation because of highway exit size.

AR seems to be particularly effective in situations with a sufficient time-budget. In a scenario where lane change distance was not limited, the distance to the manoeuvre limit point was more prolonged than in scenarios where change distance was limited. AR's situation information helps drivers understand the situation, but drivers need time to process the AR (Lindemann et al., 2019). In other words, providing peripheral information with AR seems to be positive in situations when time is sufficient for drivers to make a decision. Therefore, it may be more useful to provide direct warnings or intuitive guides in an urgent situation than to explain the surrounding situation.

Lindemann et al. (2019) used AR to provide situation and guiding information in transitions of control due to a construction site, system failure, and traffic rule ambiguity. In scenarios requiring steering control after transition, lateral deviations were reduced with AR. The information provided by AR seems to help drivers understand the situation, which is also supported by subjective evaluation results. Understanding the situation can elicit smooth manual driving in situations where steering control is required.

Eriksson et al. (2019) identified AR information's impact with 12 seconds time-budget before a collision with the front vehicle after the transition of control. If there is sufficient distance from the next lane's coming vehicle, drivers should change the lane; otherwise, drivers should use the braking pedal to slow down. Three AR displays were compared to a baseline without AR. One AR shows the front slowly moving vehicle using a sphere sign, and colour carpets or arrows guide the others. Although there was no significant difference in the initial reaction, the driving task time, such as lane change and braking time, was reduced by the carpet and arrow AR. The arrows guide more directly so that braking time is shorter than with the carpet AR.

Hence, we conclude that AR does not significantly affect drivers' initial take-over time. However, AR enhances the drivers' situation awareness and helps drivers' decision-making process after the transition. To design the AR in AV, it is necessary to adapt AR information to the circumstances since the impact on drivers' behaviour varies depending on the road situation and framed information.

2.4 Discussion

This paper reviewed the literature for empirical studies on user interface (UI) affecting automated vehicle take-over performance. Most studies showed positive effects of advanced UI, but quite some studies show no significant benefits and a few studies show negative effects. The occurrence of positive and negative results of similar UI concepts in different studies highlights the need for systematic UI testing across driving conditions and driver characteristics.

Take-over time is a prominent dependent factor in the study of performance as an apparent numerical result. However, take-over time is not sufficient to predict safety. Considering drivers' non-driving related tasks (NDRT) in Level 3 and higher, first-gaze time, hands-on time, and intervention time represent the take-over requests (TOR) detect reaction, the NDRT interruption, and the start of manual driving, respectively. However, none of these measures quantifies how well drivers regain situation awareness and are the 'in-the-loop'. Take-over UI design needs to ensure that drivers take-over safely within time budget not aiming at only reducing the take-over time. In general, a shorter take-over time is seen as positive, but it can also result from drivers acting before they have sufficient situation awareness. Hence, a somewhat longer take-over time with an advanced UI can actually present a safer transition (Langlois & Soualmi, 2016). Therefore, future studies shall jointly evaluate take-over time and quality to predict safety in TOR. In addition, trust shall be analysed, including both distrust and overtrust in automated vehicles (AV). Even though take-over time was reduced with advanced UI, trust was increased in one study (Wintersberger et al., 2018) or decreased in another study (Helldin et al., 2013). Overtrust may delay the driver's control in situations requiring driver intervention (Miller et al., 2016). Reducing trust in AV seems negative in terms of numbers but positive in terms of calibrating trust. Future work is needed to correct subjective drivers' factors, such as trust or perceived risk using UI.

It can be considered that unnecessary or overloaded information led to non-significant differences or a negative result on the driver. The higher the level of automation, the less effective it seems to be to implement continuous feedback (Norman & 1990). In addition, contextual information in urgent situations may not be helpful in the handling of urgent driving tasks. Although not all studies show significant positive results, we identify the following benefits of well-designed advanced UI in AV:

- Allow drivers to enjoy AV's advantages while maintaining situation awareness (SA) during automated driving.
- Present clear alerts, allowing drivers to easily understand the situation and enhance SA quickly when resuming control.
- Guiding information improves manual driving performance after transitions.

To improve take-over performance, the level of situation awareness needs to be increased. However, considering that there are 3 stages (Perception, Comprehension, and Projection) of SA (Endsley & 1995a), the signals may only assist in the perception phase. Therefore, the driver's SA support by providing information over the UI is suggested to supplement the limitations of the TOR perception step. Supporting to keep the level of SA from decreasing even before the take-over and speeding up the awareness of the situation after perception TOR will enable safe driving by reducing the SA gap between automated and manual driving.

During automated driving at Level 3 or higher, the driver does not have to monitor the automation. At Level 3 or higher, drivers can perform NDRT. Therefore, the feedback of the vehicle may not always affect the SA process. Some information may end at the perception level. The road glance ratio of providing vehicle action information was very low (Cohen-Lazry et al., 2017). However, drivers shall be ready to resume control when requested. Vehicle and surrounding status information may also prevent the drivers' over-trust (in Level 2) or under-trust (in Level 3 and higher). Status information allows drivers to understand the driving situation, but further research is needed on the effects of UI on trust in automation.
When TOR are presented, drivers detect the request, stop the NDRTs, become aware of the situation, and conduct the driving task. Modality and urgency levels affect TOR perception, which leads to the initial reaction. Modality stimulates drivers to detect requests. The urgency level describes the situation, incorporated into the TOR signal itself, allowing drivers to perceive an urgent TOR rather than assisting the drivers' situation awareness. It means that there is a limit to what affects the drivers' safe take-over performance. After TOR perception, drivers need time to figure out why the transition should be made and what driving tasks should be carried out. Situation explanation is expected to help drivers become aware of the situation quickly. While the effectiveness of providing explanations using auditory modalities has been demonstrated, in case of presenting visually, further verification is required as one study found longer take-over times without measurable SA improvement (van den Beukel et al., 2016).

After the TOR, transition support information leads to safe transition behaviour, and driving support information helps manual driving. AR is useful in that it can project the guiding information directly to the actual road screen. However, the information may require additional cognitive work by drivers. Some advanced UI and multimodal UI even induced slightly higher intervention times, so it seems necessary to be careful in certain situations and drivers' workload.

There are a few things to be particularly careful about designing an AV UI. Information should be accurately communicated to drivers. In AV, sharing the driver's role with the vehicle reduced the driving burden, but leads to more complex interaction between the driver and the vehicle. Since multiple information types are delivered in various ways, the interface should align with the drivers' understanding. For example, reaction time at transition was not significantly shortened when the system state was provided by various colour changes in the ambient lighting (Yang et al., 2017). This was caused by the experiment participants' misunderstanding of the interface.

NDRT devices are an important UI in automated vehicles. Several studies successfully integrated TOR in NDRT devices and showed beneficial effects on acceptance but no significant effects on intervention time. Safety shall have the highest priority, but the drivers' secondary task's usability shall also be considered in the UI design. Therefore, rather than unconditionally blocking the drivers' NDRT, it seems reasonable to provide the driving situation and vehicle information to the device or to present the TOR. It can help to enhance SA and building trust. If blocking NDRT devices are considered, it is necessary to study whether device blocking affects fast transitions in emergency situations.

There are several limitations of previous research that should be mentioned. First of all, simulation scenarios vary from study to study, making it difficult to generalise results. There are many variables in various transition scenarios and limited scenarios in the reported experiments could not cover all transition situations. Different scenarios may not have the same results when the results of one study are applied to another. Our review has shown conflicting results where similar UI concepts show apparent benefits in some papers, while benefits are not significant or even significant negative effects are found in other papers or in other conditions in the same paper. Driver's transition behaviour reacts differently depending on the time budget (Gold et al., 2013), traffic (Gold et al., 2016) and secondary task (Sol Hee Yoon et al., 2019) and these differ between papers. These differences may well explain the reported conflicting results. For example, adding auditory modality to the visual-only TOR showed time reduction (Naujoks et al., 2014; Razin et al., 2018) or non-significant difference (Politis et al., 2015). Even within one study (Langlois & Soualmi, 2016), AR's effects vary depending on the take-over situation. Hence, we recommend that future research and product developments need to evaluate a wide range of scenarios covering the essential factors across a range of conditions representing real world driving.

Furthermore, there was a limit to analysing how UI elements affect drivers due to different definitions of take-over time by the author. Looking ahead and controlling by turning the steering or pushing the brakes are different reactions. It is recommended that at least intervention time, rather than first gaze time, should be measured in order to check the driver's take-over. Measuring the take-over quality together is also suggested, since situation awareness cannot be identified by take-over time. In this review, take-over quality and attention analysis were relatively insufficient since most studies focus on take-over time.
With the development of AV, we see drivers being relieved of the manual driving task, but we also see an increase of information needed by drivers, before, during and after TOR. The resulting gap between driver safety and usefulness can be narrowed by advanced UI.

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CHAPTER

3

Interaction Challenges in Automated Vehicles with Multiple Levels of Driving Automation - an On-Road Study

This chapter is under review for publication:
Kim, S., Novakazi, F., & Karlsson, M., Interaction Challenges in Automated Vehicles with Multiple Levels of Driving Automation – an On-Road Study, Submitted to Transportation Research Part F: Traffic Psychology and Behaviour.

Abstract

With the increasing adoption of driving automation technologies, vehicles equipped with SAE Level 3 driving automation are becoming available on the market. Integrating multiple levels of driving automation within a vehicle highlights the importance of designing driver-vehicle interactions. In this study, sixteen participants drove a Wizard of Oz vehicle offering several levels of automation (SAE Level 1, Level 2, Level 3) on a public highway. During the driving sessions, they experienced two different audio-visual UIs. Data was collected during driving sessions (observations and think-aloud data) and post-driving sessions (personal interviews). Irrespective of UI, use errors were observed regarding mode transition and mode awareness. Implications for UI design could be extracted on how to support mode transition and reduce mode confusion through proper cues and feedback. However, the design of automation functions in terms of mode transition logic also contributed to drivers' mode confusion. More importantly, drivers exhibited a lack of understanding about the system, impacting their way of interacting with the system, interpreting, and responding to the information provided in the UIs. The study contributes valuable insights into designing user interfaces for Level 3 automation vehicles to improve mode awareness and trust.

3.1 Introduction

Automated vehicles have the potential to improve road safety by supporting or supplementing the driver in various situations ranging from normal driving to safety-critical events. Level 1 driving assistant systems, such as systems that provide steering or acceleration and braking support to the driver, such as adaptive cruise control (ACC), have become standard. Level 2 partial driving automation systems – systems that assist the driver with lateral and longitudinal control within predefined circumstances – are also widely available. However, with the rapid advancement of automation technologies, the market is witnessing the emergence of vehicles equipped with SAE Level 3 driving automation (Greimel, 2022; Tarantola, 2023). In other words, systems that can drive the vehicle under certain conditions (SAEInternational, 2021). Level 3 driving automation represents a significant step forward by enabling vehicles to assume full control of driving tasks, provided the necessary prerequisites are met. Compared to Level 2 partial driving automation, drivers with access to Level 3 driving automation are no longer obliged to monitor the system constantly. They can, therefore, engage in non-driving-related activities. However, drivers must still be able to take control of the vehicle at any time when requested by the system, or in the case of an emergency due to system failure.

Although it is argued that automated systems have the potential to increase road safety (Cicchino, 2017), several human-factor challenges must be addressed. These challenges include such things as the driver misunderstanding or misusing the system (Trimble et al., 2014); the driver being unable to provide suitable fallback performance (meaning that, with improved automation, the driver will pay less attention to surrounding traffic or systems and is hence less capable of resuming control); and the driver not monitoring the driving environment or being aware of the status, or mode, of automation, effectively being ‘out-of-the-loop’ (Seppelt & Victor, 2016).

3.1.1 Mode Awareness and Mode Confusion

Mode awareness comprises knowledge about the currently active automation system, its performance level and the driver’s tasks and responsibilities (Sarter & Woods, 1995). One of the most common reasons for deficient mode awareness is mode confusion, where the driver assumes the automation to be operating in a different mode than it is and thus reacts incorrectly (Bredereke & Lankenau, 2005). Mode confusion occurs when there is a mismatch between system behaviour and users’ mental models (Halasz & Moran, 1983). Mode confusion contributes to the occurrence of mode errors, resulting in users misinterpreting the information being provided and performing actions which are appropriate to the analysis of the situation but inappropriate to the actual situation (Norman, 1981).

Substantial research has been conducted into mode confusion and the resulting ‘automation surprise’ experienced by users of automated systems (Sarter & Woods, 1995). Early studies on mode confusion in vehicle automation focused on ACC systems; that is, Level 1 automation (Eom & Lee, 2015; Lee et al., 2014). Based on a driving simulator experiment, Furukawa et al.

(2003) found, for example, that participants failed to infer system behaviour correctly in that, even though the ACC function was active, some participants predicted that the system would not accelerate. Later, the results of studies of drivers' interaction with Level 2 automated vehicles reported similar confusion (Banks et al., 2018; Endsley, 2017; Wilson et al., 2020). For instance, Wilson et al. (2020) identified situations in which the participants incorrectly thought the vehicle was in the automated mode when it was not and they were, in fact, responsible for primary driving tasks. Similarly, Banks et al. (2018) found that drivers failed to engage an autopilot feature properly and did not understand that the autopilot feature was engaged even though the user interface indicated otherwise. Other examples of drivers' failure to understand system levels, system modes and drivers' responsibilities have been described by Novakazi, Johansson, Erhardsson, et al. (2021) as well as Novakazi, Johansson, Stromberg, et al. (2021). Based on an analysis of interviews with participants in a Wizard-of-Oz field trial, the former found that in Level 2 automated vehicles, the high level of control and the good performance that the system was perceived to have led participants to conclude they were not responsible for the driving task even though they were. Furthermore, it appears that drivers' awareness of the currently active mode is at particular risk when two or more automation levels are available. In a study of higher-level automated vehicles, Feldhutter et al. (2018) found that shifting modes between partially and conditionally automated driving led to a loss of mode awareness and resulted in more mode errors compared to when there was only access to one automation mode.

3.1.2 HMI Design and Mitigation of Mode Confusion

Several researchers have debated the importance of the human-machine interface (HMI) and user interfaces (UIs) as means to support drivers in developing an appropriate understanding of automation and, say, mitigate mode confusion. For instance, Carsten and Martens (2019) have argued that when the driver is decoupled from active control, the design of the HMI becomes even more critical. Seppelt and Victor (2016) disputed the need to design user interfaces to support driver situation awareness and appropriate mental model development to support the transfer of control from a higher to a lower level of automation. Lee et al. (2014) provided more detailed design guidelines by suggesting that mitigating mode confusion means providing the driver with a transparent display of the automation state and correct and concise information via different in-vehicle UIs. However, although the argument is that HMIs or UIs can enhance mode awareness (Carsten & Martens, 2019; Lee et al., 2022; Nordhoff et al., 2023), confusion can occur if the HMI/UI does not provide sufficient feedback about the state of the system, or if drivers fail to perceive or comprehend the automation mode indicated (Monsaingeon et al., 2021).

Several studies have evaluated different UI designs for vehicles offering ACC (Liu et al., 2021; Wang et al., 2020). Another range of studies has investigated the role of HMIs in attention allocation and in specific driving situations, such as requests for take-over reactions when system limits have been reached (Gold et al., 2015; Zhang et al., 2019). However, although such authors as Eom and Lee (2015) underlined the need to develop optimal HMIs for higher levels of autonomous vehicles and vehicles with multiple driving automation modes, there are few studies on drivers' interactions with systems that have several levels of automation. One example is Monsaingeon et al. (2021), who examined the influence of different UI designs on drivers' understanding of Level 2 vehicles (a system including ACC and Lane Keeping Assist, LKA). In this case, one UI provided an exocentric representation of the road scene, while the other provided information on the state of the automation. The results showed that while the exocentric UI aided the driver in comprehending system functionality, both interfaces led to mode confusion. Another driving simulator study of drivers' interaction with a Level 3 automated vehicle Eom and Lee (2022) compared a level-centred UI, which allowed the driver to increase and decrease the level of automation step by step, with a function-centred UI, in which lateral and longitudinal control were turned on and off separately. In this case, the results showed that the instances of mode confusion were twice as high with the level-centred UI as with the function-centred UI.

In summary, as automated vehicle technology advances, the design of effective in-vehicle UIs becomes increasingly important in ensuring safe, efficient and user-friendly interactions with the automated systems. The UI plays a vital role in drivers' interaction with and understanding of vehicle automation, different automated modes and the transition between them. The advent of higher-level vehicle automation adds a further layer of complexity to human-factors design challenges due to different responsibility allocations between automation levels (Kurpiers et al., 2020).

3.1.3 Research Objectives

This paper aims to provide insights into driver-vehicle interaction in automated vehicles, offering multiple driving automation modes in a real-world setting. More specifically, the presented study contributes insights into what role the design of the user interfaces plays in drivers' interaction with a vehicle with several levels of driving automation.

3.2 Methods

To search for the answers, two different user interfaces (UIs) were implemented in a vehicle prototype, simulating Level 2 and Level 3 driving automation and then evaluated in an on-road Wizard-of-OZ (Dahlback et al., 1993) driving study. The study was conducted in September 2022 in Gothenburg, Sweden and was designed to simulate real-world driving scenarios and capture the complexities of human-machine interaction in automated vehicles. The research vehicle used in the study was approved for road usage by relevant authorities and the study design adhered to the ethical principles outlined in the WMA Declaration of Helsinki. All participants provided informed consent, including their agreement to collect various data points and participate in the research project. The collected data's retrieval, storage and processing strictly followed the European General Data Protection Regulation (GDPR) guidelines.

3.2.1 Participants

Sixteen participants were recruited through a professional recruiting agency, which was provided with a screener. The average age of the participants was 44 (SD = 13.48). Seven participants were women and nine were men. All participants possessed valid driving licenses, regularly drove vehicles equipped with automatic gears and adaptive cruise control and commuted daily by car. None of the participants indicated any occupational involvement in vehicle manufacturing or companies associated with vehicle development.

3.2.2 Vehicle

A modified Volvo XC90 served as the test vehicle and Level 2 and Level 3 driving automation were simulated using the Wizard-of-Oz approach. The experimental setup is shown in Figure 3.1, with the participant in the driver's seat behind the steering wheel, the test leader in the passenger seat and a driving wizard and UI wizard in the back seat concealed from the participant. The back-seat driving wizard controlled the simulated Level 3 driving automation, while the UI wizard controlled the prompts and feedback presented to participants via a visual UI. Furthermore, two cameras were installed: one facing the driver and another facing the steering wheel and controls to capture observation data related to the driver's interaction with the vehicle and the systems.

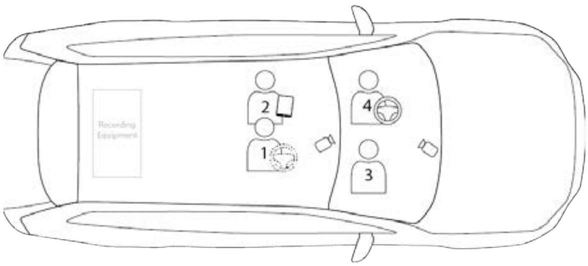


Figure 3.1 The Wizard-of-Oz vehicle, with video cameras facing the UI and (1) driving wizard, (2) UI wizard, (3) test leader and (4) participant.

3.2.3 Driving Automation Operation

During the driving session, participants could engage in three driving modes: manual driving, Level 2 supervised driving automation and Level 3 unsupervised driving automation. Participants operated manual and Level 2 supervised driving automation, while the Wizard-of-Oz vehicle operated Level 3 unsupervised driving automation.

The Level 2 driving automation was a supervised system that provided: a) longitudinal control by maintaining a set speed and adjusting the distance to the vehicle ahead and b) lateral control using lane keeping assist (LKA), automatically adjusting the steering to ensure that travel was within the lane. As it was an assistive system, the driver had to monitor the automation and the road and remain responsible for the driving task. The Level 2 supervised driving automation could be engaged at any time except during Level 3 unsupervised driving automation and participants were encouraged to use it as much as they desired. Participants could activate the Level 2 supervised driving automation by pressing a button on the left side of the steering wheel. The speed of the driving automation could be adjusted using (+) and (-) buttons on the steering wheel but there was no option to change the distance setting. The system could be deactivated by pressing the same button used to activate it, stepping on the brake, or overriding the function by prolonged pressure on the accelerator. Upon deactivation, the vehicle returned to manual driving mode. In certain driving conditions where the LKA function was unavailable (such as when the car could not detect lane markings), the driving automation continued to offer longitudinal control of the vehicle.

The Level 3 unsupervised driving automation was designed to operate without supervision within a specified operational design domain (ODD). It was described as a system that prompted the driver when it was available and requested the driver to take over when the conditional requirements were no longer met. Upon activation, the system assumed complete control of the vehicle until the specified conditions were no longer met. The participants could remove their hands from the steering wheel and engage in non-driving-related tasks. The availability conditions varied based on the external transportation environment and were defined as follows: (1) partially controlled access roads with a speed limit of up to 80 kph; (2) free-flowing traffic with a level of service (LOS) of A-B, triggering the system to prompt takeover when approaching merging traffic; and (3) clear visibility of lane markings. If these conditions were met, the driver could activate the system and the driving wizard would assume control of the vehicle. It was not possible to manipulate the speed or distance settings. Participants could engage or disengage the Level 3 unsupervised driving function by simultaneous prolonged pressure on two buttons, one on the left and one on the right side of the steering wheel. For safety reasons, the participants were instructed not to intervene in the unsupervised driving mode by any means other than pressing the buttons (not use the brake or steering wheel). A description of the respective systems' capabilities and limitations and the information that the participants received prior to the driving session is available in Table 3.1.

Table 3.1 Description of system capabilities and limitations and information participants received prior to the driving session

System	Description	Operational design domain (ODD)	Limitations	Interaction
Level 2 Supervised driving	- Supervised driving automation - Maintains speed - Adjusts speed and distance to the vehicle in front - Lane-keeping assistance	- Always available	- Clear view of lane markings - Driver responsible at all times	- Activation / deactivation via steering wheel button
Level 3 Unsupervised driving	- Unsupervised driving automation - Maintains speed - Adjusts speed and distance to the vehicle in front - Steers the vehicle	- Partially controlled-access roads - Speeds up to 80kph - Free-flowing traffic	- Clear view of lane markings	- Activation / deactivation via a long press on steering wheel buttons

3.2.4 User Interface

The HMI (or UI) refers broadly to the vehicle's controls. In other words, the steering wheel with buttons, the accelerator and brake pedals, the seatbelt, plus visual and auditory interfaces consisting of sounds and displays placed in the instrument cluster (cf. Carstens and Martens, 2019).

In the specific case, two alternative audio-visual Uis – UI A and UI B – were implemented to support manual driving as well as Level 2 supervised and Level 3 unsupervised driving automation. Both Uis were designed explicitly for the study in that both aimed to support drivers' interaction with vehicles offering several levels of automation by reducing mode confusion. Participants experienced both Uis in a different order.

UI A (Johansson et al., 2021; Novakazi, Johansson, Stromberg, et al., 2021) was designed using a minimalistic approach (Omasta et al., 2022). The designers' underlying idea was to be clear about the vehicle's intentions, as well as the driver's responsibilities at any given time, by only providing necessary information at a given moment and by removing all other information that might confuse the driver about the driving modes they would encounter.

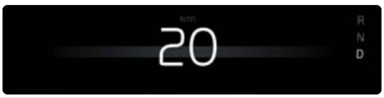
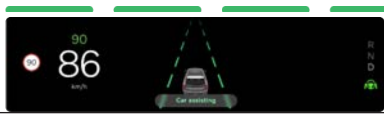
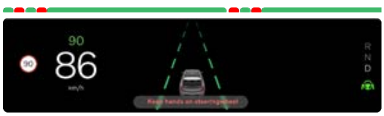
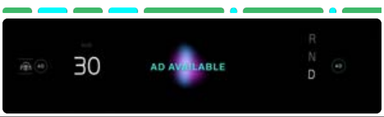
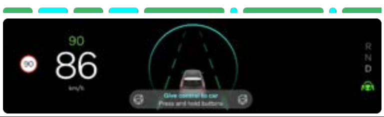
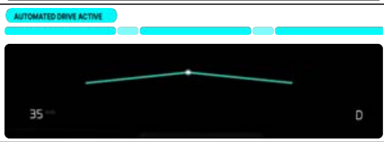
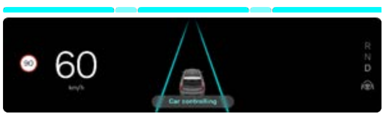
UI B was designed using a framework and design toolkit (Novakazi, Submitted). The framework and toolkit are based on a conceptual model describing the factors that influence a driver's perception and consequently shape their understanding of a driving automation system and their interaction with it. This was primarily addressed by trying to answer the following questions for every driving mode the driver would encounter: 1. When can I use the system? 2. What can the vehicle do? And 3. What do I do?

The UI wizard controlled the UIs from the back seat using a tablet, which triggered different graphics and audio feedback depending on the UI (UI A or UI B) and the vehicle's driving mode. Table 3.2 describes and compares the visual and auditory UI sequences and states. The key distinction between UI A and UI B lies in the presentation. The visual interface of UI B features a vehicle in the middle of the display and provides active functions. By contrast, the visual interface of UI A represents the current state with abstract images such as colours and icons and does not include a vehicle image.

When drivers activate the Level 2 driving automation by pressing the to State 2. UI A provided lane and steering directions with hands displayed, while UI B provided interval information from the car in front with the lane marking colour changing from white to green. If the system was deactivated by the driver pressing the button on the steering wheel or the brake pedal, the UI switched to a manual driving graphic (State 1), accompanied by no sound. When the Level 2 driving automation was deactivated by pressing the accelerator, it changed to a button on the left side of the steering wheel, the UI display in the instrument cluster changes the manual driving graphic with an audible beep. If the driver releases their hands from the steering wheel while driving, a hands-off warning (State 3) is accompanied by a short beep.

The warning persisted until the driver placed their hands on the steering wheel again.

Whenever Level 3 unsupervised driving automation was available, the UI wizard triggered a prompt (State 4) displayed in the instrument cluster with a short beep. If drivers decided to hand over control to the vehicle, they had to press and hold the two steering wheel buttons simultaneously to activate the system. The activation progress was visualised in the display. Successful activation was indicated by graphical changes (State 5). UI A announced the activation of Level 3 driving with a female voice, and a blue line appeared on the screen. UI B produced a short beep, displayed a solid blue line and provided a ‘car controlling’ message. If the Level 3 unsupervised driving automation was no longer available, drivers were prompted to resume control (State 6). For UI A, the blue line changed to orange and a ‘please take over’ message was displayed. This request was accompanied by a short beep and a sighing in Level 2 driving automation, the visual tug on the seatbelt to draw attention back to the road. After taking over, the driving mode and UI returned to manual driving (State 1). For UI B, a ‘please take over’ and ‘press and hold buttons’ message was displayed. As for UI A, UI displays this request, which was accompanied by a short beep and a slight tug on the seatbelt to draw the driver’s attention back to the road. After taking over, the driving mode and UI returned to manual driving (State 1).

	UI A	UI B
State 1 Manual driving		
State 2 Level 2 system active		
State 3 Level 2 system hands-off warning		
State 4 Level 3 system available		
State 5 Level 3 system active		
State 6 Level 3 system take-over from car		

3.2.5 Procedure

The study was divided into two parts: (i) the on-road driving session and (ii) a post-driving session. In (i), data on drivers' behaviour was collected by two video cameras mounted in the vehicle, directed at the driver and the steering wheel and dashboard (see Figure 1), with any comments made by the participants recorded by that same equipment. In (ii) data on participants' experiences was collected in semi-structured interviews that were audio-recorded.

Part I – On-road Driving Session

Before the driving session, participants received a brief explanation of the study's structure. They were then guided to the test vehicle and introduced to the driving automation systems in the car and how to interact with them. Table 3.1 provides an overview of the two systems and the information given to the drivers before the driving session. The introduction was designed to replicate the experience one would have when picking up a new car at a dealership, thus ensuring a high level of realism.

After the introduction, participants were given a moment to familiarise themselves with the car and settle in. The driving session lasted approximately 45 minutes on a partially-controlled-access city highway with speeds of up to 80 kph. The route started from the Volvo Cars Torslanda office and led to a southern part of Gothenburg (Slingan South), taking about 20 minutes. At that point, a short stop was made to switch UI (from UI A to UI B or vice versa). After the switch, the drivers returned to the car and drove the same route back to the starting point of the session (Slingan North) in approximately 20 minutes. Figure 3.2 shows the route taken, indicating the starting and ending points and the location where the UI was changed. It also highlights the predetermined stretches where Level 3 driving automation was available and the duration of availability, resulting in approximately eight minutes of automated driving and four take-over and hand-over requests in each direction.

Figure 3.2 Route of a driving session, highlighting stretches of Level 3 unsupervised driving automation availability and exposure time

Part II –Post Driving Interviews

Following the driving session, the test leader and participant returned to the Volvo Cars office and entered a designated interview room. The semi-structured interview lasted approximately 30 minutes and primarily aimed to gather insights into the drivers' understanding of the two distinct driving automation systems, including their functionalities and limitations. Additionally, the two UIs were compared and supported by presenting screenshots of their sequences and states (Figure 3.2). During this comparison, drivers were encouraged to provide feedback on any elements that aided their understanding of the systems, plus any confusing aspects.

3.2.6. Data Analysis

The data analysis aimed to examine the driver's understanding of the automated driving system and information received via the UIs by analysing the data from the driving session. This entailed the video recordings of driver behaviour and think-aloud data, plus the interviews from the post-driving session. The combined results of the data analysis are described in Section 3.3. Results, where they are grouped into the identified themes and enriched with think-aloud and interview data exemplifying drivers' comments at the moment of observation.

Driving Session Observations

As a first step, the think-aloud information collected during the driving sessions and the post-driving interviews were transcribed verbatim. Following that, Authors 1 and 2 conducted a pair-coding session using a deductive a priori template of the codes (Azungah, 2018) to analyse the video data of driver actions collected during the driving sessions. Drivers' comments from the think-aloud protocol were noted and connected to the coded observation data. Subsequently, Author 1 performed a second coding round. The initial clustering of codes relating to driving observations led to the identification of two overarching main themes categorising the use errors observed during the participants' interaction with the automated driving system: (i) Transition Challenges and (ii) Mode Confusion. These categories were discussed and chosen by the authors as they summarised the sub-themes into clusters that highlight both identified mode confusion regarding the different levels of automation and interaction-related issues with the two UIs under investigation. Each main theme contained a cluster of sub-themes describing the nature of the different errors observed. The 'Transition Challenges' theme comprised two sub-themes: (1) Unintended deactivation of Level 2 supervised driving automation, (2) Transition errors in Level 3 unsupervised driving automation, and (3) attempt to activate Level 3 drivng automation outside of ODD. The theme 'Mode Confusion' comprised three sub-themes: (1) Driver's engagement during different driving modes and (2) Mode confusion after take-over requests from the vehicle and

Post-Driving Interviews

In the next step, the authors familiarised themselves with the interview transcriptions. After the familiarisation phase, it was decided to use a deductive coding scheme (Azungah, 2018), applying a terminology proposed by Novakazi (In preparation), which identifies factors shaping the drivers' perception of driving automation systems and serves as a coding framework. Subsequently, the interview data was analysed, investigating comments and reflections from the participants regarding their interaction with the driving automation systems and the two UIs. Throughout the process, Authors 1 and 2 discussed the resulting sets of codes to address any inconsistencies. Krippendorff's Alpha was used to assess the inter-coder reliability (Krippendorff, 2004) and yielded a high level of agreement between the two authors ($\alpha = 0.917$). In the last coding round, Author 1 coded the interview data from the post-driving session by addressing the guiding question: What role does the interface play in a vehicle with several levels of automation? This led to the identification of insights where the participants described their experience with the different driving automations and respective UIs, which then were used to enrich the identified main themes and find further explanations for the use errors observed during the driving sessions. The authors then discussed and related the participant's descriptions to transition challenges and mode confusion and the role of the UI in a vehicle offering multiple levels of automation.

3.3. Results

When queried about their interface preferences overall, eleven out of the sixteen participants expressed a preference for UI B, four a preference for UI A and one answered that their preference differed depending on the driving mode. The participants had varying opinions on the visual aspects of the UIs, with UI A looking 'modern' and UI B more 'conventional'. From the participant's comments, it seemed as though the visuals of UI A were perceived as modern because it displayed less information: "The limited information I had felt more modern" (TP03), whereas the predominant reason that participants preferred UI B was that it provided more driving-mode-related information. This indicates that participants have predefined ideas about what is considered a modern look but also that they have different preferences when it comes to functionality and usefulness.

However, during the driving sessions, several recurring use errors were observed with both UIs (Table 2 and 3). The total number of use errors per UI was slightly less with UI B than with UI A. However, for certain types of errors, UI A resulted in fewer errors than UI B. Hence, both UIs had strengths and weaknesses, and it was not possible to determine a clear preference. The findings suggest that participants' preference for one UI over the other may be influenced by factors other than usability, such as aesthetic appeal or familiarity.

Considering the observed use errors, however, it became evident that both UIs posed challenges during the interaction with the driving automation. Thus, the following analysis does not compare the two UIs in detail but concentrates on identifying common themes that were observed during the engagement with both and will discuss the implications of these findings for the role of the UI during the interaction with a vehicle offering several levels of automation.

The different identified themes were categorised as Transition Challenges and Mode Confusion, under which further sub-themes are discussed in the following sections.

3.1.1. Transition Challenges

During the driving sessions, several incidents concerning hand-over and take-over requests (TOR) were observed. The observed errors could be categorised as transition challenges, as they all pertained to understanding how to interact with the driving automation system and its interfaces and controls in the transition situation. Table 3.3 provides an overview of the observed errors in this theme.

Table 3.3 Number of observations of use errors divided per main theme and sub-theme, participants and UI

Transition Challenges (N=16)				
	Number of Observations	Number of Participants	UI A	UI B
Level 2 (supervised driving automation)				
Unintended deactivation	6	3	4	2
Level 3 (unsupervised driving automation)				
Failure to activate	16	10	9	7
Failure to deactivate	19	15	16	3
Attempt to activate outside ODD	19	15	16	3

Unintended Deactivation of Level 2 Supervised Driving Automation

The Level 2 supervised driving automation could be disengaged by either pressing the button on the steering wheel, pressing the brake pedal, or through a prolonged overriding of the speed setting. Three participants were in Level 2 driving automation when they unintentionally disengaged the automation by pressing the brake pedal or overrode the speed control by pressing the accelerator. While the participants noticed after some time that Level 2 supervised driving automation was deactivated through information provided in the visual UI (such as the lane not being detected), they did not understand why it happened, as indicated by the think-aloud data: “I do not know why (it disengaged) … Maybe I am pressing something that it does not want me to.” (TP13). For these participants, deactivation of Level 2 occurred repetitively: “Disengaged. Something again.” (TP06).

Transition Errors in Level 3 Unsupervised Driving Automation

During the observations, many use errors related to transitions were observed, all of which related to Level 3 unsupervised driving. Some participants did not enable the unsupervised driving automation when offered or did not resume control from the Level 3 unsupervised driving automation when prompted.

When the system issued a hand-over request, the drivers had to make a prolonged press of two buttons on the steering wheel, to activate the Level 3 unsupervised driving automation. A loading bar in the visual UI served as feedback on successful activation (see 2.4. for a detailed description). This interaction was explained before the drive. Nevertheless, none of the participants succeeded during the first hand-over request. When attempting to activate the Level 3 unsupervised driving automation, 10 out of the 16 participants pressed the activation buttons too briefly. The failure to activate the mode resulted in participants becoming confused: “Should I try that now? … This is weird.” (TP16) and some did not understand why the problem occurred: “Should I do something when there is some instruction?” (TP10). This resulted in continued activation failures for four of the 10 participants, even though the test leader supported by giving instructions when the participants did repeatedly fail to activate the system. By contrast, the remaining six only encountered this error on their first attempt to activate the Level 3 unsupervised driving automation.

During a TOR from the system to the driver, the driver also had to make a prolonged press of the steering wheel buttons to deactivate Level 3 driving automation. A successful deactivation was in both UIs indicated by a loading bar displayed in the UI (see 2.4. for a detailed description). When acting on the request to take over control from Level 3 unsupervised driving automation, two behaviours were observed: (1) The participants only put their hands on the steering wheel without pressing the buttons, probably assuming that this action would be enough to regain control over the driving task or (2) The participants pressed the buttons too briefly (similar to a failure to activate) and not enough to transition control. This error featured prominently in UI A. When the vehicle requested a take-over of control, UI A showed ‘please take over’ in the visual interface accompanied by an auditory language-based message. On the other hand, UI B emitted an auditory signal and did not only cue a take-over request but also provided information on how to deactivate the system, by a text displaying ‘Press and hold buttons’.

However, during the interviews, it was found that the participants had varying degrees of understanding of the interaction with the steering wheel buttons and the visual UIs for activating and deactivating Level 3 unsupervised driving automation. Five participants mentioned that UI B provided clear instructions for transition control, such as the progress bar in the visual UI: “You can see from the animation as well when you were supposed to activate it (referring to Level 3 unsupervised driving automation), that you just hold the buttons, and you will see how long you have to hold for it to be activated.” (TP12). Two participants found the use of symbols and animations in UI A to be more intuitive: “In UI B, it felt like there was more text in it that you had to read … So, I had to read more and be focused more on the display in this scenario. But with UI A, it felt like it was easier to understand the symbols.” (TP12). Others preferred the text instructions in UI B: “… using the buttons, it also had a text telling me what to do. So that was more helpful.” (TP08). Noteworthy, during the interviews, participants discussed the importance of clear and concise text instructions but also the need for adequate time to read and understand them, particularly in stressful situations such as a TOR, as explained by TP13: “The text helped me understand, but it was also very fast, so I did not really have time to read it.” as well as by TP16: “It is too small and too much text. … You (the driver) do not have time to read that message. It was just clear enough with the symbols of holding the two buttons to activate it.”

Attempt to activate Level 3 unsupervised driving automation outside of ODD

Aside from the ambiguities about the necessary engagement of the driver during different driving modes, some participants repeatedly attempted to enable Level 3 unsupervised driving automation outside of its ODD. The Level 3 unsupervised driving automation was only available when specific requirements of the ODD were fulfilled (see 2.3. for detailed description) and would then prompt the driver with a hand-over request when it was available. This procedure and the ODD were explained by the test leader before the driving sessions to the participants. Nevertheless, four drivers attempted to activate the Level 3 unsupervised driving automation outside its ODD. These attempts were observed on several occasions during the drives as shown in Figure 3.3. For example, one participant stated: “Maybe this system is not possible when it is going to smaller roads, or … I am not sure how it is working.” (TP05). Drivers do not understand that they cannot activate Level 3 driving automation without a prompt from the vehicle. In addition, there was no information about the reason for the error, so they tried to activate Level 3 driving automation several times outside of ODD.

Figure 3.3 The driver attempts to activate Level 3 unsupervised driving automation using the steering wheel buttons in a situation where this mode is not available.

3.3.2 Mode Confusion

Several incidences of mode awareness errors were observed during the driving sessions. The observed errors could be categorised as mode confusion, as they pertained to understanding the driving automation. Table 3.4 provides an overview of the observed number of mode confusion during the driving sessions.

Table 3.4 Number of observations of mode confusion divided per main theme and sub-theme, participants and UI.

Mode Confusion (N=16)				
	Number of Observations	Number of Participants	UI A	UI B
Level 2 (supervised driving automation)				
Hands-off during	11	5	4	7
Level 3 (unsupervised driving automation)				
Hands-on during	12	3	7	5
TOR to manual	3	3	0	3

Driver's Engagement During the Different Driving Modes

A widely spread misunderstanding amongst the participants was the level of engagement that was expected from the driver in each of the different driving modes, i.e., Level 2 supervised and Level 3 unsupervised driving. While during engagement with the Level 3 driving automation, the driver remained in control of the driving task, they could disengage from the driving activities fully until the system requested a take-over.

Nevertheless, despite the instructions provided by the test leader before the driving session, about one-third of the participants (5 out of 16 participants) failed to place their hands on the steering wheel when using the active Level 2 driving automation. In two out of 11 observed cases, the participants seemed to be checking whether they could release their hands but with their hands still hovering by the steering wheel (Figure 3.4 left), which indicates ambiguity about the capability of the driving automation, e.g., drivers testing the limits of the system. In the remaining nine cases, participants took their hands off after activating the Level 2 driving automation (Figure 3.4 right), which leaves room to discuss whether the drivers were aware of the requirement or whether they mistook Level 2 supervised driving automation for Level 3 unsupervised driving automation: in other words, an instance of mode confusion.

Figure 3.4 Left: Driver testing the steering capability of the Level 2 driving automation; Right: Driver removing hands fully from the steering wheel during Level 2 driving automation

On the other hand, during the activation period of the Level 3 supervised driving automation, although not obliged to keep their hands on the steering wheel, three participants did so.

Two out of the three participants did this during the entire Level 3 unsupervised driving (Figure 3.5), and one of them commented: “I am trying to figure out the difference between the two different systems.” (TP14), indicating that the driver is not aware of the current mode sufficiently through the user interface.

Figure 3.5 Two drivers kept their hands on the steering wheel during all Level 3 unsupervised driving

During the interviews, the notion that drivers use user interfaces to understand driving automation and perceive control was enforced. “(If no feedback information) It makes me feel out of control.” (TP05). Four participants mentioned that displaying surrounding information detected by the vehicle (such as other road users and lane markings) in its visual display is valuable to drivers. “I would have liked to have (see) there is a car in front, there is a car passing just for my security. Maybe the car already knew that (but) I have no idea …” (TP03). It indicates that a lack of understanding of the driving automation state is likely to prevent the driver from sufficiently enjoying the performance of driving automation.

Mode Confusion after Take-Over Request from Vehicle

When the required driving context for the Level 3 unsupervised driving automation was not met any longer, the vehicle prompted the driver to take over the driving task. This transition was designed to return to manual driving when drivers took over control of the vehicle after Level 3 unsupervised driving automation. When a take TOR was issued by the vehicle, a combination of cues helped drivers become aware of the request for transition of control. In this case, not only were there visual and auditory cues provided by the UIs (State 6 in Figure 2) but also by the seatbelt, which was gently tightened. Five participants mentioned that the tightening of the seatbelt was a helpful reminder to be aware of taking back control of the car: “I realised that the seatbelt was like ‘wake up it is time to take back control’.” (TP09). Further, three participants mentioned that the distinctly different designs in UI A between Level 3 unsupervised driving automation and manual driving helped them become aware of the mode difference: “And it (line in UI A) was gone, so then I understood that this (Level 3 unsupervised driving automation) is not active anymore. So that helped me (to be aware of the mode change)” (TP10).

Nonetheless, while the participants understood the TOR, there was ambiguity about which driving mode they were in after the transition from Level 3 unsupervised driving automation.

This was made evident by statements collected during the driving sessions, such as: “I was not exactly clear on what kind of mode I was in.” (TP03). However, all observed cases of this type of mode confusion only occurred at the first TOR. Further, two out of three participants expressed confusion when the system did not revert to the previous level of assistance (level 2) when they deactivated the Level 3 supervised driving automation: “If I was in cruise control, I still wanted to be in that one when I go out and exit the Level 3 unsupervised driving automation.” (TP05). In all cases, this was the Level 2 supervised driving mode. This shows that the mode confusion was created by the expectation that the driving mode would revert to the previously active mode and not to the manual driving mode. Evidently, the indications in the interface were not enough to remove all ambiguity.

3.4 Discussion and Implications for UI Design

This study demonstrates, as do other studies (Banks et al., 2018; Feldhutter et al., 2018), the challenges associated with communicating levels of automation and mode transitions. We can see the potential to improve the challenge through designing User Interfaces (UIs). However, independent of UIs, the participants experienced problems related to mode awareness and when and how to transition between modes. Efforts to address interaction challenges in automated vehicles often focus on UI enhancements as a primary means of improvement. While UIs can undoubtedly aid in enhancing user experiences and understanding of systems, they often grapple with the constraints imposed by the system design (i.e., mode transition logic). The complexity embedded within the system’s architecture inherently influences interactions (Lewis & Norman, 1995). This reliance on system design for effective human-machine interaction implies a limit to resolving interaction issues through UI alterations alone. For example, merely enhancing the visual or auditory cues within UI may not address the root causes stemming from the system design. In essence, while UI enhancements play a crucial role, acknowledging the limitations of solely relying on UI modifications is imperative. In this section, we discuss the results, the role of the UI and the interaction challenges caused by system design in automated vehicles.

3.4.1 Support Mode Transitions

For safe and efficient use of driving automation, it is imperative that drivers possess an unambiguous understanding of when and how to transition between modes. In the study, participants faced problems transitioning from Level 2 to manual, as well as from Level 3 to manual mode, although the types of issues differed.

The transition from Level 2 automated driving to manual driving

The transition from Level 2 automated driving to manual driving was not always intentional (i.e., by pressing the steering wheel button for a few seconds). Instead, it was observed that a few participants (3/16) unintentionally deactivated the Level 2 function by pressing the brake pedal. It can be argued that the unintentional deactivation of Level 2 could be attributed to a mere mistake, but it is not unreasonable to attribute the behaviour to a lack of understanding.

It was evident that not all participants understood the reasons for the mode transition or were indeed aware of the transition despite receiving visual feedback in the UI. The traffic safety issues are evident. If drivers believe that the vehicle is in a Level 2 driving automation mode, they expect the system to control the driving operation and may only become aware of the current mode (in this case, manual driving) when the vehicle fails to slow down or deviates from its lane.

Unintentional disengagements and consequent mode confusions have also been observed in other studies due to, for example, physical control errors (Banks et al., 2018; Feldhutter et al., 2018) and, as in the present study, this led to a state of mode confusion. In the study by Wilson et al. (2020), these unintentional disengagements occurred early in their trials. Therefore, even though some participants in the present study repeated the observed error, further experience of using such systems would probably lead to a reduction in unintended deactivations. However, whereas the UI can provide information to support anticipation of upcoming changes in the automation mode (Tinga et al., 2023), it is less evident to what degree UIs can hinder unintentional disengagements.

The main role of the UI is instead considered to be to provide clear feedback on a driver's actions, intentional or unintentional, to ensure that they become aware of any mode transitions and of the present mode. The implications for the design of UI include modifications to clearly notify and differentiate between mode statuses to enable drivers to notice any changes more easily. At the same time, it is necessary to consider ways beyond simply increasing modalities. For example, it is easy to argue that adding auditory feedback to visual feedback will help drivers notice mode changes. However, in the study by Wilson et al. (2020), the driver did not notice an unintended deactivation despite the accompanying auditory feedback with visual. This highlights the need for a comprehensive approach to UI design, considering not only the addition of sensory modalities but also the complexity of driver situation awareness and system dynamics to ensure effective communication and interaction in automated driving scenarios.

The transition from Level 3 automated driving to manual driving

A mode change from Level 3 driving automation to manual driving required the drivers to intentionally press the steering wheel buttons to initiate the change at the vehicle's request. Take-over-requests (TOR) from Level 3 unsupervised driving to manual driving were provided by a tightening of the seatbelt and audio-visual elements in the UI. However, several of these requested mode changes failed as the participants only placed their hands on the steering wheel but did not press the buttons or did so too briefly. In this case, participants were not confused that a mode change had occurred (compare the transition from Level 2 to manual driving), but rather that it did not. Since most of the participants did not have the Level 3 driving activation failure after one or two errors, it can be interpreted that mode transition failures due to interaction errors will occur less after understanding the activation method.

As mentioned earlier, the UI could play a key role in communicating mode transitions and making drivers aware of the present mode by notifying and clearly differentiating between mode statuses. The transition from Level 3 to manual driving was supported by stepwise, multimodal (haptic and audio-visual) information, and most studies on TOR and the design of the HMI appear to agree with this approach (Brandenburg & Epple, 2018; Carsten & Martens, 2019; Melcher et al., 2015). In the interviews, several participants emphasised the haptic prompt as a positive reminder that further action was required. At the same time, studies have shown that long-term exposure to these multi-modal cues can lead to perceived annoyance (Mehrotra et al., 2022). The participants also made mention of the feedback on the transition provided in UI A. This is further evidence that prominent modifications to the interface in terms of, for example, layout or colour can help communicate mode changes. UI design can enhance the driver's comprehension of the mode change process by employing distinct visual cues, easily recognisable symbols, and concise instructions. In the current study, participants had different preferences as to text or symbols, but text should probably be used with caution. Most recommendations are that visual interfaces should prioritise pictographic information (for an overview of design guidelines, see Mehrotra et al., 2022).

However, not all identified issues related to the transition from Level 3 automated driving to manual driving involved the design of the UI but rather more fundamental system design features. A few participants (3/16) were confused about the driving mode following the change from Level 3 driving automation to manual driving. Based on the interview results, these individuals had expected the system to revert to the previous level of assistance (Level 2, as this was engaged before entering the Level 3 driving automation) instead of transitioning to manual driving. It is essential to note that participants' ability to remember the previous automation mode may be influenced by the duration of Level 3 automated driving. Extended periods of Level 3 automated driving may lead drivers not to recall the prior automation mode. Previous studies have shown that drivers rather expect to go from level 3 driving automation to manual driving after the transition by the TOR (Kim et al., Submitted). The confusion only occurred with UI B, but the interpretation is that the design of UI B was not the root cause of the issue. Instead, the interpretation is the participants' understanding of the automated system and their expectations for its behaviour. Nevertheless, from a user-centred design perspective, implementing a consistent mode transition logic would ensure a comprehensible transition of control, irrespective of the preceding intervention and the level of automation engaged and help drivers learn and comprehend their responsibilities regarding the driving task at any given time.

3.4.2 Enhance Mode Awareness

In Level 3,, the driver may hand over and let go of the driving task completely if the conditions allow so; in Level 2, the vehicle has longitudinal and lateral control, but the driver is still required to monitor the system and to keep their hands on the steering wheel ¬– but not all participants did so when driving with Level 2. One explanation is that these participants had not fully understood the instructions provided before the trial. Another explanation is that they wanted to test the limitations of the system and understand what Level 2 supervised driving actually meant; this claim finds some support in observations of participants' hoovering over the steering wheel and their comments. A third explanation is mode confusion, which is that they thought that they were driving with the Level 3 system as the differences between the levels were not obvious to them, either based on the vehicle's behaviour and/or the explanations of the differences had not been understood.

A related explanation is that even though the exposure to Level 3 driving was fairly short, it is possible that participants' trust in the overall driving function was elevated after the Level 3 experience and that they unconsciously adopted their habit of relinquishing control of the steering wheel at Level 2 due to their experience with Level 3 driving automation – even if they were aware of the mode change. Earlier research has shown that when an automated system operates consistently and reliably, this will build trust (Gold et al., 2015; Koustanai et al., 2012), and with increasing trust, drivers may become more complacent and more prone to distractions or engaging in secondary tasks (Parasuraman & Riley, 1997). As a result, when transitioning from Level 3 back to Level 2 driving automation, drivers might have grown accustomed to a higher level of vehicle control, leading them to believe that active supervision is not required. However, this unintended carryover of behaviour poses a safety risk, as Level 2 driving automation relies on the driver being attentive and ready to take control at any moment.

It is evident that the UI must provide timely and context-specific information about the current mode, but drivers must also be clear on their tasks and responsibilities depending on the level of automation. The driver will need clear information about the increased monitoring required for Level 2 compared to Level 3, but the design challenge- and not only for the design of the UI- becomes evident in that Level 2 and Level 3 automation may appear similar to the driver regarding functionality, but the driver's role differs significantly. In the current study, the design of UI A was based on a minimalistic approach, whereas UI B was designed with the intention to provide answers to the questions "What does the vehicle do?" and "What do I do?" (Novakazi, Submitted). The participants' comments were not conclusive regarding which UI provided the most support – or which UI was preferred. However, the comments reflect that the participants' understanding of " What does the vehicle do?" concerned their interaction with the UI.

One of the significant differences for drivers between Level 2 and Level 3 is whether they keep their hands on the steering or not. Previous studies have shown that, in the current UI, which does not provide information about the requirement for a hands-on steering wheel UI, drivers were confused about whether they should keep a hands-on steering wheel in Level 2 (Perrier et al., 2021). In our experiment, we discussed the complex reasons why drivers do not have hands on the steering wheel in Level 2, as shown above. In terms of enhancing mode awareness via UI, it seems that the vehicle needs to provide information about hands on the steering wheel ('What d I do?' information) through the user interface. At the same time, participants in the current study raised concerns regarding the potential distraction risks associated with detailed in-vehicle displays, especially considering that drivers of Level 3 automated driving do not necessarily need to monitor the external roadway continuously. Hence, it is essential to find a balance by presenting clear and concise information that assists drivers in understanding the driving automation without causing unnecessary distraction (Kim et al., 2024).

3.4.3 Support Learning

There were those participants in the study who experienced an error only once; there were others who were observed to repeat the same errors. For example (as mentioned earlier), the system was unintentionally deactivated when drivers pressed the accelerator pedal while in Level 2 supervised driving automation. Still, some drivers failed to grasp the rationale behind this deactivation and, therefore, repeated the error. Moreover, some drivers attempted to engage in Level 3 unsupervised driving automation despite the conditions not being met and did so repeatedly. Catino and Patriotta (2013) concluded that a system's functions are often learned through error experiences, and earlier studies on automated vehicles have shown trial-and-error as drivers' main approach to learning driving automation (Nandavar et al., 2023; Novakazi, Johansson, Stromberg, et al., 2021; Viktorová & Šucha, 2019). It is possible that further exposure to the systems could have mitigated the observed errors, but it is also possible that without understanding the underlying causes, users may be trapped in a cycle of repeated errors. In the current study, the UIs no doubt played an important role in drivers' interaction with automated vehicles, but it is possible the UIs could have played a more active role in participants' learning of the systems, for example, by providing more informative feedback when repeated errors occurred. Visual and auditory information could, for example, be used to explain the reasons behind deactivations or interaction errors by displaying relevant messages. However, the UI must be considered one of several information channels, in part because studies have shown that drivers use different information channels in learning about automation; information from salespersons, user manuals (Nandavar et al., 2023), help from others (Nandavar et al., 2023; Novakazi, Johansson, Stromberg, et al., 2021), from using similar systems as well as the behaviour of the vehicle and the HMI (Johansson et al., submitted).

3.4.4 Limitations

A significant volume of research on drivers' behaviour with AVs has been done in driving simulators. The driving simulator provides a controlled environment and the opportunity to systematically compare, for example, the effects of different HMI or UI designs. At the same time, drivers' behaviour and the consequences of use errors or technical failures may differ significantly between simulated and actual driving scenarios. For instance, in a simulated environment, drivers may be more likely to engage in non-driving-related activities and abandon the driving task than they would in real traffic. To the authors' knowledge, there are few on-road studies of drivers' interaction with and experience of different UI designs in automated vehicles offering several levels of automation. The study reported here took place in real traffic, providing a dynamic driving environment (Bengler et al., 2019; Pai et al., 2020), and this is believed to have increased the ecological validity of the findings. Nevertheless, there are several limitations to the current study. First, the participants only utilised the Level 3 automation feature in designated areas of the highways and for less than 60 minutes total. While the results indicate a learning curve, it is impossible to assess how prolonged usage over longer distances or various road types might affect drivers' interaction and observed use errors (Carney et al., 2022; Pradhan et al., 2023). Second, the presence of researchers was maintained for the entirety of the driving session to guarantee safety, act as wizards, and observe participant behaviour. The potential impact of researchers on participants' behaviour throughout the study may have led to deviations from their natural driving behaviour in real-world situations, for example, in terms of less trial-and-error in learning the system's limitations. Such behaviour has been observed in naturalistic driving studies (Novakazi, Johansson, Stromberg, et al., 2021). Despite the limitations, the authors argue that the study provides valuable insights into the challenges associated with drivers' interaction with and use of driving automation systems.

3.5 Conclusions

For safe and efficient use of driving automation, it is important that drivers develop an appropriate understanding of the automated system. The purpose of the study presented here was to reach further insights into what role the design of the user interfaces plays in drivers' interaction with a vehicle with several levels of automation and the implications for the design of UI in vehicles that integrate multiple automated driving modes. In conclusion:

• Use errors were observed independent of UI. These included errors in terms of mode confusion and errors related to mode transitions and confirmed earlier identified challenges associated with communicating levels of automation, modes and mode transitions to drivers. The findings underline earlier identified challenges associated with HMI design for vehicles offering several levels of automation.
• Implications for UI design could be extracted. These concerned primarily the design of the UI to support mode transition and reduce mode confusion through proper cues and feedback.
• Nevertheless, not all errors could be explained by inadequate UI design or were believed to be resolved by improved UI design. For instance, the configuration of automation functions in terms of mode transition logic contributed to drivers' mode confusion.
• The system design influences user interactions, and it implies a limit to resolving interaction issues through UI alterations alone. Errors in the way drivers interacted with the automated system suggest more fundamental issues, for example, a lack of understanding, impacting how they interpreted and responded to the information provided in the UIs.

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CHAPTER

4

Who is Performing the Driving Tasks after Interventions?
Investigating Drivers' Understanding of Mode Transition Logic in Automated Vehicles

This chapter is under review for publication:
Kim, S., Novakazi, F., Grondelle, E. D., Egmond, R. V., & Happee, R. Who is Performing the Driving Tasks after Interventions? Investigating Drivers' Understanding of Mode Transition Logic in Automated Vehicles, Submitted to Applied Ergonomics.

Abstract

Mode awareness is a critical factor affecting the safe use of automated vehicles, yet drivers' understanding of mode transitions has not been sufficiently investigated. In this study, we administered an online survey to 838 respondents to examine their understanding of control responsibilities in partial and conditional driving automation with four types of interventions (brake pedal, steering wheel, gas pedal, and take-over request). Results show that most drivers understand that they are responsible for speed and distance control after brake pedal interventions and steering control after steering wheel interventions. However, drivers have mixed responses regarding the responsibility for speed and distance control after steering wheel interventions and the responsibility for steering control after gas pedal interventions. With a higher automation level (conditional), drivers expect automation to remain responsible more often compared to a lower automation level (partial). A misalignment between actual logic and drivers' expectations regarding control responsibilities is observed by comparing survey responses to the mode transition logic of commercial partially automated vehicles. Specifically, respondents expect the driver to take over steering control after steering wheel interventions while in practice, several vehicles retain the control. To resolve confusion about control responsibilities and ensure consistent expectations, we propose implementing a consistent mode design and providing enhanced information to drivers.

4.1 Introduction

4.1.1 The challenge of designing interaction in automated vehicles

Transitions of control and monitoring create a range of driver interactions with automated vehicles (Merat & Lee, 2012). One of the key challenges is to design a natural and intuitive interaction with these automated vehicles (Ackermann et al., 2019; Naujoks et al., 2019). This requires a deep understanding of human cognition and the ability to design interactions in automated vehicles that can communicate easily (Carsten & Martens, 2019; Schieben et al., 2019) to match drivers' mental models. A mental model is a representation of a part of the world to which incoming new events are mapped, which influences the interaction (Carroll & Olson, 1988; Halasz & Moran, 1983). Norman (1983) argued that interaction design needs not to be technically accurate—and that it usually is not—but must be functionally accurate to map onto a mental model. If the interaction is inconsistent or difficult to understand, it can disrupt drivers' mental models, leading to confusion and misunderstandings, which can result in mistakes and inappropriate use (Parasuraman & Riley, 1997; Sarter & Woods, 1995). A consistent and predictable interaction helps to facilitate trust in the automation system (Ososky et al., 2013). However, the current interaction design insufficiently considers mental models which drivers use to represent their interaction with automated vehicles. Banks et al. (2018); Endsley (2017); Wilson et al. (2020) found that—in on-road studies—drivers were not sufficiently aware of which functions were active after a mode transition even when user interfaces displayed the current driving mode. It is well-known that there is often a misfit in how engineers technically design automation and the awareness of a user of these functionalities (Norman, 1983). Failure to design the interaction of mode transition in consideration of the mental model may lead to reduced trust in the automated vehicle, decreased adaptation of automation, and a higher risk of accidents and other safety issues (Becker & Axhausen, 2017; Viktorová & Sucha, 2018). Consequently, this needs to be addressed by design choices early in the development stages.

4.1.2 Current issue in driving automation

As technology advances gradually, automated driving is classified into different driving automation modes. The widely used mode classification is the SAE definition (SAEInternational, 2021), which is classified into six technology-based levels, ranging from Level 0 (No Driving Automation) to Level 5 (Full Driving Automation). Each level represents varying responsibilities between the driver and the automated vehicles. Level 1 (Driver Assistance) and Level 2 (Partial Automation) driving automation are widespread in the global vehicle market (Shirokinskiy, 2021). Level 1 driving automation includes either longitudinal control or lateral control. The main feature of Level 1 driving automation is known as Adaptive Cruise Control (ACC), which maintains a driver-set speed and distance from the vehicle ahead. Partial driving automation includes not only ACC but also Lane-keeping Assist (LKA). Therefore, partial driving automation assists the driver with steering, acceleration, and braking tasks. Level 3 (Conditional automation) driving automation can perform the driving task in specific conditions, remaining prepared to take control when prompted by the vehicles. Nowadays, vehicles can operate at several levels of automation, thus offering different driving modes to the driver, which may change during a drive cycle because of driving automation limitations or driver interventions. In these transitions, mode confusion can occur when drivers fail to understand the current automation mode in operation (Sarter & Woods, 1995). This issue is also well-recognised in the aeronautics field, where airline pilots are frequently assisted by complex automation systems (Dehais et al., 2015). The automation system in a modern aircraft is a complex structure with a variety of states in its architectural structure. The specific operational state of the automation system may not be immediately critical to the aircraft pilot. However, for human-machine interaction, it is crucial for the pilot to identify and understand the states in which the system is operating (King, 2011). Conflicts in the interaction between human operators and automated systems caused by a lack of understanding of the current state of automation can be defined as an automation surprise (Sarter et al., 1997), leading pilots to question the system's behaviour: What is it doing now? Why did it do that? What is it going to do next? (Wiener, 1989). It also results in several adverse behavioural and cognitive effects, such as risky decision-making or attentional tunnelling (Dehais et al., 2012). These effects are more likely to manifest in drivers, given their expected lower expertise in driving automation compared to the expertise of pilots in understanding aircraft automation systems. Therefore, with the introduction of several levels of automation into vehicles, the interaction with the automated vehicles and the drivers' understanding of the capabilities and limitations have become critical. Mode transitions between manual, assisted and automated driving modes will increasingly occur, making it hard for drivers to keep track of the currently active driving mode and possibly affecting the drivers' experience and acceptance of the automated driving for the negative. However, the rapid technically driven development has not allowed a human-centred design that considers drivers' understanding and expectations when interacting with automated vehicles (Homans et al., 2020; Seppelt et al., 2018; Yang et al., 2017).

Mode awareness comprises knowledge about the currently active automation, its performance and drivers' tasks and responsibilities (Sarter & Woods, 1995). An essential component in mode awareness is the user interface and how it guides transitions between automation modes (Carsten & Martens, 2019; Nordhoff et al., 2023). Table 1 presents an inventory made by the first two authors and summarises how different car manufacturers have different approaches to activating and deactivating driving automation features, i.e., ACC and LKA, in their vehicles. It indicates whether the Adaptive Cruise Control (ACC) and Lane Keeping Assist (LKA) functions of each manufacturer in the row are activated or deactivated based on the interaction method in each column. It demonstrates that manufacturers use various interaction methods for activating and deactivating the functions, which challenges drivers to develop different mental models when interacting with automated vehicles. Furthermore, there are different nuances in each of the ways of interaction, making it even more complex for drivers to follow a thread and nearly impossible to transfer knowledge from one vehicle to another. For example, when both Adaptive Cruise Control (ACC) and Lane Keeping Assist (LKA) are activated, the function that is disengaged if a driver uses the brake pedal differs per car brand and model. Therefore, rather than expecting the driver to adapt to the automated vehicles, manufacturers should understand and design the interaction with automated vehicles. Specifically, they should focus on mode transitions between different modes of automation, aligning them with the driver's expectations to support the development of a correct mental model. The driver's interaction with the automated vehicles is a critical factor affecting the transition to driving mode (Johansson et al., 2021). In this study, we investigate drivers' expectations and understanding of the transition logic while proposing interaction design recommendations.

Table 4.1 ACC and LKA ways of interacting in commercial partially automated vehicles

Way of interacting	Activation				Deactivation/Override										Source
	Button		Lever		Button		Lever		Brake		Steer		Accelerate		
Function	**ACC**	**LKA**	**ACC**	**LKA**	**ACC**	**LKA**	**ACC**	**LKA**	**ACC**	**LKA**	**ACC**	**LKA**	**ACC**	**LKA**	
Brand															
Audi		x	x			x	x		x	x			x	x	Audi A8 (2021) Owner's manual
Honda	x	x			x	x			x						Honda HR-V (2022) Owner's manual
Hyundai	x	x			x	x			x			x	x		Hyundai G70 (2022) Owner's manual
Kia	x	x			x	x			x			x	X		KIA K9 (2022) Owner's manual
Mazda	x	x			x	x			x						Mazda CX-5 (2023) Owner's manual
Mercedes-Benz	x				x				x	x		x	x	x	Mercedes-Benz S-Class (2022) Owner's manual
Tesla			x	x			x	x	x	x		x			Tesla Model3 (2023) Owner's manual
Toyota	x	x			x	x			x	x		x		x	Toyota Mirai (2022) Owner's manual
Volvo	x	x			x	x			x	x			x	x	Volvo XC90 (2022) Owner's manual

4.1.3 Research objectives

Table 4.1 exemplifies that there is not one way to implement driving automation. In addition, there is a lack of knowledge regarding how drivers understand mode transitions in their interactions with driving automation. To shed light on this topic, we developed an online survey to acquire knowledge of which actions follow different mode transition cases in partial and conditional driving automation. The understanding of mode transition by a driver is analysed according to automation driving mode (partial and conditional driving automation) and intervention type (brake pedal steering wheel, gas pedal control, and take-over request) as explanatory variables. We expect that this study contributes to filling the gap in research by examining drivers' understanding and expectations of mode transition during interaction with automated vehicles.

4.2 Methods

With a lack of existing research in this area, the online survey enables comprehensive exploration by inquiring about various mode transition cases and gathering data on drivers' understanding of mode transition in automated vehicles.

4.2.1 Respondents

In total, 926 respondents answered the survey. An initial quality filtering process was carried out to remove respondents who did not complete the entire survey and whose survey completion time was less than 180 seconds. The resulting sample size was 838 (90.50%). Within the resulting sample, the median time to complete the survey was 431 seconds.

• Age: the number of respondents per age range was 262(19-29), 281(30-39), 141(40-49), 78(50-59), 56(60-69), and 20 over 69.
• Gender: 408 were female, 420 were male, 6 preferred not to say, and 4 preferred to self-describe.
• Residence of Country: 400 were from the United States, 301 were from the United Kingdom, 58 were from the Netherlands, 21 were from Sweden, 21 were from Germany, and 37 were from Korea, Switzerland, Ireland, France, Belgium, or China.
• Knowledge of automated driving: 83 reported 'I don't have any knowledge about driving automation', 445 reported 'I have a little knowledge about driving automation', 251 reported 'I have moderate knowledge about driving automation', 38 reported 'I have a lot of knowledge about driving automation', and 21 reported 'I know the topic of driving automation extremely well'.
• Driving automation experience: 435 had experience with adaptive cruise control (ACC) and 284 with lane-keeping assist (LKA).
• Own car: 734 indicated that they have a car, and 104 indicated they don't have a car.
• Car sharing: 221 indicated that they had used car sharing, and 617 indicated they did not have a car sharing experience.

4.2.2 Recruitment and procedure

Drivers with a driving license for more than one year were eligible for the survey, including those without prior experience with automated vehicles and current users of partially automated vehicles. We distributed the survey from December 2022 to February 2023, sharing the survey link with Prolific and social networks. An online survey was created on Qualtrics. To ensure high-quality data, we implemented measures on Qualtrics to prevent duplicate responses and identify non-human respondents. Additionally, we instructed the respondents that the survey would take approximately ten minutes to complete. Prior to participating in the study, respondents were asked to provide their written consent. Upon providing consent, respondents were directed to a section that requested demographic and driving-related information. To ensure that respondents had a sufficient understanding of automated vehicles prior to completing the survey, we provided a description of the functionality of partial and conditional driving automation. Next, respondents answered the main section to answer their expectation of mode transition after interventions in partial and conditional driving automation, which is described in detail in the following section.

4.2.3 Survey content

The survey begins with a description of the context of the survey that results in the disengagement of partial and conditional driving automation as follows.

> *During your drive, there are several actions or events that may disengage the partial/conditional driving automation. This means that you, as a driver, take action or surrounding events that lead to the partial/conditional driving automation being turned off. In the following section, we will give you a couple of scenarios. Based on these, we ask you to determine the state of the car's driving.*

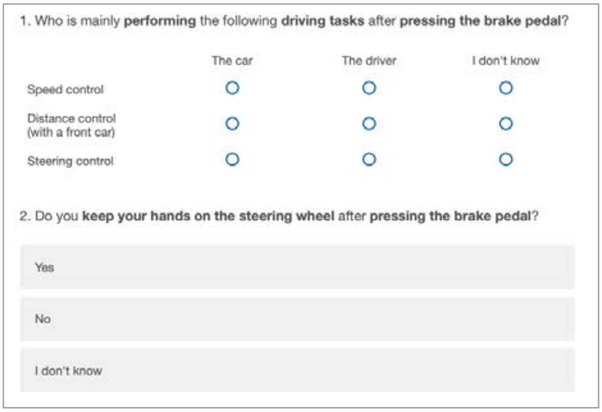
The intervention types for the study included the brake pedal, steering wheel, and accelerator. The function button-off was excluded from the intervention types because it was deemed unnecessary since drivers were expected to easily recognise and deactivate this specific function on a feature basis. Additionally, given the potential for confusion during mode transition in conditional driving automation, a take-over request by the car was added to the intervention types. To investigate tthe driver's expectations of mode transition logic regardless of the specific manufacturer's transition logic or suggested logic, no requirements such as returning to manual driving after a takeover request were provided. An overview of the survey and the intervention types used in the scenarios are presented in Table 4.2. In the partial driving automation section, respondents were presented with scenarios iinvolving "pressing the brake pedal," "turning the steering wheel", and "pressing the gas pedal." In the conditional driving automation section, scenarios also included "a take-over request from the driver." In each scenario, the automation would disengage, but this was not explained to the participants.

Table 4.2 Intervention types and automated driving of seven scenarios

	Intervention type			
	You press the brake pedal. (Brake pedal)	You turn the steering wheel to override the car steering. (Steering wheel)	You press the gas pedal to speed up above a set speed. (Gas pedal)	The car asks you to take over control of the car. (Take-over request)
Partial driving automation	Scenario 1	Scenario 2	Scenario 3	-
Conditional driving automation	Scenario 4	Scenario 5	Scenario 6	Scenario 7

For each of the seven scenarios presented in the survey, respondents were asked to indicate who would primarily perform the speed, distance, and steering control after the interventions.

Figure 4.1 shows the questionnaire of Scenario 1. Additionally, respondents were asked whether they would keep their hands on the steering wheel following the intervention. In the scenario involving a take-over request from the car, respondents were also asked to provide multiple responses detailing the actions they would take to regain control in such situations.


1. Who is mainly **performing** the following **driving tasks** after **pressing the brake pedal**?

	The car	The driver	I don't know
Speed control	○	○	○
Distance control (with a front car)	○	○	○
Steering control	○	○	○

2. Do you **keep your hands on the steering wheel** after **pressing the brake pedal**?

Yes

No

I don't know

Figure 4.1 Questionnaire of Scenario 1

4.2.4 Method of analysis

All survey questions had categorical response options. We conducted two main types of statistical analyses. First, descriptive statistics were calculated for each questionnaire item. Second, the data was analysed using a nominal logistic regression model in JMP Pro 17.0 software for statistical analysis to understand the factors influencing respondents' choices regarding control responsibility in different intervention scenarios. The analysis was conducted except for the respondents who answered, "I don't know" (less than 3% of responses averaged over questions).

4.3 Results

The results for control responsibility in partial and conditional driving automation are discussed in Sections 3.1 and 3.2, respectively.

4.3.1 Control intervention of partial driving automation

Figure 4.2 shows the respondents' choice of control responsibility (driver vs. car) by Intervention type and Control in partial driving automation. After brake pedal intervention, for all control items, more than 70% of the respondents answered that the driver controls them. 76.9% of respondents answered that the driver performs steering control, 84.8% of respondents answered that the driver performs distance control, and 87.4% of respondents answered that the driver performs speed control. After steering wheel intervention, 93.9% of respondents answered that the driver performs steering control. However, 47.1% of respondents answered that the driver would perform distance control after the steering wheel intervention, and 46.1% of respondents answered that the driver would perform speed control after the steering wheel intervention. After gas pedal intervention, 73.0% and 86.4% of the respondents answered that the driver controls distance control and speed control, respectively. However, 55.6% of respondents answered that the car would perform the steering control after the gas pedal intervention.

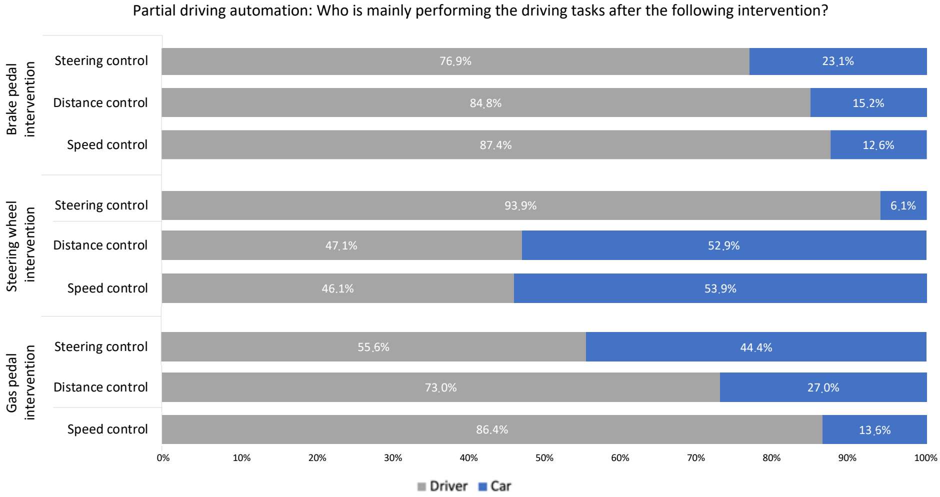


Figure 4.2 Control responsibility after intervention in partial driving automation

Regarding Hands-on requirements, more than 99% of respondents answered that drivers would keep their hand on the steering wheel after all Intervention types, as shown in Figure 4.3

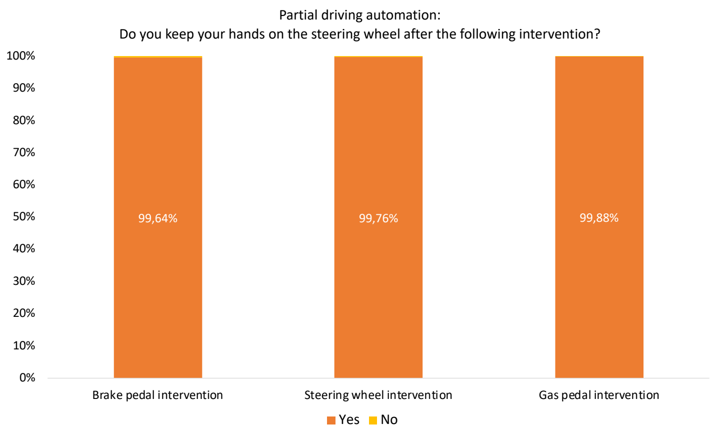


Figure 4.3 Hands-on requirement in partial driving automation

Nominal logistics analysis was conducted with Intervention type and Control as independent variables and respondents' choice of control responsibility (driver vs. car) as a response variable. The Whole Model Test revealed statistically significant evidence suggesting that the independent variables (Intervention type and Control) played a significant role in determining whether respondents chose the driver or the car as being responsible for controls ($\chi 2(8, N=7232) = 1095.03$, $p < .0001$, $R2(U) = .129$, AICc = 7411.2, BIC = 7473.15). The effect likelihood ratio tests indicated that Intervention type, control, and the interaction between Intervention type and Control were statistically significant. The results of the effect likelihood ratio test, McFadden Pseudo-R-squared, and Cramér's V are presented in Table 4.3. The McFadden Pseudo-R-squared statistic (McFadden & Zarembka, 1974) was used to assess the model's fit, and Cramér's V was employed as a measure of effect size. Table 4.4 presents parameter estimates from multinomial regression analysis of the response of control responsibility (driver vs. car) on Intervention type and Control. The coefficients of brake pedal intervention had relatively high positive values, implying that, all else being equal, respondents anticipate drivers to take control following a brake pedal intervention.

Table 4.3 Effect likelihood ratio tests in partial driving automation

Parameters	L-R χ^2	df	p-value	Pseudo-R-squared	Cramér's V
Intervention	110.29	2	< .0001	.013	.12
Control	50.18	2	< .0001	.006	.08
Intervention*Control	802.35	4	< .0001	.095	.33

**Note: Cramér's V ≤ 0.2 means the results are weak, 0.2 < Cramér's V ≤ 0.6 means the results are moderate, and 0.6 < Cramér's V means the results are strong*

Table 4.4 Parameter estimates from multinomial regression analysis of partial driving automation

Variable	Coeff.	Std Error	χ^2	p-value
Intercept	1.15	0.03	1331.8	< .0001
Intervention (Brake pedal)	0.47	0.05	106.83	< .0001
Intervention (Gas pedal)	-0.13	0.04	9.71	.0018
Control (Distance)	-0.29	0.04	46.79	< .0001
Control (Speed)	0.06	0.04	1.53	.2169
Intervention (Brake pedal) * Control (Distance)	0.39	0.06	38.95	< .0001
Intervention (Brake pedal) * Control (Speed)	0.26	0.07	16.40	< .0001
Intervention (Gas pedal) * Control (Distance)	0.26	0.06	20.68	< .0001
Intervention (Gas pedal) * Control (Speed)	0.77	0.06	149.88	< .0001

**Note: The target level is that the driver will take control after the intervention*

Furthermore, the original contingency table (Reynolds, 1977) was split up into three intervention types, as presented in Table 4.5. Each sub-table represented one level of intervention, as shown in Table 5 first column. A comparison of the fit of the sub-table to the whole model table is shown as a percentage of the model fit, indicating the contribution of each intervention level to the entire model. The analysis results demonstrate that the steering wheel intervention model accounts for 55% of the entire logistic regression model. Furthermore, Cramér's V indicated a strong effect size for the steering wheel intervention mode.

Table 4.5 Contingency analysis of the respondent's choice of partial driving automation

Intervention	n	df	-Loglikelihood	R square (U)	χ^2 (likelihood ratio)	p-value	Percentage of the model fit	Cramér's V
Brake	2431	2	16.80	.015	33.595	< .0001	31%	.12
Gas pedal	2403	2	96.53	.068	193.053	< .0001	17%	.28
Steering wheel	2398	2	305.67	.193	611.348	< .0001	55%	.50

**Note: percentage of the model fit is loglikelihood/full mode loglikelihood*

4.3.2 Control intervention of conditional driving automation

Figure 4.4 shows the respondents' choice of control responsibility (driver vs. car) by Intervention type and Control in conditional driving automation. After brake pedal intervention, 74.1% and 82.8% of the respondents answered that the driver would perform the distance and speed control, respectively. However, only 51.9% of respondents answered that the driver would perform steering control, whereas 48.1% answered that the car would perform the steering control. After the steering wheel intervention, 85.4% of the respondents answered that the driver would perform the steering wheel control, but 43.4% answered that the driver would perform speed and distance control. Regarding gas pedal intervention, 40.8% of respondents answered that the driver would perform steering control after the intervention, while 67.3% and 82.3% answered that the driver would perform distance and speed control. Furthermore, after intervention due to a take-over request, for all controls, less than 10% of respondents answered that the car would perform them.

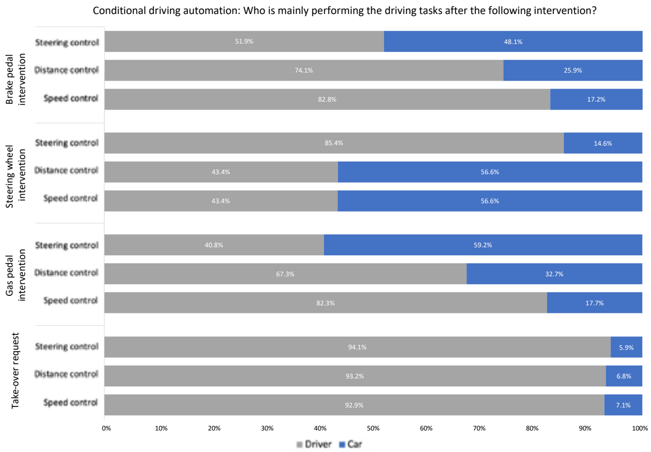


Figure 4.4 Understanding of control after intervention in conditional driving automation

As shown in Figure 4.5, 34.2%, 23.1%, and 39.7% of respondents answered that they would not keep their hands on the steering wheel after brake pedal, steering wheel, and gas pedal interventions. Moreover, 4.9% of respondents reported not keeping their hands on the steering wheel after taking over control by the take-over request.

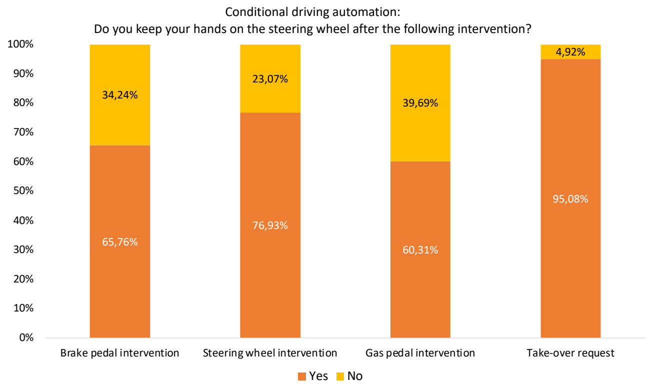


Figure 4.5 Hands-on requirement in conditional driving automation

Nominal logistics analysis was conducted with Intervention type and Control as independent variables and respondents' choice of control responsibility (driver vs. car) as a response variable. The Whole Model Test revealed that there was statistically significant evidence to suggest that the model is useful in differentiating between respondents' choices ($\chi2(11, N=9657) = 1959.64$, $p < .0001$*, $R2(U) = .170$, AICc = 9608.09, BIC = 9694.17). The effect likelihood ratio tests indicated that Intervention type, Control, and the interaction between Intervention type and Control were statistically significant. The results of the effect likelihood ratio test, McFadden Pseudo R-squared, and effect size are presented in Table 4.7. Table

4.8 presents parameter estimates from multinomial regression analysis of the response of control responsibility (driver vs. car) on Intervention type and Control in conditional driving automation. A notable proportion of respondents answered that the driver would perform control after the TOR intervention, resulting in negative coefficients for the other interventions. The interaction between Intervention type and Control demonstrates how a certain intervention has a different impact on the understanding of the driving responsibility of certain control. Specifically, the respondents answered that the driver performs the speed control after the gas pedal intervention, while relatively many respondents answered that the car performs the speed control after the steering wheel intervention.

Table 4.7 Effect likelihood ratio tests of conditional driving automation

Parameters	L-R χ^2	df	p-value	Pseudo-R-squared	Cramér's V
Intervention	879.70	3	< .0001*	.076	.30
Control	26.45	2	< .0001*	.002	.05
Intervention*Control	869.26	6	< .0001*	.075	.30

** Note: Cramér's V ≤ 0.2 means the results are weak, 0.2 < Cramér's V ≤ 0.6 means the results are moderate, and 0.6 < Cramér's V means the results are strong*

Table 4.8 Parameter estimates from multinomial regression analysis of conditional driving automation

Variable	Coeff.	Std Error	χ^2	p-value
Intercept	1.15	0.04	1600.0	< .0001*
Intervention (Brake pedal)	-0.25	0.04	31.39	< .0001*
Intervention (Gas Pedal)	-0.52	0.04	142.28	< .0001*
Intervention (Steering wheel)	-0.74	0.04	279.12	< .0001*
Control (Distance)	-0.12	0.04	8.79	.0030*
Control (Speed)	0.21	0.04	25.38	< .0001*
Intervention (Brake pedal) * Control (Distance)	0.27	0.06	19.03	< .0001*
Intervention (Brake pedal) * Control (Speed)	0.47	0.06	50.85	< .0001*
Intervention (Gas pedal) * Control (Distance)	0.21	0.06	12.48	.0004*
Intervention (Gas pedal) * Control (Speed)	0.70	0.06	118.80	< .0001*
Intervention (Steering wheel) * Control (Distance)	-0.56	0.06	87.38	< .0001*
Intervention (Steering wheel) * Control (Speed)	-0.88	0.06	213.54	< .0001*

**Note: The target level is that the driver will take control after the intervention*

Furthermore, the original contingency table was split up into four intervention types, as presented in Table 4.9. Each sub-table represented one level of intervention, as shown in Table 9 first column. The descriptive analysis showed that respondents answered that the driver would perform controls after take-over requests (TORs). Consequently, the choice model based on TORs presents a distinct perspective compared to other intervention models. As a result, the impact of the choice model by TORs on the overall model is found to be insignificant.

Table 4.9 Contingency analysis of the respondent's choice of conditional driving automation

Intervention	n	df	-Loglikelihood	R square (U)	χ^2 (likelihood ratio)	p-value	Percentage of the model fit	Cramér's V
Brake	2371	2	93.38	.06	186.76	< .0001	10%	.28
Gas pedal	2401	2	154.60	.10	309.21	< .0001	16%	.36
Steering wheel	2380	2	210.95	.13	421.90	< .0001	22%	.42
Take-over request	2502	2	0.52	.00	1.06	.588	0%	.02

**Note: percentage of the model fit is loglikelihood/full mode loglikelihood*

The study also explored the methods for transitioning the control when they receive a take-over request. The results showed that 34% of respondents chose 'pressing a button, 55% of respondents chose 'pressing the brake pedal', 73% of respondents chose 'putting hands on the steering wheel', 46% of respondents chose 'turning the steering wheel', and 4% of respondents chose 'pressing the gas pedal'.

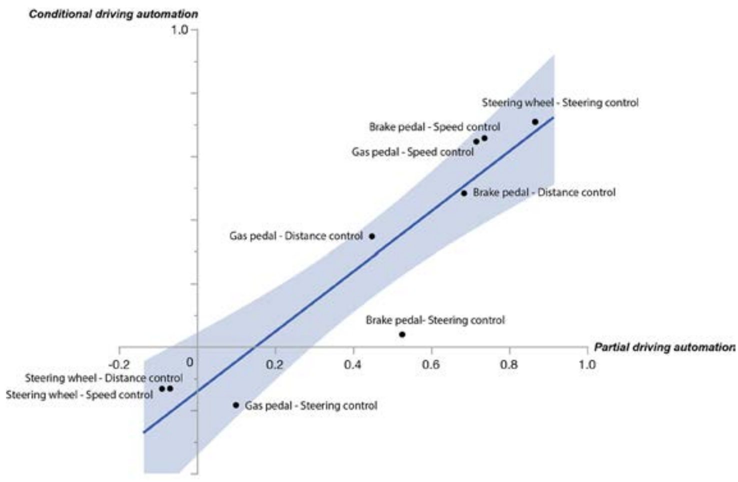
4.4 Discussion

This study investigated drivers' understanding of their responsibilities after different intervention types in partial and conditional automated driving. Although drivers seem to associate specific control interventions with driving functionalities, drivers did not have a dominant mental model for mode transition logic in certain scenarios, or drivers' mental models did not match the mode transitions at the same time.

4.4.1 Drivers' mental model on mode change logic

Our study sheds light on drivers' mental models of control responsibilities in partial and conditional driving automation. According to the results, drivers have a relatively clear mental model of their resulting responsibility for speed and distance control after brake pedal interventions and steering control after steering wheel interventions. In addition, gas pedal interventions have been associated with speed control. However, drivers' responses regarding the responsibility for speed and distance control after steering wheel interventions, as well as the responsibility for steering control after gas pedal interventions, are mixed. Respondents could also choose 'I don't know' if they were unsure of the answer, but this answer was rarely selected (less than 3% of responses averaged over questions). Hence it seems that they responded with confidence in their choice. This suggests that drivers did not have a dominant mental model for mode transition logic in these scenarios.

Figure 4.6 presents the value of the ratio difference between respondents who answered 'The car' and 'The driver' for the responsibility of each task after the intervention in partial and conditional automated driving. A value closer to zero indicates a large difference in understanding the responsibility after the intervention among the respondents. Specifically, the ratio difference in response in responsibility for the speed and distance control after the steering wheel intervention and steering control after the gas pedal intervention is close to zero for both partial and conditional driving automation. Regarding the answer difference between partial and conditional driving automation, the linear fit model in Figure 6 is Conditional driving automation = -0.15 + 0.95 * Partial driving automation ($F(1,7) = 41.33$, p-value < .001, R2 = .86). The regression coefficient of the Partial driving automation variable is almost 1, indicating that the trend of control responsibility choice on intervention is similar between partial and conditional driving automation. However, the intercept, -0.15, indicates that a higher percentage of respondents in conditional driving automation indicated that the car would perform each task after the intervention compared to partial driving automation. The difference in drivers' understanding of control responsibilities between partial and conditional driving automation will be discussed further in Section 4.4.2.



** Note: value explanation s–sequence 1 - 2: 1-intervention type, 2-control task*

Figure 4.6 Value of ratio difference of respondents who answered 'the driver' minus the respondents who answered 'the car' in partial and conditional driving automation

4.4.2 Difference in responsibility understanding between partial and conditional driving automation

Drivers' mental models of control responsibilities show similar tendencies in partial and conditional driving automation. However, with a higher driving automation level, drivers expect more often that the car will still perform the driving task after the interventions, and the intercept in Figure 6 supports this interpretation. For example, respondents expect that the driver will be responsible for the distance control after the gas pedal intervention and steering wheel control after the brake pedal intervention in partial driving automation. However, drivers' responses regarding the same scenarios are mixed in conditional driving automation. This expectation seems to have arisen from the perception that conditional driving automation is a more advanced automated driving mode compared to partial driving automation, leading to the assumption that it will continue to control the vehicle even after the intervention. In addition, a low percentage of respondents expected to put their hands on the steering wheel after the intervention in conditional driving automation compared to those who expected to do so in partial driving automation. In partial driving automation, more than 99% of respondents answered that they would keep their hands on the steering wheel regardless of the type of intervention. However, in conditional driving automation, respondents had a different expectation of whether they should put their hands back on the steering wheel after a brake pedal, gas pedal, or steering wheel intervention. Only, in the case of a takeover request, drivers understand that they have to take over all controls and keep their hands on the steering wheel since it is not the intervention of the driver but a request from the cars. As more driving automation is integrated into one automated vehicle, the complexity increases, leading to a greater chance of differences between how drivers understand driving automation and how automated vehicles operate. Therefore, it becomes important to provide clear information on control responsibilities and steering wheel requirements, indicating whether drivers should keep their hands on the steering wheel or not.

4.4.3 Mismatches in control responsibilities

With the integration of multiple levels of driving automation in an automated vehicle, it is important for drivers to comprehend the interaction, specifically the transition logic, to ensure safety and trust. Upon comparing the current transition logic in commercial partially automated vehicles (see Table 4.1) with the survey results, a discrepancy between 'he driver's expected logic and the actual logic was identified. Figure 4.7 illustrates a comparison between responses in partial driving automation and the mode transition logic of commercial partially automated vehicles. The graph on the left shows the respondents' choice of control responsibility by intervention type and control in partial driving automation (edited from Figure 4.2). The graph on the right displays the number of brands that deactivate the function after the intervention (edited from Table 4.1). For example, five 'x' marks next to 'LKA-Steering control on brake pedal intervention' means that five brands have transition logic to deactivate the steering control function after a brake pedal intervention.

Regarding brake pedal interventions, there is a high association between the response and the mode transition logic of commercial partially automated vehicles. For example, respondents expected Advanced Cruise Control (ACC) to be deactivated after brake pedal intervention. It is aligned with the mode transition logic of all commercial partially automated vehicles that Advanced Cruise Control (ACC) is deactivated after brake pedal interventions. However, in the case of steering wheel interventions, there is a misalignment between the actual transition logic and the response regarding speed and distance control. Half of the respondents expected that the driver would assume speed and distance control after steering wheel interventions, while in reality, the automated vehicles continued to handle speed and distance control. In addition, respondents expected the driver to take over the steering control after steering wheel interventions, while only half of the commercial partially automated vehicles have the transition logic to turn off the steering control after the steering wheel intervention. Regarding gas pedal interventions, there is a discrepancy between the actual transition logic and the response for speed control. Following gas pedal interventions, respondents were more likely to expect the driver to take over the speed control, while in reality, about half of the brands do not deactivate speed control. The findings reveal a misalignment between the actual logic and the drivers' expectations regarding control responsibilities. Especially if drivers expect automated vehicles to control a function but must take control after their intervention, such misalignments can lead to critical safety issues (Endsley, 2017) and negatively affect trust and acceptance.

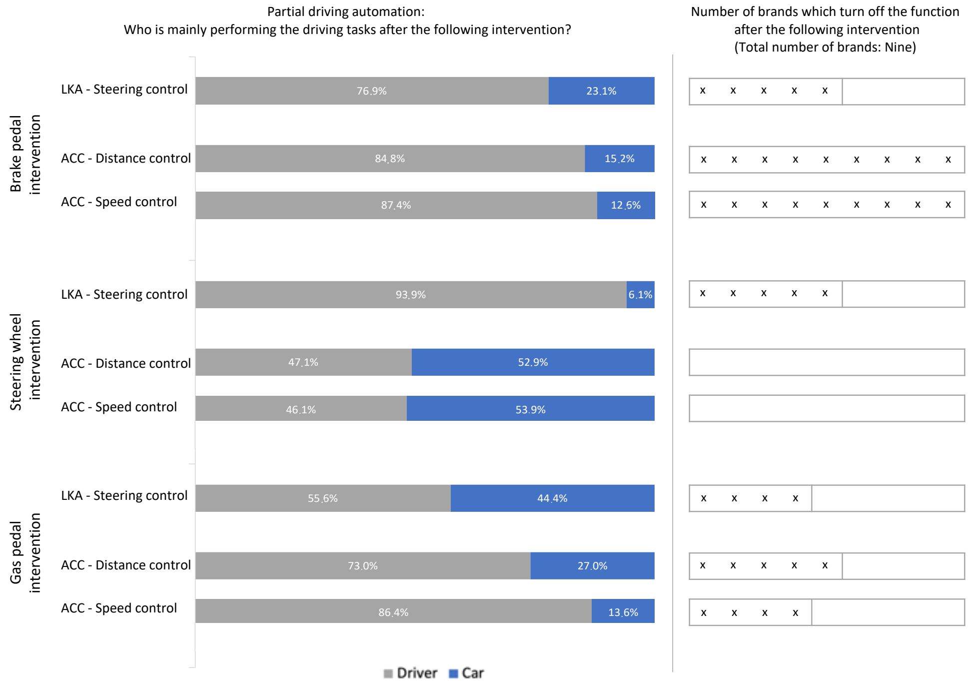


Figure 4. 7. Comparison mode logic between respondents' answers in partial driving automation in the study and commercial partially automated vehicles

4.4.4 Implications of mode transition design and driver training for safety

Recently, road incidents in which vehicles with advanced driving automation (NHTSA, 2021) have been involved led to a call for standardisation of the development of driving automation, specifically for the design of interaction patterns and feedback notifications (Reagan et al., 2021; Wansley, 2022). Our results also show a discrepancy between drivers' expectations and the intended use of designers and developers. The introduction of more conditional driving automation will most likely create more confusion with more serious consequences. In the Level 3 concept cars (TopSpeed, 2021), ahead of release in the market, after a mode transition by a takeover request from the vehicle during conditional driving automation, partial driving automation begins. This differs from the survey results, where drivers are expected to take over all controls. Additionally, when drivers anticipate partial driving automation based on previous experience with the vehicle but encounter a lower mode of automation due to technical limitations, safety concerns may arise. To enhance driver safety, we propose a logic in which automated features are disengaged (transition to the manual) after a take-over request, similar to the regulation of lane-keeping assist off logic (UNECE, 2021), to prevent critical accidents of mode confusion for the driver. Several studies (Beggiato et al., 2015; Seppelt & Lee, 2019) have shown that drivers generally have difficulties in grasping the limitations of the different driving automation systems, leading to a mismatch in the mental model and unsafe usage strategies due to a lack of understanding. Further, the loss of mode awareness due to the similarity of the different automation modes has been identified as a critical factor for the successful introduction of vehicles offering several automation modes (Carsten & Martens, 2019). Therefore, it is important to design a consistent mode transition logic for drivers to understand their responsibility over the driving task at any given time and ensure a confident transition of control, no matter the preceding intervention and engaged automation mode. In addition, it is important to improve the information provided to drivers, e.g., through educational means, to improve the mental model of control responsibilities and reduce confusion and inconsistency in driver expectations. Efforts to address this have been published, with the hypothesis that driver training has the potential to introduce drivers to central aspects of the human-automation interaction effectively. For example, Carney et al. (2022) have shown that additional training, as opposed to only exposure, is beneficial for a better understanding of ACC limitations. Notably, government agencies and traffic authorities explicitly recommend providing training (Campbell et al., 2018), and other research strongly suggests the positive effect of training on the drivers' mental model (Casner & Hutchins, 2019; Payre et al., 2017). However, while there are excessive studies on driver training incorporating a range of methods, e.g., from driving simulators to virtual reality approaches and interactive tutorials (Ebnali et al., 2019; Forster et al., 2019; Krampell et al., 2020), the driver training approach is also met with critique. Critics argue that while comprehensive training through simulations and similar means might be suitable for novice drivers in the context of driving schools, they do not address most drivers already on the roads and engaging with increasingly automated systems in their vehicles. In addition, previous research has shown that most drivers, upon collecting a new vehicle, receive none or very limited information about implemented driving automation in their vehicle (Boelhouwer et al., 2020), and very few make an effort to engage with traditional education material, e.g. reading the manuals, or have difficulties transferring the knowledge into real-life application (Oviedo-Trespalacios et al., 2021; Viktorová & Sucha, 2018). Further investigations have discussed the difficulties associated with trial-and-error learning, specifically with regard to developing an accurate understanding of driving automation (Carney et al., 2022; Harms et al., 2020; Novakazi et al., 2020). Thus, efforts have to be made to investigate alternative ways of educating drivers. For example, Feinauer et al. (2022) argue that it is important to explore different learning strategies supporting low-threshold access to support the driver while using the vehicle in understanding its capabilities and limitations.

4.4.5 Limitations and further studies

The current study provides insight into the field of driving automation and mode transitions. While it has some limitations, it presents exciting opportunities for further investigation. One limitation is that the study relied on a survey as its primary methodology, which may not accurately reflect drivers' behaviour in real-world scenarios. To address this, future studies could use on-road experiments with real-time mode transition scenarios to provide more reliable and precise results. By tracking drivers' behaviour in real time and assessing their interaction with automated vehicles, results can better reveal how to promote safe driving behaviour. In addition, it is insufficient to generalise the functionality of the automated vehicles outlined in the survey. Specifically, since commercial SAE Level 3 vehicles have not being widely introduced, our scenarios were based on SAE Level 2, the study may not reflect the upcoming regulations related to SAE Level 3, such as UNECE regulation. Notably, interpreting the results to fully reflect the current regulations is limited, as the survey primarily aimed to identify driver expectations. Nevertheless, exploring drivers' expectations regarding transition logic in each scenario holds significance, especially when drivers may not fully understand the transition logic despite being provided with interface guidance 'r an owner's manual. Furthermore, the study did not account for learning from the interaction effect between drivers and automated vehicles. Users acquire mental models by interacting with systems (Norman, 2013). Since there are few respondents with experience in SAE Level 2 and Level 3 driving, it is unlikely that the participants in the study had set mental models of system operation through the interaction. As such, further research could investigate how drivers adapt to driving automation over time and assess how their mental mode shapes as they become more familiar with the technology. This longitudinal approach could track drivers' performance over time, allowing designers to gain insights into how to promote safe driving behaviour and enhance mode awareness. Another critical aspect of automated vehicles is feedback and interface design, which can play an essential role in promoting safe driving behaviour (Kim et al., 2021). Therefore, future studies could focus on developing and testing different types of feedback and interfaces that provide clear and concise information about the current mode and limitations of the automation. In addition, the interfaces should be designed to be easy to use and understand, enabling drivers to monitor the automated vehicle's performance and develop an accurate mental model of how it works.

4.5 Conclusion

This study contributes to the investigation of drivers' understanding of mode transition logic in automated vehicles. The study found that drivers do not have a dominant mental model for mode transition logic in specific scenarios. Respondents understand that they will take over the speed and distance control after brake pedal interventions and steering control after steering wheel interventions. However, there is no prevalent mode transition logic for speed and distance control after steering wheel interventions or steering control after gas pedal interventions. Drivers' mental models of control responsibilities exhibit similar tendencies in both partial and conditional driving automation. However, in higher levels of driving automation, such as conditional driving automation, there is a greater likelihood of confusion regarding control responsibilities. As illustrated in Figure 6, drivers tend to expect the vehicle to retain control over driving tasks even after interventions in conditional driving automation, leading to a misunderstanding of driving responsibility. Notably, disparities exist between drivers' understanding and the mode change logic in current partially automated vehicles, as shown in Figure 4.7. While there is alignment in brake pedal interventions between respondents' expectations and commercial partially automated vehicles' mode transition logic, a significant misalignment occurs in steering wheel interventions. In these cases, respondents expect that drivers take control over speed, distance, and steering controls while the vehicles retain the controls. Designing mode transition logic in automated vehicles considering the mental model of drivers is important in ensuring the safe and effective operation of driving automation. Interaction for driving automation should be designed to maintain mode awareness while minimising driver workload without providing ambiguity. Hence, designers and manufacturers need to develop the mode transition logic that should be consistent and predictable. This allows drivers to develop a clear mental model of how the driving automation operates, anticipate mode transitions, and understand their responsibilities regarding the driving task at any given time.

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CHAPTER

5

Designing User Interfaces for Partially Automated Vehicles: Effects of Information and Modality on Trust and Acceptance

This chapter have been published in the following research article:
Kim, S., He, X., van Egmond, R., & Happee, R. (2024). Designing User Interfaces for Partially Automated Vehicles: Effects of Information and Modality on Trust and Acceptance. Transportation Research Part F: Traffic Psychology and Behaviour, 103, 404-419.

Abstract

Trust and perceived safety are pivotal in the acceptance of automated vehicles and can be enhanced by providing users with automation information on the (safe) operation of the vehicle. This study aims to identify how user interfaces (UI) can enhance drivers' trust and acceptance and reduce perceived risk in partially automated vehicles. Four interfaces were designed with different levels of complexity. These levels were achieved by combining automation information (surrounding information vs surrounding and manoeuvre information) and modality (visual vs visual and auditory). These interfaces were evaluated in a driving simulator in which a partially automated vehicle reacted to an event of a merging and braking vehicle in its front. The criticality of the events was manipulated by the factors merging gap (in meters) and deceleration (m/s2) of the vehicle in front. The reaction of the automation was either to brake or to change lanes. The results show that an optimal combination of automation information and modality enhances drivers' trust, communication with automation, perceived ease of use, and perceived usefulness. More specifically, the most complex UI, which provided surrounding and manoeuvre information via the visual and auditory modalities, was associated with the highest trust and acceptance ranking and the lowest perceived risk. Manoeuvre information delivered through the auditory modality was particularly effective in enhancing trust and acceptance. The benefits of the UIs were consistent over events. However, in the most critical events, drivers did not feel entirely safe and did not trust the automation completely. This study suggests that the design of UIs for partially automated vehicles includes automation information via visual and auditory modalities.

5.1 Introduction

Automated vehicle technology is rapidly developing, promising increased safety and comfort to drivers (Litman, 2017). As technology continues to progress, it is expected to bring disruptive changes to transportation systems and people's lifestyles (Shabanpour et al., 2018). Automated vehicles may enable drivers to engage in non-driving activities, such as working, reading, or resting (Krueger et al., 2016). However, the successful diffusion of automated vehicles depends on the acceptance of the new technology (Nordhoff et al., 2018). Trust is an essential prerequisite for using automation, as it is a key predictor of acceptance and a positive user experience (Choi & Ji, 2015; Cysneiros et al., 2018; Detjen et al., 2021; Hoff & Bashir, 2015; Parasuraman & Riley, 1997; Wilson et al., 2020). Trust in automation refers to the attitude that the system will help users achieve their goals in a situation characterised by uncertainty and vulnerability (Lee & See, 2004). Perceived risk captures the level of risk experienced in driving (Griffin et al., 2020). M. Y. Li et al. (2019) considered perceived safety as an antecedent of trust, while (Nordhoff et al., 2021) found that perceived safety emerges from trust. We consider trust and perceived safety (or risk) to be interacting perceptions which are essential in the interaction between drivers and automated vehicles. Trust and perceived safety primarily derive from the automation performance as perceived by the user and the driving conditions, including the (dangerous) behaviour of other road users. User interfaces can thereby help to calibrate trust and perceived risk as they can inform users of the (safe) operation of the automated vehicle and its capability to deal with other road users (M. Li et al., 2019). The potential of user interfaces to enhance trust and perceived safety and to foster acceptance of automated driving was demonstrated in our recent survey (Kim et al., 2021). However, previous research primarily focused on the overall effect of user interfaces and provided limited insights into the effects of different information types and modalities on driver's trust, perceived risk, and acceptance. In this study, therefore, we design and evaluate user interfaces conveying different types of information in various modalities to investigate their effects on trust, perceived risk, and acceptance in partially automated vehicles.

5.1.1 Trust in Automated Vehicles

Trust is crucial for the acceptance of vehicle automation (Choi & Ji, 2015; Cysneiros et al., 2018; Detjen et al., 2021; Ghazizadeh et al., 2012; Hoff & Bashir, 2015; Wilson et al., 2020). It is important to adjust users' trust to an appropriate level depending on the systems' performance (Merritt et al., 2015). To leverage advanced technologies, driver's trust needs to be maintained at an appropriate level (Haspiel et al., 2018) to avoid both under-trust (or distrust) and over-trust (Lee & See, 2004). Over-trust can lead to misuse and unintended use, which can result in various, even fatal accidents (O'Kane, 2020). Conversely, many (potential) users distrust vehicle automation, which may lead to disuse (Pew Research Center, 2017). Transparency is crucial to evoke trust (Lyons et al., 2016). Trust issues may result from a lack of information on the behaviour of a complex system, e.g., a car (Norman, 1990). Transparency, as defined by Endsley et al. (2003), encompasses the clarity and predictability of systems. It enables users to grasp the system's operations, rationale, and anticipated actions (Alonso

& de la Puente, 2018). In automated vehicles, a deficiency in transparency, such as the absence of information regarding future actions, may cause inherent distrust (Basantis et al., 2021). Well-designed user interfaces can reduce unnecessary interventions by enhancing the driver's understanding of the vehicle's intentions and capabilities (Carsten and Martens (2019). Automation system transparency has been shown to enhance trust calibration (Gao & Lee, 2006; Hoff & Bashir, 2015; Lee & See, 2004; Lyons et al., 2017; Mercado et al., 2016; Visser et al., 2014). Nevertheless, the existing studies examine the importance of transparency, with less emphasis on how transparency in user interfaces influences driver's trust. Therefore, we design user interfaces to enhance system transparency and investigate their effects on trust in this study.

5.1.2 Surrounding and Manoeuvre Information

To foster trust in and acceptance of automated vehicles, it is important to design transparent, automated vehicle behaviour supported by a user interface explaining the operation of the automated vehicle. Previous studies have emphasised the necessity of system transparency by providing automation information, which consists of surrounding and manoeuvre information (Chang et al., 2019; Hock et al., 2016; Koo et al., 2015; Ma et al., 2021; Oliveira et al., 2020; Sawitzky et al., 2019). Surrounding information includes other road users detected by the vehicle, and manoeuvre information relates to the decisions made by the automated vehicle. Both information types enable users to anticipate and understand upcoming vehicle behaviour.

Wilson et al. (2020) observed on-road driver behaviour in partially automated vehicles. They confirmed that one obstacle to trusting automated vehicles is a lack of information provided to the driver regarding what the automation "perceives" of the driving environment and how the automation will behave afterwards. When the vehicle detected other vehicles and presented this on the visual interface, drivers were reassured that the vehicle would respond adequately and continued to use the automation. Providing surrounding and manoeuvre information increases trust and convinces drivers to use automation (Hock et al., 2016). Oliveira et al. (2020) and Sawitzky et al. (2019) have shown that augmented reality displays can increase trust by providing different visual aids for displaying driving routes as manoeuvre information. Koo et al. (2015) and Ma et al. (2021) confirmed that information provided using a single modality, auditory and visual, respectively, increased trust, but the impact of different levels of automation information on drivers varied between studies. Koo et al. (2015) compared four different transparency levels of information, with and without surrounding information (the reasons for action) and manoeuvre information (how the car will act), via auditory modality and found that surrounding information increased trust, but the effect of manoeuvre information was not significant. Ma et al. (2021) investigated three transparency levels of information (1. none; 2. surrounding information; 3. surrounding and manoeuvre information) via visual modality and showed that a combination of surrounding and manoeuvre information increased trust more than surrounding-only information. Basantis et al. (2021) compared four different interfaces (1. No feedback; 2. Vehicle path on the visual display; 3. Manoeuvre notification sound 4. Mix of 2 and 3) to passengers in the rear seat. The results show enhanced trust and perceived safety with the auditory manoeuvre notification compared to only visual automation information. Although these studies highlight the benefits of providing surrounding and manoeuvre information, they typically examined the impact of these information types in isolation or did not systematically evaluate the combined effects of different modalities (visual and auditory) on trust and perceived safety.

While Mackay et al. (2020) and Chang et al. (2019) suggested that more information does not always lead to increased trust, the nuances of how different levels of information interact with modality to influence trust and acceptance in partially automated vehicles have not been fully explored. Examination of how auditory information, when synchronised with visual cues, can maintain driver attention without causing distraction or irritation is still needed, as highlighted by (Liu, 2001) and (Edworthy, 1998). Thus, further research is essential to address the current gap in understanding the interaction of modality and information and how the combination of information types and modality affects trust, perceived safety and acceptance in the specific context of partially automated vehicles. Existing studies have not fully explored the systematic effects of auditory and visual information, indicating a pressing need for further research to systematically examine the impact, guiding the design of effective user interfaces that provide the necessary information to establish an appropriate trust level in partially automated vehicles.

5.1.3 The Current Study

This study systematically investigates how different information types and modalities of user interfaces in driving automation information affect drivers' trust, perceived safety, and acceptance during partially automated driving. We hypothesised that user interfaces providing surrounding information, manoeuvre information or both enhance drivers' trust, perceived safety and acceptance in driving automation and reduce the frequency of drivers' interventions (e.g., braking) during driving automation but to varying extents. We expected that user interfaces that provide more information enhance trust and perceived safety. Correspondingly, drivers may prefer the combination of visual and auditory modalities for both information types. For the challenge of maintaining the driver's attention, we expect that visual displays impact the driver's eye gaze distribution, which is significantly correlated with the driver's trust and perceived risk levels. To validate this hypothesis, we designed four user interfaces using four combinations of information (surrounding information vs surrounding and manoeuvre information) and modalities (visual modality vs visual and auditory modality). The interfaces were intended to support drivers in understanding the reactions of automated vehicles to other vehicles merging in front, where the automated vehicles could react by either braking or changing lanes.

5.2 Methods

We designed four user interfaces (UI) providing automation information via visual and auditory modalities and evaluated the interfaces in a driving simulator, adding No UI as a baseline condition in a partially automated vehicle (Table 5.1). Effects of UI were assessed objectively through brake behaviour and eye-gaze behaviour, as well as subjectively through perceived risk, trust and acceptance. In a preliminary experiment (see Appendix A), participants evaluated one type of UI among these five UI conditions (between-subject experiment design). The results showed significant benefits for all four UIs compared to the No UI condition, but differences between the four UIs were not significant, presumably due to large individual differences. To further investigate the effects of UI information type and modality, the main experiment was performed using a within-subject design, which is less sensitive to individual differences.

5.2.1 Participants

Twenty-two drivers participated in the experiment. All had driving licenses for more than a year. The average age of the participants was 28.3 years (SD=13.1). Thirteen were male, and nine were female. Eleven had experience with adaptive cruise control (ACC), seven with lane-keeping assist (LKA), and four with both ACC and LKA. Eight drove a few times per year, ten drove a few times per month, and four drove a few times per week.

5.2.2 Apparatus

Participants experienced the scenarios in the DAVSi driving simulator with a Toyota Yaris cockpit (Figure 5.1) at Delft University of Technology. It used three high-quality projectors to display the environment on a cylindrical 180-degree screen. Two 7-inch tablets were used as side mirrors. The automation UI presented visual information on a 10.1-inch tablet at the centre console, while an in-vehicle embedded speaker presented the auditory information. A 5.8-inch tablet was placed on the left side of the steering for a questionnaire. The instrument panel showed vehicle speed and engine revolutions per minute. A fixed four-camera Smart Eye Pro tracked the participant's eye gaze and was used to classify the region of interest.

Figure 5.1 Exterior and interior of the DAVSi simulator,
with visual UI right of the steering wheel and tablet for the questionnaire left of the steering wheel

5.2.3 Experimental Conditions

The experiment evaluated the effects of two information types (i.e., surrounding and manoeuvre) and two modalities (i.e., visual and auditory). The visual modality was used to provide continuous information, and event-based information was presented using visual or auditory cues. We always included surrounding information in four UIs, which was shown beneficial in a range of studies as outlined above, and explored the benefits of adding manoeuvre information. Table 5.1 shows the five UI conditions: 1) Baseline (No UI), with no additional (automation) information provided, 2) Surrounding information via the visual modality (S-V UI), 3) Surrounding and manoeuvre information via the visual modality (SM-V UI), 4) Surrounding information via the visual and auditory modality (S-VA UI), 5) Surrounding and manoeuvre information via the visual and auditory modality (SM-VA UI). Each participant executed all five UI conditions in randomised order.

Table 5.1 User Interface Conditions (Note. baseline is No UI)

	Information	
Modality	Surrounding	Surrounding & Manoeuvre
Visual	S-V UI	SM-V UI
Visual & Auditory	S-VA UI	SM-VA UI

5.2.4 Scenario Design

This experiment selected highway driving scenarios with other vehicles merging into the driving lane of the ego-vehicle. Participants drove partially automated vehicles where they monitored the driving environment and kept their hands on the steering wheel. An adjacent vehicle (the yellow car in Figure 5.2) entered the highway and approached to merge into the right lane where the ego-vehicle (the blue car in Figure 5.2) was driving. Participants could see the adjacent vehicle approaching their lane. After detecting the merging vehicle, the ego-vehicle braked (Figure 5.2 left) or steered to the left lane (Figure 5.2 right). The velocity of the ego-vehicle and the traffic vehicles was set to 100 km/h. In the braking manoeuvres, the braking lasted until the merging vehicle velocity decreased to 60 km/h, followed by acceleration back to 100 km/h. In the lane change manoeuvres, the ego-vehicle steered into the left lane, overtook the merging vehicle and returned to the original lane. No accidents or automation failures were designed.

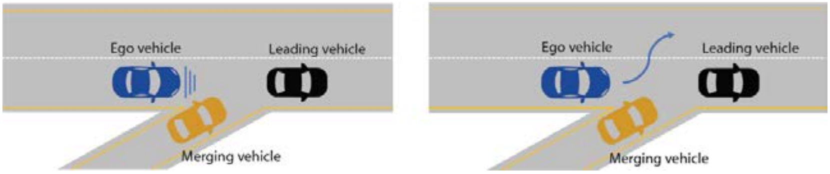

Figure 5.2 Merging scenario (Blue: ego-vehicle, Black: leading vehicle, Yellow: merging vehicle), slowing down manoeuvre (Left) and lane change manoeuvre (Right)

Six merging events were studied (Table 5.2) varying in terms of merging gap (5 m and 25 m) and automation action (-2 m/s2 or -8 m/s2 deceleration, or lane change). The slowing-down manoeuvre and lane change manoeuvre contained four and two merging events with different criticalities (automation action), respectively. To integrate these into a single drive, a series of onramps were designed along the road with one-minute intervals between merging locations. In total, merging events occurred in eight of the ten ramps. The order of events was randomised for every drive.

Table 5.2 Event types

Manoeuvre	Event elements	
	Merging gap (m)	Automation action
Slowing down	5	-2 m/s^2 deceleration
		-8 m/s^2 deceleration
	25	-2 m/s^2 deceleration
		-8 m/s^2 deceleration
Lane change	5 *	Lane change
	25 *	Lane change

** Lane change events were repeated twice*

5.2.5 UI Design

Visual interface

A bird-eye view with pop-up messages provided visual surrounding information (Figure 5.3 left). The bird-eye view was visible the entire time while driving. It showed the driving environment 60m forward and 10m backwards, including two adjacent lanes. The colour of the ego-vehicle was red to ensure that participants easily recognised their car, while the colour of other vehicles was grey. A pop-up message displayed safety-related surrounding information (i.e., merging vehicle detected). In SM-V UI and SM-VA UI conditions, manoeuvre information was also provided as a pop-up message with text and an icon after the surrounding information pop-up message in the same location (Figure 5.3 right) and was presented just before the ego-vehicle performed a manoeuvre (i.e., when the ego-vehicle is slowing down or changing lane).

Figure 5.3 Visual UI with surrounding and manoeuvre information. Bird-eye view with pop-up message of surrounding information (Left) and pop-up messages for manoeuvre information (Right)

Auditory Interface

A combination of abstract sounds and language-based explanations was used. An abstract sound of a low alarm level was provided to draw attention to prevent participants from being surprised by the language-based explanations. A wood and xylophone sound with a fundamental frequency of 625Hz was two times repeated and lasted a total of 1.24 seconds. It was chosen because it can provide a feeling of simplicity (Özcan & Egmond, 2012). Comprehension-level perception information was provided (Avetisyan et al., 2022) as surrounding information. Explanations were generated using a female voice to be more likeable and comfortable (Dong et al., 2021) on the Google text-to-speech engine. The surrounding information was provided as: 'merging vehicle detected' of 1.4 seconds. Manoeuvre information used a first-person pronoun (i.e., 'we') as an anthropomorphism to increase trust (Waytz et al., 2014) Manoeuvre information was provided as: 'we are slowing down' of 1.0 seconds or 'we are changing lane' of 1.1 seconds.

Timing

The provision of automation information prior to the action of the automated vehicle has been found to improve trust, as demonstrated in previous studies (Du et al., 2021; Haspiel et al., 2018). Therefore, the information was provided before the vehicle took action in the experiment. To determine the optimal timing for information provision, we conducted a pilot test using an online survey to compare on-time and early-timing conditions. The on-time condition provided surrounding and manoeuvre information as soon as the merging vehicle changed direction to the ego-vehicle lane. The early-timing condition provided the information four seconds before the on-time condition. Twenty-four participants watched videos with different information provision timing and answered the trust comparison question. The manoeuvre was when a merging vehicle approached with a 5m merging gap with -5m/s2 deceleration. As a result, fifteen participants answered that they trusted automation more with early timing. One participant trusted more on time, and eight had no preference. Therefore, we decided to provide the information four seconds before the merging started. Hereby, we assumed the AV to timely detect the merging intention from the directional indicator or V2V communication.

5.2.6 Measurement

During the simulation, brake pedal signals, eye gaze behaviours, trust, and perceived risk were collected. The brake pedal signal was recorded by the driving simulator automatically as braking is an effective indicator of distrust and perceived risk during automated driving (He et al., 2022; Li et al., 2020; Tenhundfeld et al., 2020). We deactivated the option for participants to take over control by steering to ensure a controlled study environment because different traffic conditions in the left lane influence the driver's steering behaviour, which would introduce additional factors into the analysis. Eye gaze behaviour, an indicator of the driver's attention and situation awareness, is impacted by user interfaces as they can change the driver's eye gaze distributions (Goncalves et al., 2022). The redistribution of eye gaze is particularly important as it is indicative of the driver's engagement with the driving environment and the automated system. Eye gaze behaviour was recorded at 60Hz using a smart-eye system with four infrared cameras mounted in the vehicle cockpit. It was measured to evaluate the eye gaze fixation time ratio on the display and the road and the eye gaze transition numbers between the display and the road. Participants were requested to report the level of trust and perceived risk after each merging event on the tablet on the left side of the steering wheel (He et al., 2022). After each merging event, the experimenter verbally asked two 10-point Likert scale questions: “how much do you trust the driving automation according to the previous performance of the system?” and “how risky do you perceive the previous event”. After each UI condition, participants answered a 7-point Likert scale questionnaire regarding communication with automation and acceptance. Communication with automation measured whether drivers understood the system operation through the interface. We measured perceived usefulness and perceived ease of use to evaluate acceptance based on the Technology Acceptance Model (TAM) (Davis, 1989). Perceived usefulness measures the degree to which the technology is useful and enhances driving performance. Perceived ease of use measures the degree to which the technology is easy to use and understandable. After participants experienced five UI conditions, they were asked to rank the five UIs on communication with automation, perceived usefulness, and perceived ease of use. In addition, the preferred modality (visual vs auditory vs both) of given the type of information was evaluated using a 7-point Likert scale questionnaire.

5.2.7 Procedure

Participants were welcomed and introduced to the experiment. They were asked to read the experiment information and sign an informed consent form before they filled out a demographic questionnaire, including age, gender, and vehicle automation experience. After finishing the questionnaire, they moved into the driving simulator. Participants adjusted the sitting position according to their individual preferences, and an experimenter calibrated the eye-tracking system. Participants were informed that they would be driving a partially automated vehicle, with the vehicle performing lateral and longitudinal motion control while they monitored the driving automation and kept their hands on the steering wheel. They were instructed that they could intervene in the automation by braking whenever they felt it was necessary, and partially automated driving would automatically reactivate right after their intervention. In the training session, participants drove partially automated driving on the highway to familiarise themselves with the simulator and learn how to answer the trust and perceived risk questions in the tablet when they were asked. This training lasted until participants could handle all tasks well. Then, the simulator experiment started. For each UI condition, participants experienced eight merging events in randomised order. Participants were informed they could stop if they felt uncomfortable or experienced motion sickness. During driving, participants rated their level of trust and perceived risk using a 10-point Likert scale questionnaire on the tablet located on the left side of the steering wheel after each event. Each UI condition took around ten minutes. After each UI condition, participants answered the questionnaire about communication with automation and acceptance. This was repeated five times to experience five UI conditions. The order of five UI conditions was randomised. Participants had a break between the third and the fourth UI conditions. After five UI conditions, they answered the ranking questionnaire and preferred information and modalities. The entire procedure took around two hours.

5.2.8 Data Analysis

Statistical analysis was conducted using IBM SPSS ver.27. A two-way repeated-measure ANOVA was used to analyse the effects of UI and Event type on trust, perceived risk and eye gaze behaviour. The data were analysed using a separate repeated-measures analysis for each dependent variable (trust, perceived risk and eye gaze behaviour) with independent factors UI (5 levels) and Event type (6 levels) as within-subject variables. To analyse the effects of UI on communication with automation, perceived ease of use, and perceived usefulness, a one-way ANOVA was used. Effects were declared statistically significant if $\alpha<0.05$. Post-hoc analysis was conducted with a Bonferroni test where the α value was adjusted by dividing it by the number of comparisons. Therefore, 0.005 and 0.003 were used as α for post-hoc analysis on the effects of UI and event type, respectively.

5.3 Results

All twenty-two participants completed the experiment, and no motion sickness was reported. Eye gaze signals were successfully collected in 106 simulations (22 participants × 5 UIs with four UI conditions missing eye gaze data). 880 answers (22 participants × 5 UIs × 8 events) about trust and perceived risk and 110 answers (22 participants × 5 UIs) about communication with automation and acceptance, and 22 answers (22 participants) about information and modality preference were collected from questionnaires and analysed.

5.3.1 Trust and Perceived Risk

Figure 5.4 shows the mean score for trust (Left) and perceived risk (Right) over all events for each user interface. The SM-VA UI received the highest trust. The effect of user interface on trust was significant ($F(4, 84) = 5.30$, $p < .001$, $\eta2 = .20$). The SM-VA UI received significantly higher trust compared to the S-V UI ($p = .029$) and the S-VA UI ($p = .025$) (Figure 5.4 left). As expected, perceived risk showed an opposite trend as trust, where the lowest risk was perceived with the SM-VA UI (Figure 5.4 right). However, the effect of UI conditions on perceived risk was just not significant ($F(4, 84) = 2.48$, $p = .050$, $\eta2 = .11$).

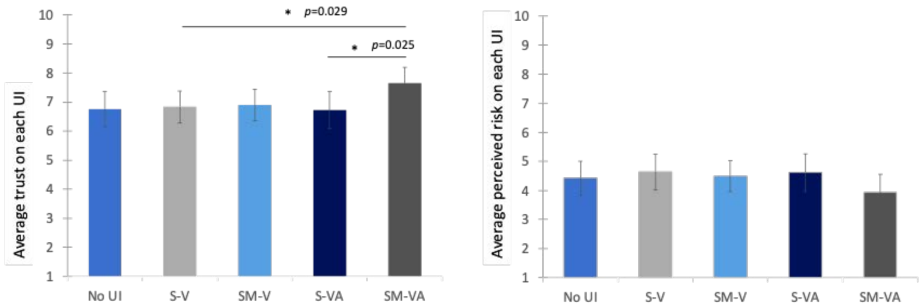

Figure 5.4 Drivers' Trust (Left) and Perceived risk (Right) on each user interface over all events, means and standard error over 22 participants (* $p < 0.05$)

Figure 5.5 shows the mean score for trust (Left) and perceived risk (Right) over all user interfaces for each event type. Here, no significant effects of the order were found between these events so lane change results were averaged over the two equivalent events tested. The most critical event (Slowing down with a 5m merging gap and -8m/s2 deceleration) received the lowest trust and the highest perceived risk. The least critical event (Slowing down with a 25m merging gap and -2m/s2 deceleration) received the highest trust and the lowest perceived risk. As shown in Table 2, the effect of each event element (merging gap and automation action) on trust and perceived risk was analysed. The merging gap included 5m and 25m, and the automation action included -2m/s2 and -8m/s2 deceleration and lane change. The merging gap significantly affected trust ($F(1, 21) = 89.48$, $p < .001$, $\eta^2 = .81$) and perceived risk ($F(1, 21) = 179.09$, $p < .001$, $\eta^2 = .90$). The post-hoc analysis indicated that 25m merging gap events received higher trust and lower perceived risk than 5m merging gap events ($p < 0.001$). The automation action also significantly affected trust ($F(1.28, 26.88) = 55.03$, $p < .001$, $\eta^2 = .72$) and perceived risk ($F(1.64, 34.52) = 76.97$, $p < .001$, $\eta^2 = .79$) with a Greenhouse-Geisser adjustment. The post-hoc analysis indicated that -2m/s2 deceleration events received the highest trust and the lowest perceived risk ($p < .001$), and -8m/s2 deceleration events received the lowest trust and the highest perceived risk ($p < .001$). There was an interaction effect between the merging gap and automation action on trust ($F(1.44, 30.28) = 45.88$, $p < .001$, $\eta^2 = 0.69$) and perceived risk ($F(1.40, 29.34) = 58.84$, $p < .001$, $\eta^2 = .74$) with a Greenhouse-Geisser adjustment. The trust and perceived risk difference between -2m/s2 deceleration or lane change and -8m/s2 deceleration were much greater when the merging gap was 5m than 25m. There was no interaction effect between UIs and elements of events on trust and perceived risk.

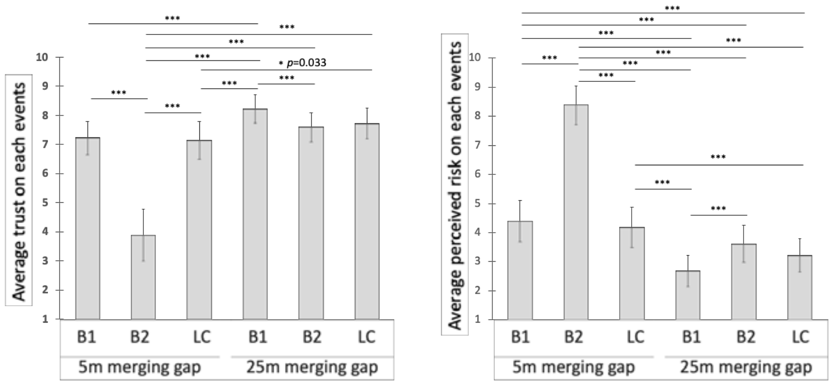

Figure 5.5 Drivers' trust (Left) and perceived risk (Right) as a function of automation action and merging gap (* p<0.05, *** p<0.001). B1:-2 m/s^2braking intensity; B2:-8 m/s^2 braking intensity; LC: Lane change

5.3.2 Braking Behaviour

The use of the brake pedal was detected in 58 out of 110 UI conditions (22 participants × 5 UIs). All instances of braking occurred in the most critical events (slowing down with a 5m merging gap and-8 m/s2 deceleration). Eight participants braked in all five UI conditions in at least one event, two participants used the brake pedal in four UI conditions, three participants in three, and one participant in one UI condition, whereas eight participants did not use the brake pedal at all. As shown in Figure 5.6, there is almost no brake pedal behaviour difference between the five UI conditions. The eight participants who braked in all UI conditions had lower trust levels ($F(1,14) = 4.96$, $p = .04$) and higher perceived risk levels ($F(1,14) = 4.56$, $p = .05$) than the eight participants who never braked. There was no effect of experiment order on braking behaviour.

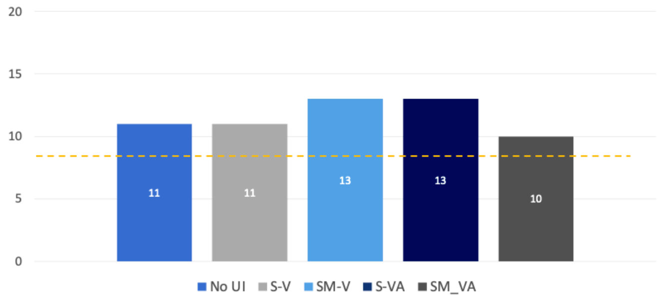

Figure 5.6 Number of participants who used the brake pedal in at least one event with each user interface (The yellow dashed line represents the eight participants who braked in all five UI conditions)

5.3.3 Eye gaze Behaviour

As shown in Figure 5.7, eye gaze behaviour (i.e., the eye gaze fixation time on the display and the road and the eye gaze transition number between the road and the display) differs over all four UIs (S-V, SM-V, S-VA, and SM-VA UI), compared to No UI, primarily due to the visual display on the centre console. No significant difference was found between the four UIs. UI presence significantly impacted the eye gaze fixation time ratio on the display ($F(4, 72) = 8.56$, $p < .001$, $\eta 2 = .32$), the eye gaze fixation time ratio on the road ($F(4, 72) = 7.69$, $p < .001$, $\eta 2 = .30$), and the transition number between the road and the display ($F(4, 72) = 10.38$, $p < .001$, $\eta 2 = .37$). The Bonferroni test reveals that the eye gaze fixation time ratio on display and the eye gaze transition number between the road and the display are significantly higher with the four UIs than with No UI. Significant differences were also found with the four UIs and with No UI except SM-V UI regarding the eye gaze fixation time ratio on the road. No significant effect of different events on eye gaze behaviour (i.e., the fixation duration ratio on the road and the display and the transition number between the road and the display) was found, as shown in Figure 5.8 and Table 5.3. A marginally significant ($p = .045$) interaction was observed between the merging gap and automation action on eye gaze fixation time ratio on the display.

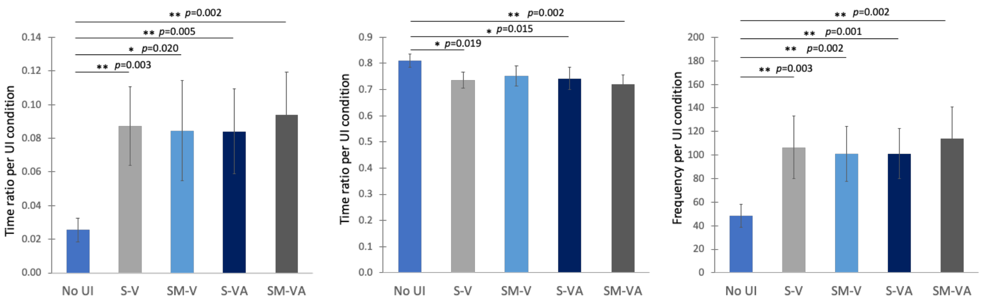

Figure 5.7 Eye gaze fixation time ratio on the display per UI (Left); Eye gaze fixation time ratio on the road per UI (Middle); Transition numbers between the road and the display per UI (Right)
(*p < 0.05, **p < 0.01)

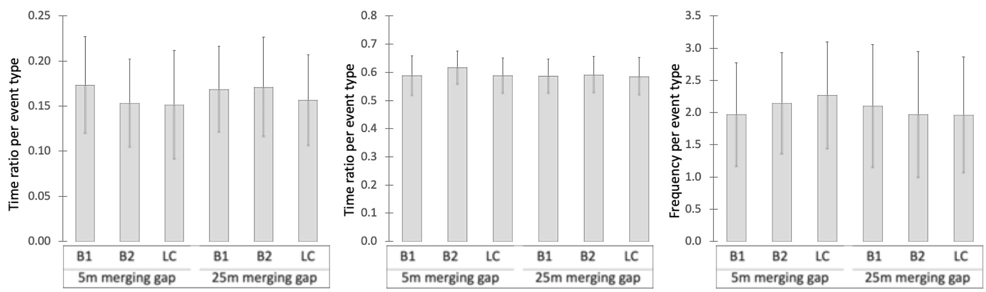

Figure 5.8 Eye gaze fixation duration ratio on the display per event (Left); Eye gaze fixation duration ratio on the road per event (Middle); Transition numbers between the road and the display per event (Right). B1:-2 m/s^2braking intensity; B2:-8 m/s^2 braking intensity; LC: Lane change

Table 5.3 Statistics of the event's effect of merging gap and automation action on eye gaze behaviours

	Event elements	F	Sig.	Effect size (η^2)
Eye gaze fixation time ratio on the display	Merging gap	F(1.00, 15.00) = 2.04	.112	.15
	Automation action	F(1.05, 15.73) = 0.08	.860	.01
Eye gaze fixation time ratio on the road	Merging gap	F(1.00, 16.00) = 3.33	.087	.17
	Automation action	F(1.26, 20.20) = 0.62	.478	.04
Eye gaze transition numbers between the road and the display	Merging gap	F(1.00, 16.00) = 1.52	.236	.09
	Automation action	F(2.00, 32.00) = 0.10	.908	.01

The results showed insignificant effects of user interface on the eye gaze distribution (except UI versus No UI). However, there was a notable individual difference in the average eye gaze distribution on the display. Cronbach's analysis showed the high reliability between each participant's fixation duration ratio on the display of four interfaces, excluding the No UI (Cronbach's $\alpha = 0.86$). There was no correlation between the fixation duration ratio on the display of each participant and their trust and perceived risk. The eye gaze behaviour results indicate that participants indeed checked the visual display during driving but kept the same eye gaze behaviour regardless of different event types and UI.

5.3.4 Communication with Automation, Perceived Ease of Use and Perceived Usefulness

As shown in Figure 5.9, the SM-VA UI received the highest score on all attributes. The main effects of UI were significant for communication with automation ($F(4, 84) = 5.08$, $p < .001$, $\eta 2 = .26$), perceived ease of use ($F(4,84) = 4.54$, $p < .001$, $\eta 2 = .62$) and perceived usefulness ($F(4, 84) = 3.99$, $p < .001$, $\eta 2 = .42$). The post-hoc analysis indicated that participants preferred the SM-VA UI to the No UI, and S-V UI on all attributes ($p < .001$).

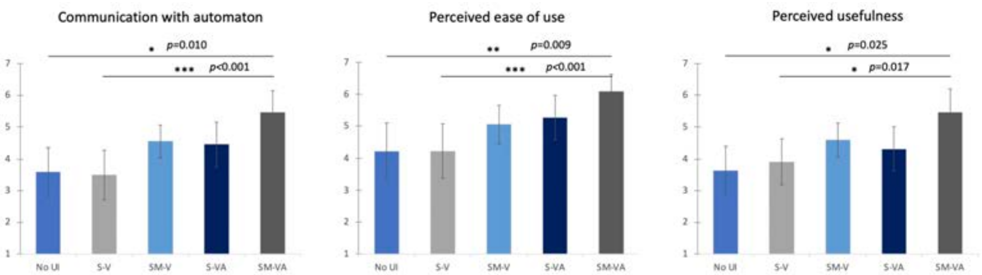

Figure 5.9 Drivers' communication with automation (Left), perceived ease of use (Middle) and perceived usefulness (Right) scores on each User interface (*p < .05, **p < .01, ***p < .001)

Concerning the UI ranking, (ordinal) data were analysed using categorical principal component analysis (CATPCA). Answers from two participants were shown to contain outliers, according to CATPCA, and therefore, we excluded all answers from these two participants.

The Friedman test examined the differences in the ranking among UI conditions. Participants ranked the five UI conditions significantly different on communication with automation ($\chi2(4, 20) = 69.80$, $p < .001$), perceived ease of use ($\chi2(4, 20) = 70.77$, $p < .001$), and perceived usefulness ($\chi^2(4, 20) = 69.92$, $p < .001$). As the results of CATPCA, biplots of all attributes (communication with automation, perceived ease of use and perceived usefulness) on the five UIs are shown in Figure 5.10. The eigenvalues and percentage of total variance are presented in Table 5.4. The results of the analysis explained 100% of the total variance. Dimension 1 accounted for around 90% of the variance in the ranking of communication with automation, perceived ease of use and perceived usefulness. SM-VA UI is ranked highest over the three attributes (communication with automation, perceived ease of use and perceived usefulness), followed by S-VA UI, SM-V UI, S-V UI, and No UI. The No UI and S-V UI were least preferred in perceived ease of use. When examining the x-coordinate pertaining to Dimension 1 across all three attributes in Figure 5.10, participants are consistently positioned on the right side of the graph. This is because participants tended to evaluate the UI with the ranking SM-VA UI, S-VA UI, SM-V UI, S-V UI, and No UI, which were displayed from left to right in the graph. Dimension 2 accounted for around 10% of the total variance. It corresponds to the difference in the preferred interface between S-VA UI and SM-V UI. The results showed differences in preference for S-VA UI and SM-V UI as the second highest-rank interface, depending on the individual. Considering the y-coordinate reflecting Dimension 2 in Figure, the S-VA UI and SM-V UI are positioned on opposite sides, while the remaining UIs congregate around zero. This discrepancy arises from varying participant preferences, particularly regarding the SM-V UI ranking. Participants clustered around zero expressed a preference for SM-V UI as their third choice. Conversely, participants positioned near the SM-V UI reported a lower preference for it compared to other participants. Notably, participants in proximity to the S-VA UI indicated a heightened preference for SM-V UI compared to their counterparts, resulting in a relatively lower ranking for S-VA UI.

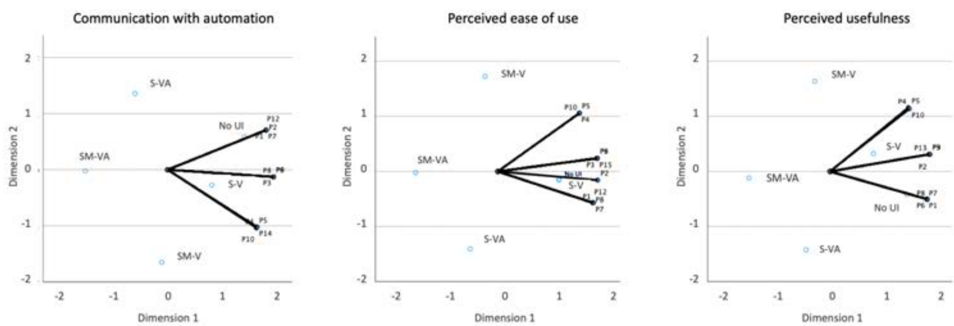

Figure 5.10 UI ranking, CATPCA results of communication with automation (Left), perceived ease of use (Middle) and perceived usefulness (Right)

Table 5.4 UI ranking, CATPCA eigenvalues and % total variance explained

	Communication with automation			Perceived ease of use			Perceived usefulness		
	Total	% of Variance	Cronbach's Alpha	Total	% of Variance	Cronbach's Alpha	Total	% of Variance	Cronbach's Alpha
1	17.80	89.00	0.99	18.06	90.31	0.99	17.86	89.32	0.99
2	2.20	11.00	0.57	1.94	9.69	0.51	2.14	10.68	0.56
Total	20.00	100.00	1.00*	20.00	100.00	1.00*	20.00	100.00	1.00*

** Total Cronbach's alpha is based on the total eigenvalue*

5.3.5 Information Type and Modality Preference

Participants highly appreciated both UI information types, where surrounding information received 6.18 (SD = 1.2) points and manoeuvre information received 6.50 (SD = 0.96) points on a 7-point Likert scale. Figure 5.11 shows the preferred modality for surrounding and manoeuvre information. Participants preferred receiving the surrounding information via both visual and audio modalities. Among twenty-two participants, fourteen participants (64%) preferred surrounding information in both visual and audio, four participants (18%) chose only audio, and four chose only visual (18%). The right figure indicates the modality preference for manoeuvre information. Compared to the surrounding information modality preference, more participants preferred to receive the manoeuvre information through audio only. Ten participants (45%) preferred both visual and audio manoeuvre information. Nine participants (41%) preferred only audio, and three participants (14%) preferred only visual.

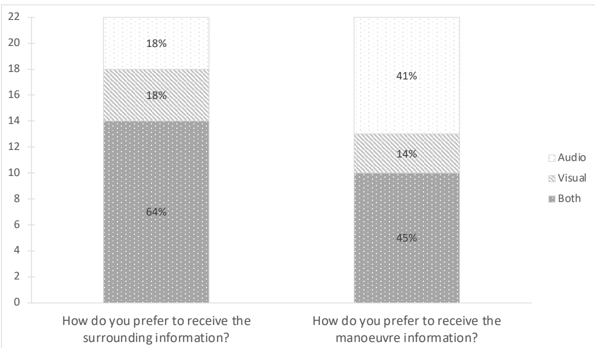

Figure 5.11 Ratio of drivers' modality preference on surrounding information (Left) and manoeuvre information (Right)

5.4 Discussion

This study investigated the effects of user interface (UI) on trust, perceived risk, and acceptance in partially automated highway driving with a simulator experiment. Four interfaces were designed combining surrounding and manoeuvre information and visual and auditory modalities.

5.4.1 Effects of UIs on Trust, Perceived Risk and Acceptance

This study confirms that UI can enhance drivers' trust, communication with automation, perceived ease of use, and perceived usefulness of partially automated vehicles, which supports our hypothesis. In addition, the study showed that different types of automation information and modalities result in different levels of driving behaviour, trust and acceptance. The most advanced UI, SM-VA UI providing surrounding and manoeuvre information via visual and auditory modality, received the highest trust and lowest perceived risk scores and the highest communication with automation and acceptance scores. This is supported by the ranking results, in which participants chose SM-VA UI as the best and No UI or S-V UI as the worst ranking communication with automation, perceived ease of use and perceived usefulness. Drivers evaluated both the surrounding and manoeuvre information positively. However, compared to surrounding-only UI, trust and acceptance increased when manoeuvre information was added. Regarding modality, manoeuvre information through the auditory modality showed a larger effect on trust and acceptance than through the visual modality. Eye gaze behaviour showed that drivers check the UI at the centre console when present. However, at the same time, there was no significant difference in UI gaze time between the four UIs. Presumably, drivers check the driving situation on the road after receiving surrounding information instead of perceiving visual manoeuvre information. Interestingly, the effects of UIs show more significance in acceptance compared to driving behaviour, trust and perceived risk. Acceptance increases when receiving more information with more modalities. Drivers want to monitor the safe operation of partially automated vehicles (Buckley et al., 2018). Therefore, regardless of the actual use of the interface, the presence of the interface can support the acceptance of automation (Kim et al., 2024).

Drivers evaluated both the surrounding and manoeuvre information positively. However, the preference for modality differed between participants and between surrounding and manoeuvre information. More than half of the participants preferred that surrounding information be delivered in both visual and audio modalities. When the surrounding information was provided in both visual and auditory modalities, there was no significant difference in the gaze time on the display compared to when it was provided only in the visual modality. Hence, surrounding information via auditory modality can be interpreted as supplementing the visual modality, not replacing it. On the other hand, the participants preferred manoeuvre information to be delivered in only an auditory modality or a combination of visual and auditory modalities. Drivers checked the centre console display when it showed the detected vehicle. After the participants perceived the merging car, their view moved to the road, with no difference in gaze time across the four UIs. Hence the visual manoeuvre information, was presumably not attended to, explaining the lack of benefits of SM-V vs. S-V and SM-VA vs. S-VA.

The preliminary between-subject design experiment presented in the Appendix A already indicated that UI could increase trust, compared to no UI, but disclosed no significant differences between the four UIs. The main experiment, using a within-participant design, disclosed significant differences between the four UIs, with the best overall results for the most advanced SM-VA UI. A possible explanation is that individual differences obscured the effects of UI in the between-subject experiment. An alternative explanation is that being exposed to multiple UIs, participants develop expectations regarding automation behaviour and UI affecting their behaviour and subjective evaluation. This could include learning and trust calibration with exposure to specific UIs affecting responses with following UIs. However, we found no significant effects of order in the main results, which indicates that such learning has no strong effects. Anyhow, we see benefits in both the within and between-participant experimental design. The within-participant design discloses significant effects with a limited cost-effective sample, whereas the between-participant design better represents real-life exposure where users will presumably use one UI only.

5.4.2 Effects of Criticality of Event Types and Individual Differences

Event criticality (Figure 5.5) had a much larger effect on trust and perceived safety as compared to UIs (Figure 5.4). We additionally compared the effects of UI on trust and perceived risk in the most critical event (slowing down with 5m gap and-8m/s2 deceleration) and least critical event (slowing down with 25m gap and -2m/s2 deceleration). In both events, the effect of UIs on perceived risk was not significant. The effect of UIs on trust was just not significant in the most critical event ($F(4, 84) = 2.43$, $p = .054$), but the effect was significant in the less critical event ($F(4, 84) = 3.06$, $p = .021$). Apparently, the effects of UI on trust and perceived risk are insufficient to make participants feel entirely safe and trust automation in the most critical events. This may be explained by Hoff and Bashir (2015), who described three layers of variability in human-automation trust: dispositional trust, situational trust, and learned trust. Situational trust depends on the context of interaction, while learned trust represents users' evaluations of systems drawn from previous experience or the current interaction. The surrounding and manoeuvre information through the interface affects the learned trust, at the same time, situational trust is affected by the driving situation, such as different events. This study evaluated three automation manoeuvres: strong braking (-8 m/s2), mild braking (-2 m/s2) and lane changing. The latter two manoeuvres were tested with identical behaviours of the merging vehicle and resulted in similar trust and perceived safety, where the UIs provided similar benefits with positive effects of manoeuvre information.

The relationship between UI and braking behaviour appears to be moderated by individual driver characteristics. Eight out of twenty-two participants did not brake in any of the five UI conditions, while another eight used pedals in all five UI conditions. Those who used the brake pedal less tended to have higher trust and lower perceived risk, which is consistent with findings by (He et al., 2022), where trust of the braking group is lower than that of the non-braking group. It will be interesting to investigate trust calibration and its expected effect on braking in prolonged experiments or observations. The braking behaviour was quite different in the preliminary experiment, where participants braked the most in the No UI and the least in the SM-VA UI. However, the individual differences in braking behaviour may mask UIs' effect on the braking behaviour in the preliminary experiment (Niels et al., 2019). Regarding the eye gaze behaviour, each participant looked at the display similarly regardless of the interface condition, which supports the notion that it is challenging to evaluate drivers' understanding of information in vehicles as eye gaze behaviours, as noted by (Cohen-Lazry et al., 2017). The result is aligned with the preliminary experiment (see Figure A3 in the Appendix) and confirmed the trend with significant effects between the No UI and other UI conditions on drivers' eye gaze behaviour.

5.4.3 Limitations and Perspective

Several limitations must be considered when interpreting our findings. The sample size, while sufficient to identify trends, is relatively small, which could potentially lead to biased effects. The artificial nature of the experimental setting, despite its high control level, may not fully capture the complexity of real-world driving dynamics. In addition, the results of user interface experiments under controlled conditions may vary depending on changes in the user interface (Albers et al., 2021) (i.e., aesthetics and layout) or changes in the environment (i.e., the urgency of the scenario) (Kim et al., 2021). These factors could limit the ecological validity of our findings. For example, the lack of significant variation in eye-tracking measures across UI conditions prompts further investigation into how different designs may influence drivers' visual attention. Nevertheless, our results show significant benefits of UIs enhancing trust and acceptance and reducing perceived risk. We provided a visual interface in the centre console display, which is common in commercial cars. However, a head-up display (HUD) could yield even better results, allowing drivers to keep their eyes on the road. HUD cannot easily present spatial surrounding information but can present event-based information such as pop-up messages. We should also consider that drivers may not perceive the auditory UI correctly when engaged in secondary tasks or may find it annoying if presented too often (Hashimoto et al., 2019). For auditory UI recognition, the volume of other audio systems shall be controlled. It is also necessary to consider irritation or stress when exposed to auditory information for a longer time. Future research will focus on interfaces providing a broader range of manoeuvre information, considering various human factors such as annoyance, workload, as well as trust and acceptance. Additionally, future studies should be extended towards UI enhancing trust and perceived safety in higher automation levels, allowing users to take their eyes off the road.

5.5 Conclusion

This study confirms that automation UI can enhance drivers' trust and acceptance of partially automated vehicles. Significant benefits were found for both surrounding (perception) and manoeuvre (action) information. Specifically, the most advanced UI (SM-VA UI), which displayed surrounding and manoeuvre information via the visual and auditory modalities, received the highest trust and acceptance ranking and the lowest perceived risk among drivers. Manoeuvre information displayed through the auditory modality was particularly effective in enhancing drivers' trust and acceptance. Current partially automated vehicles show the image received by sensors on the display, similar to the UI in our study that displays surrounding information visually (S-V UI). Our study shows that the surrounding information displayed via the visual modality draws the driver's attention to the display, but it needs additional auditory communication by the UI to enhance driver's trust and acceptance. Therefore, including manoeuvre information via the auditory modality should be considered for partially automated vehicles. This may make the UI more complex but also more understandable and acceptable. To paraphrase Donald Norman, people hate things to be complicated but like complexity, which this study supports. Furthermore, the study has shown the impact of the user interface in relation to the risk level of the driving situation. When the driving situation poses a high risk, even with UI, drivers do not feel entirely safe and do not trust the automation completely. At the same time, drivers accept driving automation more with UI, regardless of perceiving the information, which was also shown by Kim et al. (2024). This demonstrates both the impact and limitations of UI.

5.6 Appendix A. Preliminary experiment

The appendix describes the method and results of the preliminary experiment.

5.6.1 Method

Experiment conditions

The five interface conditions were the same as in Main Experiment, but the experimental design was between-subjects; each participant experienced one of five user interfaces.

Scenario

In Table A1, the scenarios of the preliminary experiment are described, where seven different event types were repeated twice, and the order was randomised but fixed.

Table A1 Events of the preliminary experiment

Manoeuvre	Merging gap (m)	Automation action	Event	
			Exposure 1	Exposure 2 (Repetition)
Braking	5	-2 m/s^2 deceleration	EI1a	EI1b
		-8 m/s^2 deceleration	EI2a	EI2b
	15	-2 m/s^2 deceleration	EI3a	EI3b
		-8 m/s^2 deceleration	EI4a	EI4b
	25	-2 m/s^2 deceleration	EI5a	EI5b
		-8 m/s^2 deceleration	EI6a	EI6b
Lane Change	25	Lane change	EI7a	EI7b

Apparatus
The apparatus was the same as in the main text experiment, but there were no side mirrors on the simulator. To prevent feeling unsafe, drivers were informed that there were no other vehicles on the left lane when changing the lane as a manoeuvre (Kohn et al., 2019; Lorenz et al., 2014).

Measurements
During the experiment, brake pedal signal and eye gaze behaviours were recorded. In addition, trust and perceived risk questions using a 10-point Likert scale (He et al., 2022) were collected on a tablet on the left side of the steering wheel in English.

Participants
In each UI group, seventeen drivers participated, with a total of eighty-five participants (twenty-one females) holding a driving license for more than one year. The average age of participants was 30.7 years (SD= 13.1 years). Twenty-four participants had experienced adaptive cruise control (ACC), seventeen lane keeping assist (LKA), and eleven combination of ACC and LKA.

5.6.2 Results
Braking behaviour
Participants' brake pedal usage of each interface condition is shown in Figure A1. In the No UI condition, most participants used the brake pedal, and the least number of participants used the brake pedal in the SM-VA UI condition. Participants who used the brake pedal all used it in the most critical events EIa and EIb, slowing down with 8 m/s2 deceleration and 5 m merging gap.

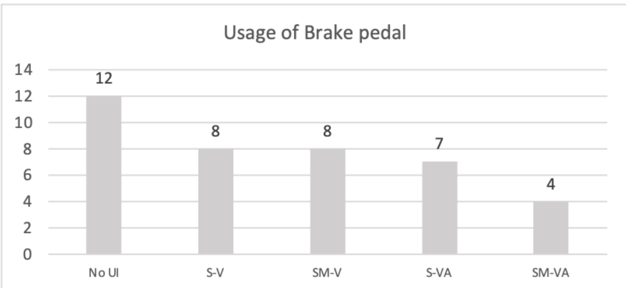

Figure A1 Number of participants who used brake-pedal on each User interface

Trust and Perceived risk
Average trust and perceived risk for each user interface are shown in Figure A2. There was an effect of UI on trust, but no effect on perceived risk. We analysed the effect of UI on trust and perceived risk using repeated-measure ANOVA. Participants' trust and perceived risk on each UI were used as the dependent variable and the interface condition as an independent factor.

The main effect of user interface conditions on trust was significant (F (4, 84) = 4.23 p=0.004, η2=0.18). The post-doc analysis indicated that No UI condition is lower than SM-V, S-VA, and SM-VA. Participants had the highest perceived risk in No UI, but there was no significant effect of user interface condition on perceived risk (F (4, 84) = 1.48 p = 0.217, η2=0.07).

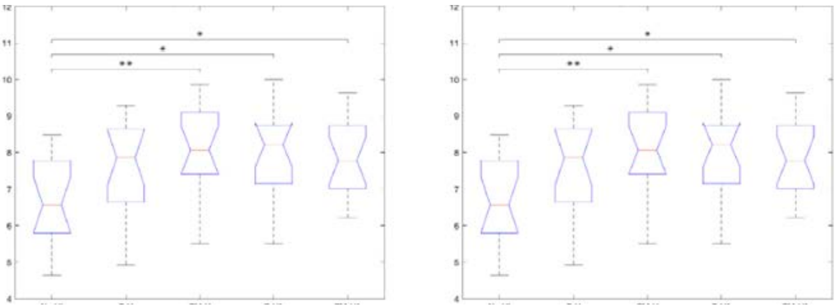

Figure A2 Trust (Left) and Perceived Risk (Right) in each user interface condition
(*p < 0.05, **p < 0.01, ***p < 0.001)

Eye gaze behaviour
Participants gazed almost (i.e., more than 90% of the simulator drive duration to the road and the UI display area. Hence, it is reasonable only to analyse the gaze fixation duration and the gaze transitions between these two areas.

Eye-tracking results did not show a significant effect of UI conditions on the fixation duration towards the road (F(4, 72) = 1.46, p = 0.225) and the gaze transition frequency between the road and the display (F(4, 72) = 1.47, p = 0.221), but the gaze fixation duration towards the display area with S-V UI is significantly higher than that with No UI (F(4, 72) = 3.32, p = 0.015). However, we cannot conclude that the surrounding information via visual UI can attract drivers' attention because of the between-subject experiment design, which will be discussed later. In general, the average fixation duration towards the display and the average transition frequency are higher in all UI conditions than No UI conditions, as shown in Figure A3.

We merged the two exposures of specific event types to analyse their effects. In most of the cases, event types did not significantly influence the fixation duration towards the road, the display area and the transition number between the road and the display. However, the 50 percentile of the boxes in Figure A4 generally indicates that drivers concentrated more on display in non-critical events with a -2m/s2 deceleration but focused more on the road in critical events with a-8m/s2 deceleration.

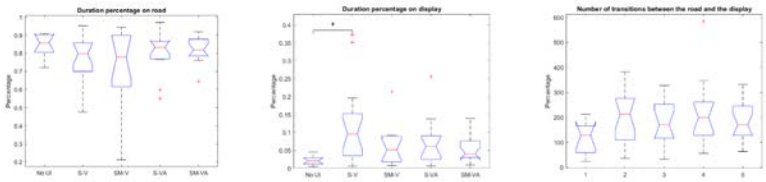

Figure A3 Left: Fixation duration ratio on the road; Middle: fixation duration ratio on display (*$p < 0.05$); Right: Transition numbers of fixations between the road and the display

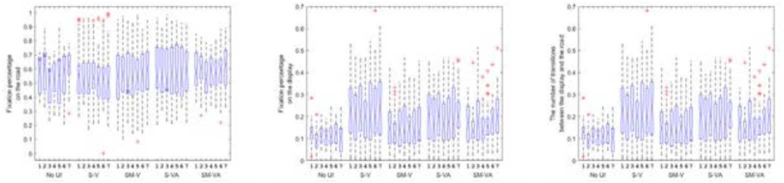

Figure A4 Left: Fixation duration ratio on the road (per event); Middle: fixation duration ratio on display (per event); Right: Transition numbers of fixation between the road and the display (per event). Numbers 1~7 represent EI1~EI7, including both exposures

5.7 Appendix B. Experiment Data

Experiment data from this article can be found online: http://doi.org/10.4121/18bb5d48-c1e5-4d50-ad71-d9010e4494d9.v2.

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CHAPTER

6

How Manoeuvre Information via Auditory (spatial and beep) and Visual UI can Enhance Trust and Acceptance in Automated Driving

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Abstract

In conditionally automated driving (SAE level 3), drivers may take their eyes off the road but will still need to be ready to take control and will, therefore, benefit from information on automation. This study aims to investigate the effectiveness of automation manoeuvre information provided through spatial sound, traditional notification sound, and a visual interface. Spatial sounds were designed differentiating four distinct driving manoeuvres: overtaking a leading car, slowing down, turning right, and passing a roundabout. The notification sound consisted of one beep being identical for all manoeuvres. The visual interface showed the automation mode with an image and manoeuvre information with text and images. The impact of these interfaces on trust, workload, acceptance, situation awareness, and sense of control was evaluated with questionnaires and visual attention was evaluated with eye tracking, while participants engaged in a visual-motor secondary task in a driving simulator. The results indicate that, with all interfaces tested, manoeuvre information enhances trust, acceptance, situation awareness, and sense of control, without significantly affecting the overall workload. These benefits were more profound, adding auditory information and differed marginally between the traditional notification (beep) and the spatial sound, as the effectiveness of the different auditory interface types varied depending on the specific manoeuvre. Findings highlight the importance of designing user interfaces for automation manoeuvre information using auditory cues to improve the user experience in automated driving.

6.1 Introduction

Automated vehicles are one of the technologies to signal an evolution toward a behaviour change in society (Othman, 2021; Taiebat et al., 2018). Automation in vehicles is expected to be beneficial to safety and comfort and to change the way people use cars (Milakis et al., 2017), such as relaxing or watching while driving. A successful adaptation of technology requires a sense of trust in the collaboration between humans and automated systems. To this end, transparency is crucial to evoking trust in humans (Lyons et al., 2016). Transparency is defined as the understandability and predictability of systems (Endsley et al., 2003). Transparency allows users to understand what the system is doing, why, and what it will be doing next (Alonso & de la Puente, 2018). Lack of transparency in automated vehicles (e.g., Automated vehicle does not inform how they will react in the upcoming situation) will lead to inherent distrust (Basantis et al., 2021). User interfaces (UIs) are used to display information that can improve transparency, such as sensor performance, system state and the abilities of automated vehicles. In this study, we have designed user interfaces to enhance transparency and evaluate the effect of the user interfaces on trust and acceptance in conditionally automated vehicles.

6.1.1 Information Needs in Conditionally Automated Vehicles

As the performance of automated vehicles (AV) advances, the need for drivers to monitor will reduce. In SAE Level 3 automated vehicles (conditionally automated vehicles), the vehicle can perform driving actions conditionally and requires drivers to serve as fallback-ready users (SAEInternational, 2021). Automotive manufacturers emphasise the ability of automated vehicles to reduce the cognitive load of driving, allowing users to engage in secondary tasks such as handling a smartphone and watching videos (Cunningham et al., 2019). Nevertheless, it is shown that drivers still want to receive information concerning the actions of their vehicles (Beggiato et al., 2015; Feierle et al., 2020). In addition, this information will enhance trust (Ekman et al., 2018). Furthermore, a driver with a certain level of situation awareness will regain control of a vehicle faster (Lyons, 2013). Moreover, to keep the driver in the loop, continuous feedback improves the driver's ability to know the vehicle's state and detect anomalies (Norman, 1990). Even in conditionally automated driving, it is deemed beneficial to provide automation information (driving situation detected by the system and decisions made by the automated vehicle) to drivers to increase transparency (Carsten & Martens, 2019; Endsley, 2015). Transparency should be designed based on the level of vehicle autonomy and human states, such as acceptance, situation awareness, and workload (Lakhmani, 2019). During conditionally automated driving, it is not mandatory for drivers to monitor all driving situations. Therefore, drivers may only need limited but highly abstracted information. Very detailed information could increase the driver's workload, cause annoyance, and sometimes be unnecessary. Auditory warnings are often designed such that they evoke a sense of high urgency (Politis et al., 2015) or unpleasantness (Özcan & Egmond, 2012). However, the purpose of automation information during automated driving is different from that of warnings. Even though drivers receive information from the vehicle, they do not need to react. The interaction in conditionally automated driving needs to satisfy the demanding conditions that make the driver aware of the situation without causing annoyance. Therefore, driving scenarios and user experience should be considered in the design, especially what information is required and which modality to use to display this information.

6.1.2 Automation information to enhance transparency in automated vehicles

During conditionally automated driving, the system operates the vehicle instead of the driver, and user interfaces can communicate vehicle action. Previous studies have shown that automation information providing vehicle action increases trust and acceptance (Basantis et al., 2021; Ma et al., 2021; Oliveira et al., 2020; Sawitzky et al., 2019; Yucheng Yang, 2017). Oliveira et al. (2020) and Sawitzky et al. (2019) have shown that augmented reality displays can increase trust by providing different visual aids for displaying driving routes. Basantis et al. (2021) found that participants expressed feelings of comfort, trust, and safety when presented with auditory manoeuvre notifications by comparing four distinct interfaces designed to communicate automation actions to rear-seat passengers, which included 1) no feedback, 2) a visual display of the vehicle's path, 3) auditory notifications of vehicle manoeuvres, and 4) a combination of auditory notification and display of the vehicle's path. However, the auditory interface exhibited limitations in directing participants' attention to environmental details. Ma et al. (2021) also found significant effects of visual vehicle action information on drivers' levels of trust in a driving simulator. These studies found requirements of system transparency for automated vehicles. However, there is a lack of studies reporting the impact of different user interfaces on understanding automated driving. Although a few studies (Basantis et al., 2021; Oliveira et al., 2020; Sawitzky et al., 2019) have compared the effects of different interfaces, they did not fully consider the automated driving experience, in which drivers' visual attention is often required for secondary tasks (Cunningham et al., 2019). Hence, the requirements for user interface design for system transparency are not yet very clear. Therefore, in this study, we compared specifically designed interfaces to understand the benefits of system transparency in fostering trust and acceptance and to compare different interfaces presenting manoeuvre information as automation information.

6.1.3 Effect of auditory UIs in vehicles

Visual and auditory interfaces serve as the primary modalities used in vehicles. An auditory interface offers the advantage of capturing attention from all directions (Siwiak & Jame, 2009), regardless of where the driver's visual focus is directed (Liu, 2001). Visual interfaces have the advantage of presenting more information than auditory interfaces in a limited time; auditory interfaces are advantageous for users to provide a somewhat faster response than a visual interface in automated vehicles (Petermeijer et al., 2017; Politis et al., 2015). However, the potential for annoyance among users remains a significant concern in the design of auditory displays (Edworthy, 1998). In addition, sound can draw attention, but there is a limit to providing explanatory information only with sound. While speech can convey narrative information, its use can quickly lead to driver annoyance in automated vehicles (Forster et al., 2017). Furthermore, speech messages are generally longer than abstract sounds, resulting in longer response times. Spatial sounds, characterised by their directionality and movement, offer an intuitive audio expression that can effectively convey automated driving manoeuvres to drivers. These sounds can provide a driving context within the auditory interface. Previous studies (Beattie et al., 2014; Gang et al., 2018; Wang et al., 2017) have found that spatial sound affects drivers in the way of behaviour, situation awareness, sense of control and workload. Beattie et al. (2014) found that spatial cues related to driving actions in both manual and automated driving, such as braking, acceleration, indicator signals, and gear shifts, improved situation awareness and fostered sense of control. Furthermore, the inclusion of additional traffic information through spatial sound has been shown to enhance situation awareness in both manual (Wang et al., 2017) and automated driving (Gang et al., 2018) and reduce the auditory demands (Ho & Spence, 2005) in manual driving. The effect of information delivery may appear differently depending on the modality type, and multimodal is not always effective in automated vehicles (Kim et al., 2021). In this study, we aim to evaluate the impact of visual and auditory interfaces, including spatial sounds, on delivering manoeuvre information to drivers in conditionally automated vehicles.

6.1.4 Aim of the current study

This study investigates how manoeuvre information affects drivers during conditionally automated driving. We designed and evaluated four user interfaces to provide detected driving situations and manoeuvre of driving automation as manoeuvre information. This study was conducted to find the answer to the following research questions.

1. How do user interfaces of manoeuvre information affect trust and acceptance in conditionally automated vehicles?
2. Does providing detailed auditory information via spatial sounds improve understanding of the vehicle action during automated driving?

As automation advances, it becomes important not only to provide information to enhance trust and acceptance of automated vehicles but also to consider automated driving situations. In this study, we addressed gaps in existing research, the oversight of user experience in conditionally automated vehicles. Specifically, we conducted a consolidated sound design process, including validation, to provide manoeuvre information via spatial and simple sound without annoyance. The study contributes to addressing a sound design approach to provide information taking account of the context of automated driving and provides insights into the impact of different levels of transparency and modalities on trust and user experience.

In the following sections, we will detail our research methodology, including UI and experiment design, present the results of the simulator experiment, and discuss their implications for the design of UIs in conditionally automated vehicles.

6.2 Methods

We designed four user interfaces (UIs) providing automation manoeuvre information via visual-only, visual plus notification sound, visual plus spatial sound, and no manoeuvre information as a baseline. The UIs were evaluated by measuring eye-gaze behaviour, situation awareness, trust, sense of control, workload, and acceptance in a driving simulator.

6.2.1 Participants

Twenty-seven drivers volunteered in the experiment. Twelve were female, and fifteen were male. The average age of participants was 31 years (SD= 8.58, Min = 24 and Max = 59). All had a valid driving license for more than one year and had no problem with visual and auditory acuity. Participation was recruited through a local communication application or university mailing, and the respondents were financially compensated with €15. The study was approved by the Human Research Ethics Committee of the TU Delft.

6.2.2 Apparatus

Participants experienced UIs in scenarios in the DAVSi driving simulator with a Toyota Yaris cockpit (Figure 6.1) at Delft University of Technology. It used three high-quality projectors to display the environment on the cylindrical 180-degree screen. The visual UI consisted of a 10.1-inch tablet on the centre console. Auditory information was presented using a 5.1 channel speaker system, which was strategically placed on the front of the centre console, as well as on the left and right front, left and right rear under the door trim of the vehicle. A woofer, located under the passenger seat, was used to amplify the sounds. To collect eye-gaze behaviour data, we used a fixed four-camera called Smart-Eye, which tracks the participant's pupil to determine the region of interest. The cameras were placed on the left and front side of the upper cockpit, right downside of the centre console, and rear mirror, and data was extracted using MATLAB R2022.

Figure 6.1 Exterior and Interior of the DAVSi simulator

6.2.3 Experimental design

The simulator experiment had a within-subjects design, so one participant experienced four UI conditions in random order as shown in Table 6.1: 1) Baseline, 2) Visual-only, 3) Notification, and 4) Spatial sound. The baseline only included the automation mode symbol in the visual display. In the visual-only, in addition to automation mode, manoeuvre information was provided using a visual interface without sound. The Notification and the Spatial sound condition present manoeuvre information through visual and auditory modalities. In the Notification, an abstract sound (beep) was provided. In the Spatial sound, the sound position in the interior dynamically reflected the vehicle manoeuvre and the position of other road users.

Table 6.1 Experimental design with information and modality as independent variables

	1. Baseline	2.Visual-only	3. Notification	4. Spatial sound
Visual	Automation mode icon		Automation mode icon + Manoeuvre information	
Sound	No sound	No sound	Abstract sound (beep) which is identical for all manoeuvres	Spatial sound which is different for each manoeuvre type

6.2.4 Scenario

The experiment consisted of highway driving scenarios, each featuring four different manoeuvres. While driving, participants drove conditionally automated vehicles and were asked to engage in a tablet typing task as a secondary task. The four manoeuvres- 'Overtake', 'Turn right', 'Slow down', and 'Roundabout' - were selected by the H2020 HADRIAN project (Stojmenova & Sodnik, 2019). Throughout these manoeuvres, no automation failures or take-over requests were designed, and hence, drivers were not expected to take any action. The timeline of the scenario is illustrated in Figure 6.2. The scenario began with the participant driving at a speed of 90km/h in the right lane of a two-lane highway. During the first manoeuvre, the speed of the preceding vehicle was slow, so the participant's vehicle moved to the left lane and overtook the preceding vehicle before returning to the first lane. The vehicle continued driving on a straight road until it encountered a traffic jam, causing the speed to decrease with a-5 m/s2 acceleration. After the traffic jam cleared, the vehicle sped up and continued driving on the straight road. The next manoeuvre involved changing lanes to the exit lane of the highway, followed by a change in the road to a one-lane road. Finally, the vehicle passed through a 20-meter-diameter roundabout and exited the opposite road. The vehicle continued driving on a straight road until it stopped.

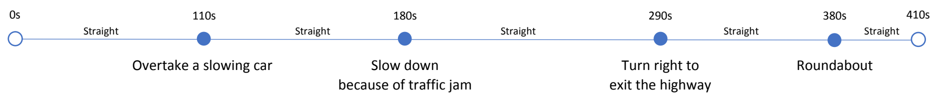


Figure 6.2 Scenario timeline

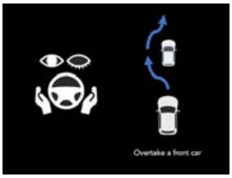
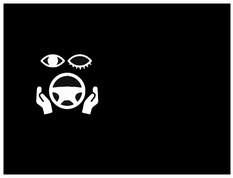
6.2.5 UI Design

Visual UI

The visual interface always showed the automation mode even in the baseline (Figure 6.3) with a driving symbol designed in the H2020 HADRIAN project (Trösterer et al., 2021). The visual-only interface added visual manoeuvre information with five states presented with text and images (Table 6.2).

Figure 6.3 Visual UI in Baseline

Table 6.2 Visual UI - The right parts provide manoeuvre information shown in conditions Visual-only, Notification, and Spatial sound

Situation	Normal driving	Manoeuvres	
		Overtake	Slowdown
Visual interface			
		Turn right	Roundabout
			

Auditory UI

Auditory UIs were played through the surround Dolby 5.1 speakers slightly before vehicles began a manoeuvre. The manoeuvres did not represent emergency situations, and drivers were not expected to react. Hence, sounds were designed to be informative rather than urgent. Sounds were created in Logic Pro X, a digital audio designing and editing software. Its Sculpture's physical model (Figure 6.4 left) was used for sound design as a basis. It enables quick exploration of timbres based on materials like nylon, wood, glass, and steel and according to spectral properties in timbre, harmony, and intensity. We used the wood and xylophone style as the main timbre, which is universal in nature and of which it is shown it evokes a sense of simplicity for listeners (Özcan & Egmond, 2012). Using Final-cut Pro version 10.6.4, output speakers were assigned to produce a spatial effect (Figure 6.4 right).

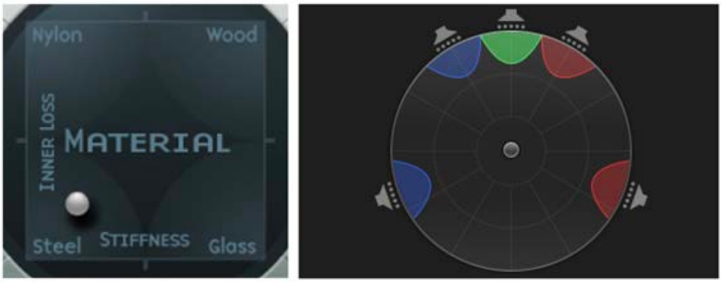


Figure 6.4 Left: Logic Pro X, Right: Final-cut Pro

The beep in the Notification condition was designed for automated vehicles and validated in our previous study (Kim et al., 2022). The spectrogram of the sound is displayed in Figure 6.5. The duration of the sound is 1 second, and it begins with a 0.05-second sound at a frequency of 989 Hz, followed by a combination of frequencies of 989 Hz and 1478 Hz for the subsequent 0.07 seconds. After that, the sound consists of a mix of frequencies of 989 Hz, 1478 Hz, and 656 Hz for the remaining 0.84 seconds.

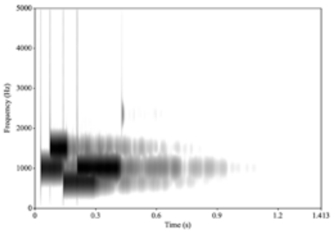


Figure 6.5 Spectrogram of the notification beep

Figure 6.6 includes a spectrogram of the four spatial sounds that were used to discriminate the four manoeuvres. During the Overtake manoeuvre, a 4.5-second sound with a mix of 145 Hz, 192 Hz, and 385 Hz every 1.5 seconds is played through the front left speaker to indicate that the vehicle is moving into the left lane to overtake the vehicle ahead. As the driver's vehicle passes the leading vehicle on the right lane, 1174 Hz and 1564 Hz are played through the right front speaker and then gradually shifted to the rear speaker. When the overtaking is completed and the vehicle returns to its original lane, a 9-second blend of 145 Hz, 192 Hz, and 385 Hz every 1.5 seconds is played through the front right speaker. Once the vehicle returns to the main lane, a 3-second sound is played through both side speakers. In the slowdown manoeuvre, the sound starts from the front left and right speakers to provide a deceleration feeling, gradually decreasing the volume from the front speakers while increasing it from the back left and right speakers. This sound ranges from 14 Hz to 334 Hz and lasts 3.1 seconds. In the right turn manoeuvre, the right front speaker plays mixed sounds of 145 Hz, 192 Hz, and 385 Hz for 6 seconds with a 1.5-second interval. After the vehicle moves to the right lane, the front left and right speakers play a sound for 4.5 seconds.

During the Roundabout manoeuvre, a sound mixture of frequencies consisting of 68 Hz, 260 Hz, and 1050 Hz starts from the front left speaker and moves to the front right speaker and back right speaker to indicate that the vehicle is passing through the roundabout. This sound lasts for 13 seconds while driving through the roundabout. Additionally, a mixed sound of 145 Hz, 192 Hz, and 385 Hz is played through the front right speaker for 6 seconds with a 1.5-second interval starting from 4 seconds to indicate that there is a right turn to pass through the roundabout. After passing through the intersection, a sound is provided from both the left and right front speakers for 4.5 seconds.

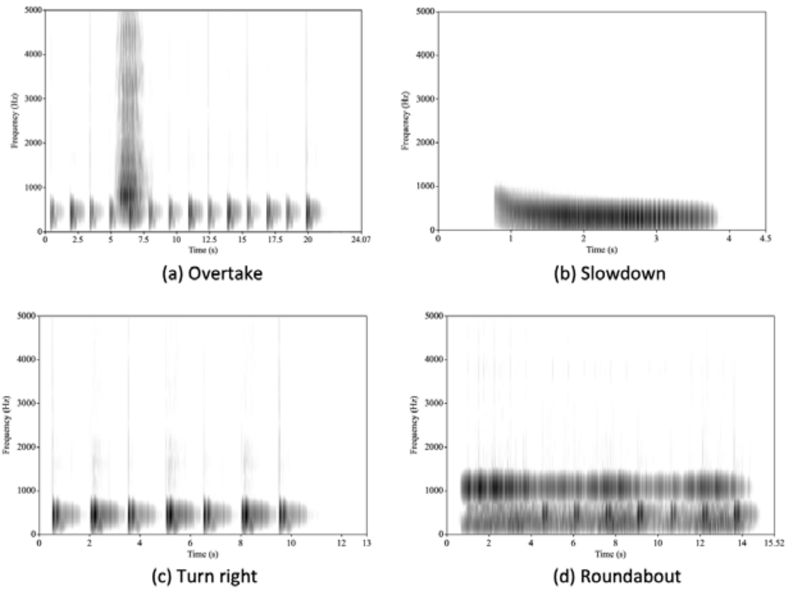


Figure 6.6 Spectrogram of the spatial sound of four manoeuvres

Sounds were designed over multiple iterations, with indirect feedback from the research group with experts in sound design. After the sound design, sounds were validated to ensure the design intention was aligned with the driver's perception. The validation results are described in 3.1. These sounds can be found in the digital appendix. The beep and spatial sound level was 60-80 dB during the experiment. An in-vehicle embedded speaker presented the underlying sound (road noise), which was 40-50 dB recorded by the SCANNER driving simulation.

To prevent a design malfunction in the experiment, the sound validation process was conducted separately from the simulator evaluation, with no experimenters participating in both phases. During the validation process, participants viewed videos depicting various manoeuvres accompanied by spatial sounds. Subsequently, they were asked to complete a 7-point Likert scale questionnaire, evaluating the perceived spatiality of the sounds (how well the sound corresponded to the vehicle's direction of movement) and the level of annoyance caused by the sounds. The results are described in section 6.3.1.

6.2.6 Secondary task

Participants were asked to perform a typing task, a visual-motor task without sound, to simulate engagement in a non-driving task during automated driving. The task was conducted using an application called 'Speed Typer-Typing Test'. The driver typed the given text without a time limit. The task is visually and cognitively demanding, self-paced and interruptible, so participants could pause it whenever they want to check the driving environment. Participants were instructed to engage in the typing task with a tablet on their lap.

6.2.7 Measurement

During driving, eye-gaze behaviour and situation awareness were collected. Eye gaze behaviour was recorded at 60Hz using a smart-eye system with 4 infrared cameras mounted in the vehicle cockpit. We measured the percentage of time, where the eyes were on the road when participants glanced within the windshield area and the percentage of time eyes were on the automation display in the centre console. This captures whether participants showed different monitoring behaviours. Situation awareness was measured with the Situation Awareness Global Assessment Technique (SAGAT) (Endsley, 1988). After each manoeuvre, participants answered questionnaires related to perception, understanding and projection of the present situation (C. Nadri et al., 2021). Participants received a score of 1 if they correctly (1) perceived the situation (2) understood what was happening in the situation and (3) could predict the car's action. They could receive partial scores based on correctly answering one(1/3) or two(2/3) SA components. After each interface condition, participants answered a questionnaire regarding trust, sense of control, workload, and acceptance of the automated vehicle. Trust in automation systems was assessed using a 7-point Likert scale questionnaire based on (Jian et al., 2000) including four trust-related items (Mistrust (the system behaves in an underhanded manner), Suspicion (I am suspicious of the system's intended action or outputs), Confidence (I am confident in the system), and Reliable (The system is reliable)). The sense of control was evaluated using a 7-point Likert scale questionnaire to state whether they felt in control of the vehicle at any point during each scenario (Beattie et al., 2014). Workload was evaluated using a DALI (Pauzie, 2008) questionnaire, which is a modified NASA-TLX (Sandra G.Hart, 1988) and adapted to the driving task workload. It was deemed useful to determine the effect of different user interfaces on driver workload. Participants answered a 20-interval questionnaire consisting of 6 items (effort of attention, visual demand, auditory demand, temporal demand, interference, and situational stress). To evaluate acceptance, participants answered nine items (1. Useful- useless, 2. Pleasant-unpleasant, 3. Bad-good, 4. Nice-annoying, 5. Effective-superfluous, 6. Irritating-likeable, 7. Assisting-worthless, 8. Undesirable-desirable and 9. Raising alertness-sleep inducing) using a 7-point Likert scale questionnaire (Laan et al., 1997). The scores for items 1, 2, 4, 5, 7 and 9 were reversed in the calculation. After all UI conditions were completed, participants were asked to rank the four types of interfaces on usefulness. Finally, in a short-constructed interview, participants answered preferences for manoeuvre information and sounds.

6.2.8 Procedure

Participants were welcomed and introduced to the experiment. They were asked to read the experiment information and sign an informed consent form before they filled out a demographic questionnaire (age, gender, driving experience, and visual and auditory acuity). After finishing the questionnaire, they moved into the driving simulator. Participants adjusted the sitting position according to their individual preferences, and an experimenter calibrated the eye-tracking system. Participants were informed that they would be driving a conditionally automated vehicle, with the vehicle performing lateral and longitudinal motion control while they engaged in a secondary task and did not need to intervene in driving at all if the system did not ask for take-over control. Participants drove a training session to familiarise themselves with the simulator and learn how to answer situation awareness questions while driving. This training lasted until participants could handle all tasks well. Then, the simulator experiment started. Before each UI condition, participants experienced each UI with an explanation in the training scenario to reduce the learning impact of each UI. Then, the main experiment was started. For each UI condition, participants experienced four manoeuvres in a fixed order. Participants were informed they could stop if they felt uncomfortable or experienced motion sickness. During driving, participants answered situation awareness verbally after each manoeuvre. Each UI condition took around seven minutes. After each UI condition, participants answered the questionnaire about t trust, sense of control, workload, and acceptance. This was repeated four times to experience four UI conditions. The order of four UI conditions was randomised. Participants had a break between the third and the fourth UI conditions. After four UI conditions, they answered the ranking about the preference of interfaces and had a short interview. The entire procedure took around one and a half hours.

6.2.9 Data analysis

Statistical analysis was conducted using IBM SPSS ver.27. The data were analysed using a separate repeated-measures analysis for each dependent factor (eye-gaze behaviour, situation awareness, trust, sense of control, workload, and acceptance) with UI as an independent factor (four levels). To analyse the effects of UI eye-gaze behaviour, situation awareness, trust, sense of control, workload, and acceptance, a one-way ANOVA was used. Effects were declared statistically significant if $\alpha < .05$. Post-hoc analysis was conducted with a Bonferroni test where the α value was adjusted by dividing it by the number of comparisons. Therefore, $\alpha = .008$ was used as α for post-hoc analysis on the effects of UI.

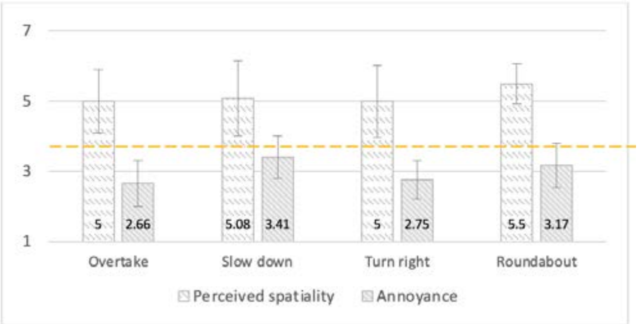
6.3 Results

Twelve participants were involved in validating the sounds prior to the simulator experiment to ensure the accuracy of the spatial sounds and prevent interface manipulation errors. Subsequently, twenty-seven participants participated in the simulator experiment to evaluate the impact of the user interfaces. None of the participants in the sound validation participated in the main experiment.

6.3.1 Sound validation results

A total of twelve participants, including four females, were involved in the validation of spatial sounds. The average age was 31.33 years (SD =4.51). Sounds were rated higher than the mid-point of the 7-Likert scale on perceived spatiality (mid-point = 4, Overtake p = .03, Slow down p = .04, Turn right p = .04, Roundabout p < .001) and lower than the mid-point on annoyance (mid-point = 4, Overtake p < .001, Slow down p = .04, Turn right p < .001, Roundabout p = .01) as shown in Figure 6.7. These findings indicated that the sounds communicated the spatiality of the driving situation and did not elicit significant annoyance. Based on the results, it was determined that the sounds would be suitable for use in the main experiment.

Figure 6.7 Perceived spatiality and Annoyance of sounds for all manoeuvres
The yellow dashed line represents the mid-point (4)
(Error bars reflect standard error of the mean)



6.3.2 Main experiment results

Trust

Trust-related items' scores for the user interfaces are shown in Figure 6.8. Notification condition received the highest trust, and Baseline received the lowest trust in all items ('Mistrust', 'Suspicion', 'Confidence', and 'Reliable'). Significant differences were found between the different UI conditions for all items with a Greenhouse-Geisser adjustment. (Mistrust: $F(2.32, 60.40) = 7.01$, $p = .001$, $\eta 2 = .212$, Suspicion: $F(2.24, 58,20) = 16.63$, $p < .001$, $\eta 2 = .390$, Confidence: $F(2.26, 58.85) = 6.59$, $p = .002$, $\eta 2 = .202$, Reliable: $F(2.20, 57.24) = 6.52$, $p = .002$, $\eta 2 = .201$). Pairwise comparisons showed that the Notification and Spatial sound condition received significantly higher trust than the Baseline for all items.

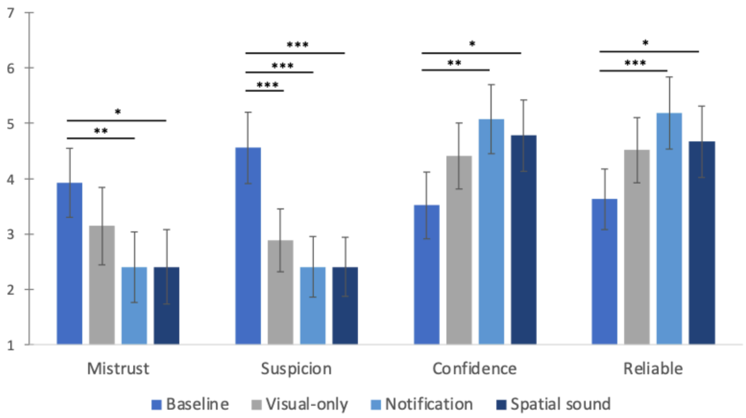


Figure 6.8 Trust for UI conditions (*p < .05, **p < .01, ***p < .001)
(Error bars reflect within-subject standard error of the mean)

Acceptance

Figure 6.9 shows the mean score of nine acceptance-related items for UI conditions. Cronbach's analysis showed the high reliability between each participant's score of nine items (Cronbach's alpha = .93). The results showed that Baseline received the lowest acceptance. There was a significant difference between UI conditions (($F(3, 78) = 50.31$), $p < .001$, $\eta 2$ = .66). A pairwise comparison showed that the Notification condition was significantly higher than the Baseline and Visual-only conditions. The baseline received significantly lower scores of acceptance than other conditions.

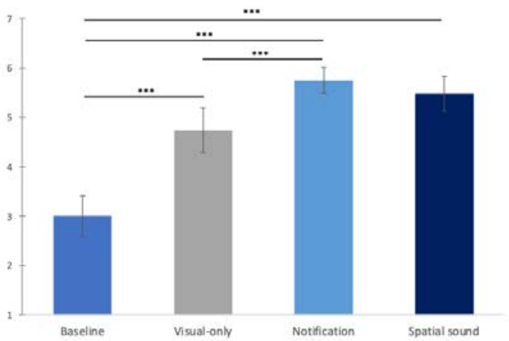


Figure 6.9 Acceptance for UI conditions (***p < .001)
(Error bars reflect within-subject standard error of the mean)

Eye-gaze behaviour

The eye-gaze data of 18 participants out of the 27 was used in the analysis. The data of the nine excluded individuals was not used due to bad quality. The results showed that the eye-gaze behaviour did not differ over UI conditions. and was similar for the visual display and driving environment. Averaged over conditions, participants watched the road 5% of time and the UI 4% of time. Because there was a breach of homogeneity a Greenhouse-Geisser correction was used. There was no significant difference in the ratio of gaze fixation on the display ($F(3, 51) = 0.641$, $p = .592$, $\eta 2 = .036$) and the ratio of gaze fixation on the road ($F(1.83, 31.10) = 0.568$, $p = .557$, $\eta 2 = .032$). There was no correlation between the eye-gaze ratio on the visual UI of each participant and their situation awareness, trust, and workload.

Situation awareness

Figure 6.10 presents the situation awareness scores for the different UI conditions. The Baseline received the lowest score in all manoeuvres. The Spatial sound condition scored the highest in the Turn right and Slow down manoeuvres and the Notification condition scored the highest in Overtake and Roundabout. Note that situation awareness scores reached the maximum level in the Overtake manoeuvre in the Notification condition and the Turn Right manoeuvre in the Spatial sound condition because the task was easy for participants. Significant differences were found between the different UI conditions for all manoeuvres with a Greenhouse-Geisser adjustment except Roundabout (Overtake: $F(2.12, 54.99) = 27.10$, $p < .001$, $\eta 2 = .510$, Slow down: $F(2.01, 52.36) = 8.78$, $p < .001$, $\eta 2 = .252$, Turn right: $F(2.08, 54.10) = 37.36$, $p < .001$, $\eta 2 = .590$, Roundabout: $F(3, 78) = 12.11$, $p < .001$, $\eta 2 = .318$). Pairwise comparisons showed that the Spatial sound and Notification conditions induced higher situation awareness scores for all manoeuvres. The Spatial sound and Notification conditions resulted in significantly higher situation awareness scores than the Baseline for all manoeuvres and higher situation awareness scores than Visual-only for all manoeuvres except for Roundabout. The Visual-only conditions resulted in significantly higher situation awareness scores than the Baseline in the Overtake manoeuvre. In addition, Cronbach's analysis showed the high reliability between each participant's score of SA of four manoeuvres (Cronbach's alpha = .73).

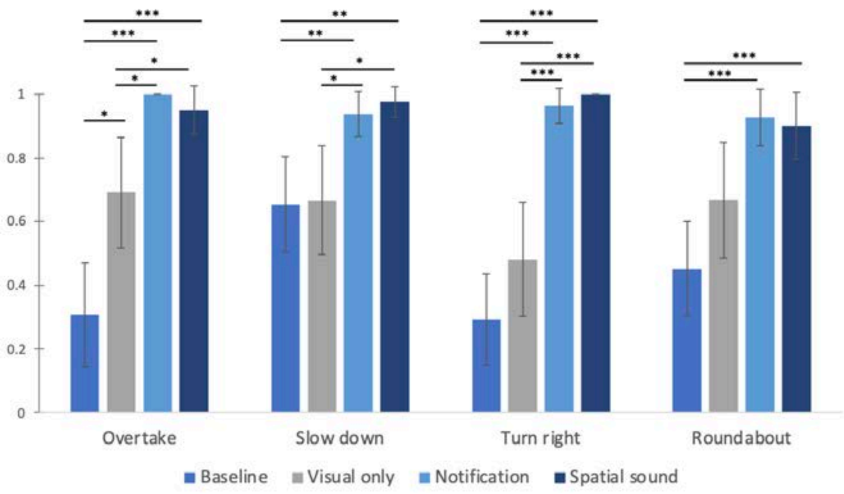


Figure 6.10. Situation awareness for manoeuvres and UI conditions (*p < .05, **p < .01, ***p < .001)
(Error bars reflect within-subject standard error of the mean)

Workload

A summary of workload results is shown in Figure 6.11. The overall workload is the average score of the six questions in DALI. Cronbach's analysis showed the high reliability between each participant's score of the six questions (Cronbach's alpha = .85). No significant main effect was found in the effort of attention ($F(2.15, 55.77) = 2.86$, $p = .099$, $\eta 2 = .062$), visual demand ($F(1.92, 50.38) = 3.00$, $p = .061$, $\eta 2 = .103$), temporal demand ($F(3, 78) = 0.528$, $p = .664$, $\eta 2 = .020$), interference ($F(3, 78) = 0.799$, $p = .496$, $\eta 2 = .030$), and overall workload ($F(2.20, 57.07) = 1.95$, $p = .148$, $\eta 2 = .070$). There was a significant difference in two items with a Greenhouse-Geisser adjustment: auditory demand ($F(1.94, 50.40) = 4.80$, $p = .013$, $\eta 2 = .156$) and situational stress ($F(2.25, 58.45) = 14.73$, $p < .001$, $\eta 2 = .362$). Auditory demand workload was significantly lower with the Visual-only condition in comparison to the Baseline and Spatial sound conditions. Regarding situational stress workload, the Notification condition was significantly lower than the Baseline and Visual-only conditions. The Spatial sound condition also received significantly lower scores than the Baseline.

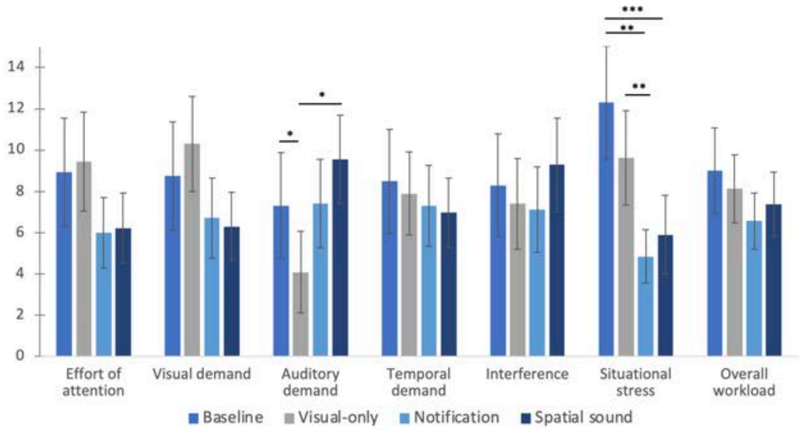


Figure 6.11 Workload for UI conditions (*p < .05, **p < .01)

Note: Error bars reflect within-subject standard error of the mean

Sense of control

As shown in Figure 6.12, the Baseline received the lowest sense of control scores, and the Spatial sound condition received the highest scores. There is a significant difference between the different UI conditions with a Greenhouse-Geisser adjustment ($F(1.75, 45.44) = 10.33$, $p < .001$, $\eta 2 = .28$). The Baseline received a significantly lower sense of control scores than other UI conditions.

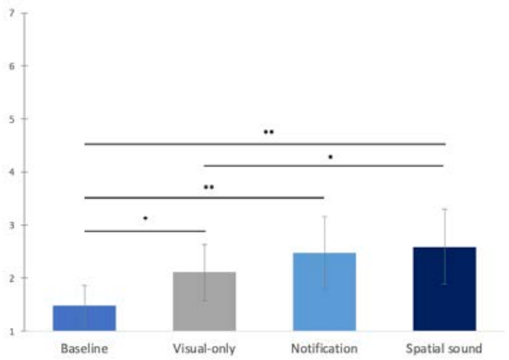


Figure 6.12 Sense of control for UI conditions (*p < .05, **p < .01)
Note: Error bars reflect within-subject standard error of the mean

Usefulness of UI

Concerning the ranking of the UI usefulness, the Friedman test showed that participants ranked four conditions of UI types significantly differently ($\chi^2(3,27) = 59.49$, $p < .001$). Post-hoc comparisons indicated that participants gave the lowest usefulness ranking when presented with the Baseline and the highest when presented with the Notification or Spatial sound condition. There was no significant difference in usefulness ranking between the Notification and Spatial sound conditions.

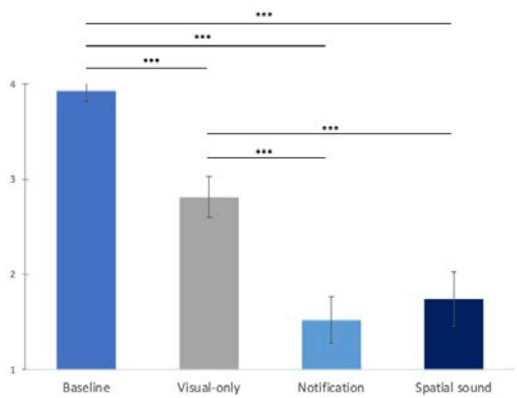


Figure 6.13 Usefulness of UI ranking (1: best, 4: worst) (***p < .001)
Note: Error bars reflect within-subject standard error of the mean

Short Interview

Twenty-six out of twenty-seven participants mentioned that the UI conditions with sounds (Notification or Spatial sound condition) were useful. Regarding the feedback on auditory UIs, fifteen mentioned that the Spatial sounds were annoying because the duration was longer than necessary or the meaning was unclear. Only one participant mentioned that the Notification sound was annoying.

6.4 Discussion

This study investigated the impact of automation manoeuvre information on user trust, situation awareness, acceptance, sense of control, and workload. To this end, we designed four user interfaces through which information was presented via visual and auditory modalities. The results showed that providing manoeuvre information enhances trust, acceptance, situation awareness, and sense of control. Especially, presenting the information through the auditory modality showed higher ratings than when using only visual information. In addition, a marginal difference has been found between the traditional notification (beep) and the innovative spatial sound.

The results show that vehicle-to-driver communication about automated vehicle manoeuvres strongly enhances drivers' trust and acceptance in automated vehicles. The Baseline, which had no manoeuvre information, received the lowest trust and acceptance score. This result is analogous to (Basantis et al., 2021; Ma et al., 2021), who found that manoeuvre information increases driver trust. For our study, in particular, the high effect size of the Suspicion indicates that drivers distrust automation because they do not know the intention of the vehicle without manoeuvre information. The lowest acceptance in the Baseline may be due to the users' expectations of a modern UI design and the perception that the Baseline was not up to par with their expectations. This is consistent with our previous research (Kim et al., Submitted), which showed that the mere provision of a user interface providing manoeuvre information increases acceptance in partially automated vehicles. Furthermore, more elaborate information via auditory and visual modalities does not significantly affect workload. Only the auditory demand workload was higher in the Baseline and Spatial sound conditions compared to the Visual-only. Remarkably, there is a higher auditory workload demand in the Baseline condition, which only provides engine sound. Perhaps participants' efforts on visual interface mitigate perceived auditory workload. On the other hand, with Spatial sound, auditory work may increase due to information given by spatial sounds.

The results highlight that automation manoeuvre information using the auditory modality is highly beneficial for the user experience by enhancing trust, acceptance, situation awareness, and sense of control. Especially, providing manoeuvre information via auditory modality may alleviate situational stress in automated driving. Interestingly, the effectiveness of the different auditory UI types varied depending on the specific manoeuvre. For example, the Notification condition received the highest situation awareness score in the Overtake and Roundabout manoeuvres, while the spatial sound performed better in the Turn right and Slow down manoeuvres. The spatial sound is preferred in scenarios where drivers are already familiar with sounds similar to spatial sounds, such as indicator sound when changing lanes or driving noise when slowing down. It is interpreted that the relatively low situation awareness of spatial sound at the Roundabout and Overtake manoeuvre is not due to the complexity of the sound but relates to how familiar sounds are in this situation. If drivers become familiar with hearing sounds in the situation, there is a possibility that the situation awareness will increase during this manoeuvre. Note that long-term sound exposure can irritate the driver (Edworthy, 1998) or increase the auditory workload (Wiese & Lee, 2004). Therefore, further research is needed to design sound scenarios for long-term sound exposure or when performing non-driving-related auditory tasks while minimising sound-related annoyance.

When comparing the Notification and the Spatial sound, no significant differences were found when combining all manoeuvres. However, the Notification condition appeared to be more widely accepted than the Spatial sound condition. Some participants expressed dissatisfaction with the Spatial sound, citing issues such as long durations and unclear meanings. The Notification (beep) is an incremental change for users, so it may be acceptable. On the other hand, the spatial sounds are considered a radical change because users have not previously been provided or become familiar, so the acceptance and usefulness ranking of the Spatial sound conditions was relatively low compared to Notification. These findings emphasise the importance of careful design in integrating auditory feedback to avoid interference and frustration for users. The principles of MAYA (Most Advanced, Yet Acceptable) introduced by Raymond Lowe (1951) have primarily been explored in the visual domain (Hargadon & Douglas, 2001), but their applicability can be extended to the auditory domain (Hekkert, 2006). Participants who are accustomed to familiar abstract sounds, such as beeps, may initially find it challenging to embrace the novelty presented by spatial sounds. Consequently, it is anticipated that users' acceptance of auditory designs will likely increase if the design successfully introduces novelty while maintaining the typicality of the sound. Achieving the balance is critical to ensure that the auditory experience remains understandable and familiar enough to be accepted by users while incorporating novel elements that engage their interest. While the learning time was short and could not be fully evaluated in the experiment, during prolonged periods of automated driving with spatial sounds, it can be possible that the driving situation can be comprehended through sound (Beattie et al., 2014; Gang et al., 2018; Wang et al., 2017) without the need for visual confirmation. This aspect is vital in keeping the driver engaged in the driving loop. Therefore, further research can address the relationship between novelty, typicality, and user acceptance of spatial sounds. Shedding light on these specific mechanisms will facilitate the development of effective strategies for improving the acceptance and integration of spatial sounds in UI for automated driving.

6.4.1 Limitations and Perspectives

Some limitations of the study provide an opportunity for future research to build on the findings and explore the topic further. For example, conducting studies in real-world driving environments may provide a more accurate representation of how users interact with manoeuvre information. Additionally, exploring the long-term effects of exposure to different types of manoeuvre information can help understand how user perceptions and experiences may change over time. Furthermore, the study suggests that sound design may be an important consideration for the effective design of automation interfaces. While the study validated the sound design before the experiment, some participants still found the sounds to be annoying or ambiguous, indicating the need for more iterations and careful design considerations for sound. If there are more scenarios in which spatial sound is used, it is necessary to consider how to convey the situation as sound intuitively and whether there is no confusion between sounds. In addition, as we designed a fixed-order manoeuvre scenario, introducing a random order of manoeuvres may lead to different sound perceptions. Overall, while the study's limitations should be considered, they also highlight areas for future research and provide opportunities for further development and improvement in the field.

6.5 Conclusion

The study emphasises that automation manoeuvre information using auditory modality can improve the driving experience by enhancing user factors such as trust, situation awareness, sense of control, and acceptance, and indicates that it is important to carefully design sounds to avoid user frustration and ensure a positive user experience. The results underscore the importance of vehicle-to-driver communication regarding automated vehicle performance. The absence of manoeuvre information reduces trust and acceptance, highlighting the necessity of transparency in automated systems. Notably, the inclusion of auditory information, whether in the form of traditional notifications or innovative spatial sounds, amplifies these benefits, with implications for improving user experiences in automated driving scenarios. For example, imagine a scenario where a driver hears a clear and informative spatial sound when their automated vehicle is about to overtake another vehicle. This not only enhances trust in the vehicle's capabilities but also improves situation awareness, as the driver precisely understands the vehicle's intentions. Additionally, we have revealed nuances in the effectiveness of auditory user interfaces across different driving manoeuvres. This knowledge can guide the selection of interface types based on user familiarity and situational context. Furthermore, the study raises important considerations for the integration of auditory feedback, emphasising the need for designs that strike a balance between novelty and familiarity to ensure user acceptance and usability. Overall, this study contributed to understanding the impact of the manoeuvre information and auditory user interface in automated driving, with potential implications for improving the design and acceptance of automated vehicle interfaces in the future.

6.6 Appendix A. Supplementary data

Supplementary data to this article can be found online https://doi.org/10.1016/j.trf.2023.11.007.

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CHAPTER

7

Beyond Beeps: Designing Ambient Sound as a Take-Over Request in Automated Vehicles

This chapter has been published in the following research article:
Kim, S., Happee, R., & van Egmond, R. (2023). Beyond Beeps: Designing Ambient Sound as a Take-Over Request in Automated Vehicles. In CEUR Workshop Proceedings (Vol. 3394). CEUR-WS.

Abstract

Human-Machine Interfaces aim to support the interaction between automated vehicles and drivers to improve safety and driver experience. Previously, sounds were mainly used for alarms, but they can be used in other ways in automated vehicles. Therefore, a new approach to sound design is needed. We proposed an interactive approach for sound design to improve driver safety and user experience in automated vehicles. The design of take-over requests in automated vehicles traditionally focuses on safety and reaction time. We are interested in how take-over requests can be designed from a broader user experience perspective while ensuring safety. This paper proposes designs for ambient sound (i.e., soundscape) and driving noise to inform the driver of transition situations. Drivers must take-over control within the time budget, the time from the take-over request to the automation system limit. The time required for a safe transition depends on the complexity of the driving environment. In a scheduled take-over, which is not an emergency, there is an opportunity for an interaction that gradually introduces the driver into the transition process. Soundscape is expected to lead the driver back to the loop with comfort, creating a novel transition experience as well as safety. This study proposed designing soundscape that can enhance vehicle and driver interaction.

7.1 Introduction

As automated vehicle performance becomes advanced, the need for driving monitoring will reduce (SAEInternational, 2021). In highly automated vehicles, drivers do not have to stay in the loop and do not have to supervise the driving scenario. Automotive manufacturers emphasise the ability of automated vehicles to reduce the cognitive load of driving, allowing users to engage in secondary tasks such as using a smartphone and watching videos (Cunningham et al., 2019). The critical challenge in interaction research is the design of the control transition phase, where drivers should take-over the driving control due to automation limitations. Previous studies (Forster et al., 2017; Politis et al., 2015) have investigated user interfaces that can lead to fast and safe transitions to manual driving. Beep or language-based sound is mainly used as a notification cue or to convey urgency. However, the transition does not always take place in an urgent situation. The Operational Design Domain (ODD) refers to the specific operating conditions and environments in which automated vehicles can safely and effectively operate. In the event that the vehicle encounters a situation outside of the ODD, it will schedule a transition to a safe state where it can no longer operate autonomously. During this transition, a take-over request can be initiated, which is not an emergency but is designed to provide sufficient time and information to allow a driver to take control of the vehicle safely.

The bustling sound of a mall tells us that there are many people nearby, while the popcorn-popping sound of engine noise tells us to watch for fast-speed cars. Sound is not only complementary to visual information but can also provide information about the structures of the world (Gaver, 1993). Drivers' visual attention is often needed in automated vehicles' secondary tasks. Capturing omnidirectional attention is an important advantage of an auditory interface (Siwiak & Jame, 2009). Sound is suitable for drawing the driver's attention regardless of the direction of the visual attention (Liu, 2001). In this position paper, we propose ambient sound as a novel transition interface for take-over requests.

Ambient systems provide information in the attention periphery of a user. This aims to display information without directly interfering with primary tasks (Matviienko et al., 2015). Gradually changing the level of ambient stimuli stimulates human perception and allows users to become aware of a new situation. Studies of ambient light in automated vehicles have already been conducted, such as changing colours according to automation modes or providing transition information. On the other hand, there is a paucity of research on ambient sound in automated vehicles. Although explicit sounds such as beeps provide direct information about the transition scenario, ambient sound can progressively support the driver to enter the transition phase. The driver's perception of the pre-awareness of the transition situation before the final take-over request increases safety. van der Heiden et al. (2017) showed that auditory pulse (beep) pre-alerts that occurred well before the take-over request resulted in a safer transition situation. At the same time, the pulse beep made drivers annoyed. Consequently, there lies an opportunity to design a more elaborate sound experience for interaction scenarios that support transition situations. A sound experience that goes beyond beeps! We explore ambient sounds that have the potential to lead the driver back to the loop with comfort, creating a novel transition experience as well as safety. Further, we will discuss the design challenge.

7.2 Ambient sound

We propose two types of ambient sound as a take-over request: 1. designed soundscape and 2. driving noise, which is an ambient sound in a driving situation.

7.2.1 Soundscape design

A soundscape is an acoustic environment perceived by listeners in contexts (Schafer, 1976). Soundscape exists through human perception of the acoustic environment, and it can provide context information (Aletta et al., 2016). Drivers perceive a situation inhabiting a soundscape formed during driving, and it develops into a driving experience (Bull, 2001). Our case at the 'Interactive Audio Design' master course at the Faculty of Industrial Design Engineering provided some excellent examples of the possibility of forming soundscape as a take-over request and new interaction about how it designs driving experience. Students designed context-relevant soundscapes for automated vehicles, including take-over requests. Students received the following scenario description on which they had to base their sound design: The driver is around 35 years old and runs a startup company. The vehicle is highly automated. The vehicle is a B-segment-sized, commonly described as a small car with an enormous volume in Europe (i.e., Toyota Yaris, Renault Clio). Students made a persona based on the scenario description, analysed scenarios which need sound for interaction, and designed a soundscape for scenarios using a sound design tool.

Figure 7.1 Creating soundscape using a sound design tool

The deliverables showed that soundscapes could be used in various ways in highly automated vehicles, including take-over situations. Although soundscape does not directly present explicit alert, it could provide tension that the situation in which action was to be taken was approaching by controlling the elements of sound. The design brought forward the possibility that sound could inform drivers about contextual information (transition) and gradually lead them into the loop. Driver-vehicle interaction through soundscapes can provide a new way of designing user experiences for drivers. This is the use of sound in a more advanced way that enables situation awareness of the driver.

7.2.2 Driving noise

Gaver (1993) argued that the perceptual dimensions and attributes of attention correspond to those of the sound-producing event and its environment, not to those of the sound itself. In other words, the distinction between everyday and musical listening is between experience, not sound. For example, pedestrians recognise the approach of the car by engine noise based on previous experience, and it is related to a regulation generating artificial sound in electric vehicles for safety.

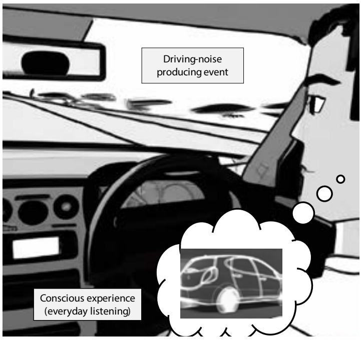

Figure 7.2 Apply the theory of every day listening to the driving experience to driving noise

Driving noise is the 'everyday listening' in the driving scenario. It is called 'noise', and long-term exposure has a harmful effect on the driver, so vehicle designers generally aim to reduce noise. However, drivers can recognise information about vehicles or road events through noise (Gang et al., 2018). When drivers perceive a change in noise while driving, i.e., engine ticking sound, road friction sound, or passing vehicle sound, they pay attention to the cause of the noise.

As NVH (car noise, vibration, and harshness) technology has advanced, it has become possible to control driving noise. A noise control system can actively reduce noise by emitting sound waves inverted to the incoming noise, resulting in a quieter ride. In other words, noise can be intentionally exposed. Suppose that the noise control function reduces the driving noise during autonomous driving. In that case, if vehicles gradually expose the noise (but to the extent that the driver notices the magnitude of the change) as the transition approaches, drivers may notice an approaching mode change. While most auditory user interface designs focus on creating new sounds, noise exposure amplifies the existing ambient sound, providing information about the approaching transition situation. Driving noise can provide drivers with awareness of the automated driving mode when the noise is blocked and the approach to the manual driving mode when the noise is heard. Note that this does not mean that drivers are exposed to driving noise for an extended period. It is using the noise, the source of everyday listening that drivers are already accustomed to recognising information, to draw the driver's attention to the transition situation.

7.3 Design Consideration

An ambient sound can be used to communicate information and provide feedback to users. However, designing an ambient sound as a take-over request in automated vehicles requires careful consideration of various factors. First, the ambient sound should be recognisable from other sounds in the vehicle, even if they are listening to music or talking to passengers. Listening to secondary tasks needs to be considered to design ambient sound. If drivers listen to music or watch videos, the solution can be to control the volume of the secondary task so that the ambient sound can be recognised. This method is already in use on the vehicle. The music volume is momentarily lowered for drivers to listen to navigator information while driving. Further, the soundscape should be easily distinguishable to prevent the ambient sound from being confused with other sounds in the vehicle or on the road. At the same time, it should not be too loud to cause discomfort. Regarding a designed soundscape, it is necessary to validate whether the sounds suit the transition situation or cause annoyance before the evaluation phase to prevent soundscape manipulation errors. In the case of driving noise, the exposure noise level of the sounds should be recognisable so that drivers can perceive the noise level difference. In the experiment, several human factors will be evaluated to identify the effect of ambient sounds in takeover situations. We selected situations with a sufficient time budget, as we focus on acceptance rather than only on TOR performance. Therefore, physiological factors such as gaze tracking or electrocardiogram can be measured to detect situational awareness, and subjective measurements can include trust and acceptance.

7.4 Conclusions

In this paper, we introduce ambient sounds, which are currently in the design phase of our study. The sounds do not necessarily have to communicate their source but rather their function and the feeling they should evoke. The sound of take-over requests has been designed to focus on the user's recognition time or reaction time due to safety or performance-related situations. Therefore, an abstract sound (a beep) has been used instead of an ambient sound. While designing an ambient sound would require careful consideration, the use of ambient sound as a take-over request in automated vehicles has great potential. By designing a sound that is easily recognisable, attention-grabbing, and pleasant, we can make the transition from automated driving to human driving smoother and safer. The success of the ambient sound will depend on the specific design and implementation of the sound, as well as evaluations to ensure its effectiveness and safety for drivers taking over control. The design of road noise as a take-over request in automated vehicles has many potential benefits, including improved safety and driving experience.

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CHAPTER

8

Discussion and Conclusion

This chapter summarises and reflects on the research outcomes and discusses the vision and implications for interaction design.

8.1 Main Findings of the Thesis

In this chapter, I reflect on the three main findings in relation to the two research objectives:

Objective 1. Understand the driver-automated vehicle interaction.
Objective 2. Contribute towards the development of interaction design guidelines.

The first finding concerns the impact of interaction through the user interface on the driver. In the literature review (Chapter 2) and field study (Chapter 3), drivers engage in continuous interaction with the vehicle - during automated driving, transitions, and post-transition - significantly influencing their experience. Collaboration involves synchronising activities and providing explanations and reasons. User interfaces serve as the medium through which drivers comprehend vehicle information, driving statements, and their respective roles. Consequently, these interactions impact not just driver trust or acceptance but also performance metrics, such as take-over reaction time, closely linked to safety. Furthermore, experiments in Chapter 5 and Chapter 6 demonstrate that although the interface might not directly alter actual performance, the perception of information from all newly designed user interfaces positively influences acceptance. Through this study, the goal of understanding the role of the interface in the vehicle has been accomplished.

The second finding is that, while UIs undoubtedly play an important role in improving user experience and system understanding, there are limitations to relying solely on UI design. Efforts to address interaction challenges in automated vehicles often focus on UI design as a primary means of improvement. While UI can help improve user experience and understanding of the system, UI encounter constraints imposed by system design complexities, mental models, and various contexts. The complexity embedded in the system architecture essentially influences the interaction (Lewis & Norman, 1995). This dependence on the design of the system for effective human-machine interaction means that UI changes alone are limited in solving the interaction problem. Chapter 3 and Chapter 4 reveal discrepancies between driver expectations during mode transitions and actual system logic. These discrepancies, caused by system design, may be solved beyond the simple improvement of visual and auditory signals. Systems may be redesigned, and UIs may possibly support building mental models based on a deeper understanding of drivers' behaviour and mental models. Moreover, the impact of the interface varies according to situational context. For example, the impact of user interfaces is attenuated in high-urgency situations (Chapter 5). In addition, similar UI concepts are shown to provide contradictory results depending on the scenario in the literature review (Chapter 2). In summary, while UI plays an important role, it is essential to recognise the limitations of relying solely on UI design.

The third finding concerns the design of information and modality of the user interface. The knowledge gained from the literature- interactions while driving also affect the driver's trust and acceptance- led into the development of two prototype UIs for partially automated driving (Chapter 5) and conditionally automated driving (Chapter 6). Partially automated driving is a situation where drivers and vehicles cooperate to perform driving tasks, so drivers need to be aware of the surrounding information detected by the vehicle and the vehicle's manoeuvre information. If drivers do not understand the state of driving automation, it can lead to a disruption in the continued use of automated driving. In conditionally automated driving, although drivers are not required to monitor the vehicle, they still desire involvement in the driving process. In automated driving, the provision of information has positively affected trust and acceptance. Regarding modality design, trust and acceptance increased when information is provided through auditory. It is advisable to provide information through sound to ensure that the driver is more likely to perceive the information. For this, the design process requires sound validation that is minimally intrusive yet effective in conveying necessary information.

Chapter 6 and Chapter 7 of the doctoral thesis suggest a sound design approach for a natural interaction. Sound has been known to be effective in drawing attention, yet it can induce annoyance. In previous automated vehicle user interface studies, it has been used in high-urgency situations, such as emergency take-over. A better way to design future things is to use richer, more informative, less intrusive signals: natural signals (Norman, 2009). All of this is done so automatically, so naturally, that people often do not know how much they rely on sound for their knowledge of the events in the world. Ordinarily, when driving, drivers' attention is centred on looking at the road or listening to the radio, but not the noise of the engine or road. However, when an unusual noise is noticed immediately, they adapt to the surrounding noise and pay attention quickly. In scheduled take-overs, where high urgency is not present, but drivers need awareness of imminent changes in driving modes, road noise can serve as a user interface to naturally alert drivers about upcoming alterations in driving modes.

8.2 Vision and Implication for Interaction Design in Automated Vehicles

Future automated vehicles are ready to undergo a transformation based on the insightful findings presented in this doctoral thesis. These results provide a foundation for a vision of what future automated vehicles might look like and the implications they may carry.

Holistic Driver-Vehicle Interaction
The future of automated vehicles will likely prioritise a more holistic approach to driver-vehicle interaction. Recognising that the driver is in a constant state of interaction with the vehicle, encompassing diverse phases of automated driving, transitions, and post-transition periods, future designs are ready to prioritise a seamless collaboration between the human

and the machine. This collaborative paradigm suggests a departure from the traditional role of the interface as a mere information provider. Instead, the interface is envisioned as an active collaborator in the decision-making process and supports building a mental model. It goes beyond the transmission of data and enters the realm of synchronised activities and explanations. This implies that the vehicle interface becomes an intelligent partner, engaging in a continuous dialogue with the driver, providing not only information but also offering insights, reasoning, and justifications for the vehicle's actions. Imagine a scenario where the vehicle, through its interface, doesn't just display a navigation prompt but actively discusses route choices, considers user preferences, and even provides educational insights about the surrounding environment. This collaborative interaction may create a more human-centric driving experience, where the vehicle is not just a tool but a co-pilot, fostering a sense of trust and shared decision-making. In essence, the future of automated vehicles is moving towards a dynamic partnership where drivers and vehicles work together seamlessly. The interface, evolving into a collaborative entity, strives to enhance the overall driving experience by integrating the cognitive strengths of both humans and machines, ultimately shaping a future where the journey is a shared endeavour between the driver and the vehicle.

Natural Interaction Paradigm

Future designs may incorporate a more diverse range of interaction modalities than traditional user interfaces. My emphasis on a sound design approach for natural interaction suggests that future vehicles will utilise richer, less intrusive signals. This could lead to a departure from traditional UI-centric approaches, with a greater reliance on natural signals like road noise to alert drivers about upcoming changes in driving modes. Picture a scenario where auditory signals seamlessly integrate into the driving experience. Beyond the traditional beep or alert, vehicles may communicate through nuanced sounds, providing drivers with an additional layer of information. The auditory cues could mimic the subtle sounds of the environment, alerting drivers to imminent changes in driving modes or potential hazards. This auditory symbiosis not only transcends the limitations of visual interfaces, especially in high-urgency situations, but also establishes a more natural and unobtrusive channel of communication. Moreover, by leveraging natural signals akin to the organic sounds of the environment, vehicles can establish a more harmonious connection with drivers. This could involve utilising richer, more informative, and less intrusive signals, aligning with the innate human proclivity for interpreting and responding to the world through various senses. This approach not only addresses the limitations of existing interfaces but also heralds a new era where the interaction between drivers and automated vehicles becomes a multisensory, intuitive, and immersive journey.

Systemic Design Overhaul

The complexity embedded in the system architecture, as highlighted in the findings, may lead to a systemic overhaul of vehicle design. This overhaul transcends superficial adjustments, delving into the very fabric of vehicle design to forge a synergy between automated systems and driver expectations. The system architecture is not designed in line with technological advances, but the system design is rebuilt around the driver. This comprehensive transformation isn't a mere reaction to identified issues; it's a proactive strategy to nurture a seamless and intuitive user experience. By addressing the foundational intricacies, the systemic overhaul aims to build a new paradigm in driver-vehicle interaction. The systemic redesign, therefore, charts a course towards a future where automated vehicles aren't just technologically advanced but inherently attuned to the intricacies of human interaction. For example, it's a vision where every mode transition becomes a harmonise between system intelligence and driver expectations, ensuring a journey that is not only automated but profoundly aligned with intuitive interaction with drivers.

Future automated vehicles are poised to embrace a more collaborative and systemic approach to interaction. Designers will focus on enhancing trust, exploring natural signals, and moving beyond the constraints of traditional UI design. These changes aim to create a more intuitive, responsive, and safer driving experience in the era of automated vehicles.

8.3 Contributions

This section highlights the contributions of this dissertation. Four main scientific contributions are as follows:

This dissertation investigates interactions in driving automation with multiple automation levels and deals with in-depth interaction challenges. Furthermore, it demonstrates the issue of the discrepancy between the driver's mode transition expectations and the commercial vehicles' mode transition logic. This corresponding contribution has led to the publication and submission of the following journals.
Kim, S., Novakazi, F., & Karlsson, M., Interaction Challenges in Automated Vehicles with Multiple Levels of Driving Automation – an On-Road Study, Under review in Transportation Research Part F: Traffic Psychology and Behaviour.
Kim, S., Novakazi, F., Grondelle, E. D., Egmond, R. V., & Happee, R. Who is Performing the Driving Tasks after Interventions? Investigating Drivers' Understanding of Mode Transition Logic in Automated Vehicles, Under review in Applied Ergonomics.

This dissertation investigates interactions in the continuous driving context. Collaboration gains trust that can be built through experience and understanding, which comes from the overall driving experience, not a specific scenario. Based on an empirical evidence analysis, it is shown that interactions during automated driving, during transition, and after transition affect the driver's trust and performance. This corresponding contribution has led to the publication of the following journal.
Kim, S., van Egmond, R., & Happee, R. (2021). Effects of User Interfaces on Take-Over Performance: A Review of the Empirical Evidence. Information.

This dissertation includes a systematic evaluation of the interaction and the combined effects

of different information types and modalities in different driving situations. Furthermore, the results of the simulator experiment demonstrate both the impact and limitations of the interface. This corresponding contribution has led to the publication of the following journals.
Kim, S., van Egmond, R., & Happee, R. (2024). How Manoeuvre Information via Auditory (spatial and beep) and Visual UI can Enhance Trust and Acceptance in Automated Driving. Transportation Research Part F: Traffic Psychology and Behaviour, 100, 22-36.
Kim, S., He, X., van Egmond, R., & Happee, R. (2024) Designing User Interfaces for Partially Automated Vehicles: Effects of Information and Modality on Trust and Acceptance. Transportation Research Part F: Traffic Psychology and Behaviour, 103, 404-419.

This dissertation develops an implicit communication design approach using natural signals in automated vehicles. Implicit communication is a natural, interpretable communication that does not require specific learning, training, or transmission (Ju, 2022). It proposes designing implicit communication intentionally by suggesting the soundscape as a natural signal to provide the state of the automated vehicle. The corresponding contribution was presented at the following conference.
Kim, S., Happee, R., & van Egmond, R. (2023). Beyond Beeps: Designing Ambient Sound as a Take-Over Request in Automated Vehicles. In CEUR Workshop Proceedings (Vol. 3394). CEUR-WS.

8.4 Limitations and Recommendations for Future Research

In the doctoral thesis, on-road driving (Chapter 3), an online survey (Chapter 4), and simulator driving (Chapter 5 and Chapter 6) were used. Drivers' behaviour and the consequences of interaction or user error may differ significantly between simulated and actual driving scenarios. The artificial nature of the experimental setting, despite its high control level, may not fully capture the complexity of real-world driving dynamics. In addition, the results of user interface experiments under controlled conditions may vary depending on changes in the user interface (Albers et al., 2021) or changes in the environment, such as the urgency of the scenario (Kim et al., 2021). These factors could limit the ecological validity of our findings. de Winter et al. (2021) pointed out the risk that interaction study in automated vehicles is a matter of convenience and academic productivity rather than having the aim of realism and meaningfulness, using the study of take-over requests as an example, and I acknowledge this to some extent. Although it may be difficult to overcome these limitations immediately, it is recommended that future research in a wide range of scenarios cover the essential factors across a range of conditions representing the real-world driving context. Conducting studies in real-world driving environments may provide a more accurate representation of how users interact with manoeuvre information. Additionally, exploring the long-term effects of exposure to different types of manoeuvre information can help understand how user perceptions and experiences may change over time.

Designers must design technologies for the way people actually behave, not the way designers would like them to behave. One common fallacy is to absolve design errors as mere human errors, such as human memory or habit. For example, although car manufacturers say that the driver should remember the mode of the car's automation regarding mode confusion, that is no excuse for poor design. Designers bear the responsibility to anticipate human tendencies and integrate them into the technological framework. Furthermore, while the user interface is important to solve problems in automated vehicles, designers need to acknowledge the inherent limitations. Designing interaction that seamlessly interacts with users within the complex dynamics of vehicle automation is challenging. While the interface plays a pivotal role, designers must acknowledge and address the constraints and idiosyncrasies of human behaviour. It prompts designers to strive for solutions that navigate these constraints, enhancing usability without disregarding the intricacies of human behaviour. Hence, while the user interface remains central, designers must constantly refine their approaches, aiming for interfaces that align with human behaviour while acknowledging their inherent limitations. This dual awareness fosters a design ethos that prioritises adaptability, functionality, and user-centricity in the evolution of automated vehicle interfaces.

Chapter 6 includes a sound validation step in the design phase with the aim of enhancing functionality and user experience, and Chapter 7 presents a new approach to sound design. While this design contributes to enhancing the user experience while achieving the information delivery as a primary objective of the interface, it is necessary to consider the outcome of the design is highly dependent on the capability of the interaction designer. The interaction designer needs to understand the driving context and consider the driving experience in its design. In addition, the interaction designer is required to have adequate technical design skills or work in close collaboration with a design engineer to produce user interfaces. Although the impact of the interface was positive in one study, the results of unvalidated user interfaces are difficult to apply in other cases, and it is difficult to ensure that the interface can be used universally. User-centred design is an iterative design process in which designers focus on the users and their needs in each phase of the design process. It does not mean that designers ask (or evaluate) all design elements in every single design phase to users, but interactions are designed under the leadership of designers, and ongoing evaluation and refinement are needed to improve their effectiveness further. This requires constant research and learning from designers.

8.5 Concluding Remarks

I would like to conclude my doctoral dissertation by saying that my four-year journey was enlightening and enriching, filled with various research endeavours. Throughout my doctoral studies, I expanded and dug my view by challenging and seeking resolutions in the complex domain of driver-automated vehicle interaction. Looking forward, I am optimistic that the insights gained, and the solutions proposed will contribute to going beyond the expectations of conventional cars.

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LIST OF PUBLICATIONS

Journal papers:

* 1. **Kim, S.**, van Egmond, R., & Happee, R. (2024). How Manoeuvre Information via Auditory (spatial and beep) and Visual UI can Enhance Trust and Acceptance in Automated Driving. Transportation Research Part F: Traffic Psychology and Behaviour, 100, 22-36.

* 2. **Kim, S.**[#], He, X.[#], van Egmond, R., & Happee, R. (2024). Designing User Interfaces for Partially Automated Vehicles: Effects of Information and Modality on Trust and Acceptance. Transportation Research Part F: Traffic Psychology and Behaviour, 103, 404-419.

* 3. **Kim, S.**, Novakazi, F., & Karlsson, M. Interaction Challenges in Automated Vehicles with Multiple Levels of Driving Automation – an On-Road Study, Under review in Transportation Research Part F: Traffic Psychology and Behaviour.

* 4. **Kim, S.**, Novakazi, F., Grondelle, E. D., Egmond, R. V., & Happee, R. Who is Performing the Driving Tasks after Interventions? Investigating Drivers' Understanding of Mode Transition Logic in Automated Vehicles, Under review in Applied Ergonomics.

5. **Kim, S.**, Nordhoff, S., van Egmond, R., Happee, R. Shaping Drivers' Understanding of Control: The Effect of Visual User Interfaces on Control Responsibilities in Automated Vehicles, Under review in Transportation Research Part F: Traffic Psychology and Behaviour.

6. **Kim, S.**, Anjani, S., van Lierop, D. How will women use automated vehicles? Exploring the role of automated vehicles from women's perspective, Under review in Transportation Research Interdisciplinary Perspectives.

* 7. **Kim, S.**, van Egmond, R., & Happee, R. (2021). Effects of User Interfaces on Take-Over Performance: A Review of the Empirical Evidence. Information, 12, 162.

8. Kabbani, T., **Kim, S.**, Serbes, D., Ozan, B., van Egmond, R., & Hartavi, A.E. (2023). Improved Autonomous Trucker-Vehicle Dialogue under Critical Scenarios through fluid-HMI, Transportation Research Procedia 72, 674-680.

9. El Jouhri, A., El Sharkawy, A., Paksoy, H., Youssif, O., He, X., **Kim, S.**, & Happee, R. (2023). The influence of a colour-themed HMI on trust and take-over performance in automated vehicles. Frontiers in Psychology, 14.

Conference papers:

* 1. **Kim, S.**, Happee, R., & van Egmond, R. (2023). Beyond Beeps: Designing Ambient Sound as a Take-Over Request in Automated Vehicles. In CEUR Workshop Proceedings (Vol. 3394). CEUR-WS.

2. **Kim, S.**, Kabbani, T., Serbes, D., Happee, R., Hartavi, A. E., & van Egmond, R. (2022). A new approach to sound design in automated vehicles. In Proceedings of the Human Factors and Ergonomics Society- Europe Chapter 2022 Annual Conference.

Workshop organisation:

1. **Kim, S.**, van Zeumeren, I., & Vroon, J. (2023). Shaping Emotion in Human-Machine Interaction: an exploratory role-playing workshop. IASDR.

2. **Kim, S.**, Shi, E., Novakazi, F., & oviedo-Tresplalacios, O. (2023). Stakeholder-Centred Taxonomy Design for Automated Vehicles. Automotive UI.

3. **Kim, S.**, Grondelle, E. D., van Zeumeren, I., Mirnig, A., & Stojemenova, K. (2022). Let's Negotiate with Automation: How can Humans and HMIs Negotiate Disagreement on Automated Vehicles?. Automotive UI.

** : Included in this thesis*
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About the Author

Soyeon Kim was born in Seoul, Republic of Korea. She began her doctoral studies in 2020 at Delft University of Technology, at the Department of Human-centered Design within the Faculty of Industrial Design Engineering. Her research is funded by the European Union and focuses on designing interactions between automated vehicles and drivers from a holistic perspective as part of the Horizon 2020 HADRIAN project.

Prior to her PhD research, Soyeon started working as a research engineer at Hyundai Motor Company in 2017. She was involved in UX strategy and development across the entire process, from conceptualising future car designs to developing production vehicles. In 2017, she earned a master's degree in Industrial and Systems Engineering from the Korea Advanced Institute of Science and Technology (KAIST). Her master's thesis was titled 'Predicting the Easiness of Exploratory UI Use based on Informational Complexity.' During her master's program, she participated in an exchange program at Tsinghua University in China. She received her bachelor's degree in Industrial and Systems Engineering from the same university in 2015, where she was awarded the top prize in the undergraduate research program for her project on 'Optimizing Distribution of Items in Fashion Industry using Big Data and Business Analytics.' Her background in industrial and systems engineering has influenced her research focus on practical problem-solving.

Soyeon Kim is not only a curious researcher, but also curious person who enjoys travelling, new experiences and discovering art and new cultures.