Understanding and Improving User Comfort in Automated Driving

Chen Peng

Submitted in accordance with the requirements for the degree of
Doctor of Philosophy

The University of Leeds
Institute for Transport Studies

January 2024

INTELLECTUAL PROPERTY AND PUBLICATIONS

The candidate confirms that the work submitted is her own, except where work which has formed part of jointly authored publications has been included.

Three publications or manuscripts have been produced from research that was undertaken as part of this thesis. Each publication or manuscript is listed below with a full reference and details of its location within this thesis. The contribution of the candidate and the other authors to this work has been explicitly stated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

1. The work in **Chapter 2** has been published as follows:

Peng, C., Merat, N., Romano, R., Hajiseyedjavadi, F., Paschalidis, E., Wei, C., Radhakrishnan, V., Solernou, A., Forster, D., & Boer, E. (2022). Drivers' Evaluation of Different Automated Driving Styles: Is It Both Comfortable and Natural? *Human Factors*, https://doi.org/10.1177/00187208221113448

The candidate interpreted the data to address the research idea, performed the data analysis, and drafted the manuscript. The rest of the co-authors were responsible for the study design and data collection, which happened before the candidate started her PhD. FH, EP, and CW provided information regarding the study design and partly wrote the draft of the Method section. NM and CW were responsible for supervision. The manuscript was improved by comments from all the co-authors.

2. The work in **Chapter 3** has been submitted to a peer-reviewed journal and is under review:

Peng, C., Wei, C., Solernou, A., Hagenzieker, M., & Merat, N. (submitted). *User comfort and naturalness of automated driving: The effect of vehicle kinematics and proxemics on subjective response*. https://doi.org/10.31219/osf.io/8hkb5

The candidate developed the main research idea, interpreted the data, performed the data analysis, and drafted the manuscript. The data used in this study was from the same study reported in Chapter 2, with an interpretation from a different angle. NM, MH, and CW were responsible for supervision. AS provided assistance for interpreting driving simulator data. The manuscript was improved by comments from all the co-authors.

3. The work in **Chapter 4** has been published as follows :

Peng, C., Horn, S., Madigan, R., Marberger, C., Lee, J. D., Krems, J., Beggiato, M., Romano, R., Wei, C., Wooldridge, E., Happee, R., Hagenzieker, M., & Merat, N. (2024). Conceptualising user comfort in automated driving: Findings from an expert group workshop. *Transportation Research Interdisciplinary Perspectives*, 24, 101070. https://doi.org/10.1016/j.trip.2024.101070

The candidate developed the main research idea, conducted the expert workshop, performed the data analysis, and drafted the manuscript. SH provided assistance for ideation, workshop conduction, and part of the data analysis. RM provided assistance for part of the data analysis. NM was responsible for supervision. RM, CM, JL, JK, MB, RR, CW, EW, and NM were the experts who joined the workshop and provided verbal and written contributions. RH and MH were invited to provide comments at the time of writing. The manuscript was improved by comments from all the co-authors.

It is noteworthy to highlight the following conference papers that have been partly or wholly generated from the current PhD project:

Peng, C., Hajiseyedjavadi, F., & Merat, N. (2022). A comparison of two methodologies for subjective evaluation of comfort in automated vehicles. *12th International Conference on Methods and Techniques in Behavioral Research and 6th Seminar on Behavioral Methods, May*, 192–199.

Peng, C., Öztürk, İ., Nordhoff, S., Madigan, R., Hoogendoorn-Lanser, S., Hagenzieker, M., & Merat, N. (2023). *Exploring user comfort in automated driving: A qualitative study with younger and older users using the Wizard-Of-Oz method*. 15th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI '23 Adjunct), Ingolstadt, Germany. https://doi.org/10.1145/3581961.3609853

In addition, the following work is in preparation for publication based on a joint experiment with BOSCH, conducted during the candidate's secondment as part of the PhD project:

Peng, C., Horn, S., Marberger, C., & Merat, N. (in preparation). Physiological indicators of motion sickness: A test track study of reading in an automated vehicle.

ACKNOWLEDGEMENTS

First and foremost, I would like to show my deepest gratitude to my supervisors, Natasha Merat, Marjan Hagenzieker, and Chongfeng Wei, for their invaluable mentorship, patience, encouragement, and support throughout my PhD journey. Particularly, I am grateful to have learned from Natasha and Marjan about the boundless potential that female researchers can achieve, and the inspiration will stay with me forever. I am grateful for the fascinating and enlightening discussions with my examiners, Professor Peter Hancock and Professor Gustav Markkula.

I would like to express my heartful thanks to my friends/colleagues from the Human Factors and Safety research group. Their kindness, support, and shared joy have been a source of strength and happiness. Special thanks go to Rafael Goncalves, Yue Yang, Yang Li, Stefanie Horn, Yueyang Wang, Vishnu Radhakrishnan, Athanasios Tzigieras, Yee Thung Lee, Ibrahim Ozturk, Kai Tian, Amir Hossein Kalantari, Jorge Garcia de Pedro, Wei Lyu, Mickael Perrier, Edward Lambert, Davide Maggi, Foroogh Hajiseyedjavadi, Evangelos Paschalidis, Tyron Louw, and many others. I cherish the memories of our lunch breaks, online chats during the tough COVID period, fun activities, and inspirational discussions. Extra special thanks to Yee Mun Lee and Ruth Madigan for their insightful discussions and unforgettable emotional support. My great gratitude extends to friends from other research groups at the Institute for Transport Studies: Zhuoqian Yang, Zihao An, Shuwei Lin, Siyi Lin, Ruifan Tang, Maximiliano Lizana Maldonado, Songfeng Shen, Oguz Tengilimoglu, Pinar Bilgin, and many more. I enjoyed the friendly environment and have learnt so much from them. Particular thanks to Zhuoqian for always listening, understanding, and supporting me with great empathy, and to Zihao for always generously sharing invaluable experiences and encouraging me to become stronger and better. It has also been my pleasure to have friends from other institutions sharing interests and supporting each other: Hailong Liu, Zhe Zeng, and Hao Cheng.

A huge thank you to our SHAPE-IT project, which is funded by the European Commission's Horizon 2020 Framework Programme (Grant agreement 860410), for providing me with such a wonderful opportunity to get on this adventure and work with many brilliant people. The project was much more than research. I would also like to express my great appreciation to my amazing fellow ESRs from the SHAPE-IT project: Xiaolin He, Siri Berge, Nikol Figalova, Wilbert Tabone, Chi Zhang, Xiaomi Yang, Naomi Mbelikani, Sarang Jokhio, Yuan-Cheng Liu, Amna Pir Muhammad, and Ali Mohammadi. Our gatherings, whether online or in person, were always enjoyable. It would have been far more challenging to go through the journey without their companionship. Great thanks to Jonas Bärgman and Jacqueline Plette for always taking care of us and strongly supporting us. Thanks to our brilliant supervisory team for sharing invaluable feedback and life/career suggestions along the project. Additionally, I extend my gratitude to Claus Marberger and Dietrich Manstetten from BOSCH, and Sina Nordhoff from TU Delft for kindly hosting my secondments.

Last but certainly not least, I want to express my heartfelt love and gratitude to my parents, Jiao Lihong and Peng Bin, and my brother, Peng Shihang. The unconditional love and support have been my foundation and safe harbour along my journey.

ABSTRACT

Comfort is an important factor that affects user acceptance and the subsequent uptake of automated vehicles (AVs). In highly and fully automated driving, the transition of control from drivers to the automation system transforms the role of onboard users from active drivers to passive riders. This transition removes the need to control the vehicle and monitor the environment, which allows users to engage in non-driving-related activities. This, in turn, makes it difficult for users to predict the vehicle's manoeuvres, which potentially challenges user comfort. Evidence suggests that designing AVs' driving styles in certain ways, such as mimicking users' manual driving styles, may affect user comfort. However, our knowledge about the influences of AVs' driving styles on user comfort is limited. There also remains a significant gap in understanding the complexities of the concept of user comfort in automated driving. Addressing these research gaps is crucial for a comprehensive understanding of user comfort in automated driving and improving cross-study comparability.

This thesis aims to investigate user comfort in highly automated driving, and how different driving styles of AVs affect comfort. The research examined a) users' subjective evaluations of different driving styles, b) the relationship between objective vehicle metrics and subjective evaluations, and c) a conceptual model explaining how driving styles affect user comfort, involving related concepts and factors.

This thesis adopted a mixed-method approach. Based on a driving simulator experiment, quantitative methods were used to understand users' subjective preferences for human-like versus non-human-like driving styles and the effect of vehicle metrics on such subjective evaluations. Based on a focus group workshop with experts, qualitative methods were used to establish a conceptual model of user comfort.

The quantitative exploration showed that two representative human-like driving styles (defensive and aggressive) were perceived as more comfortable and natural

than the non-human-like, robotic, driving style. Particularly, the defensive one was rated as the most comfortable, by both low and high sensation seekers, especially for more challenging roads. Results further showed that several lateral and rotational kinematics of the vehicle were significantly associated with both comfort and naturalness evaluations, while only one longitudinal factor was associated with comfort. Results also suggested that enhancing the human-likeness of automated driving by aligning it with users' manual driving, in terms of several vehicle metrics like speed, could improve user comfort and naturalness. However, it also noted that such human-like patterns in lateral jerk might adversely affect evaluations.

The qualitative study found a range of aspects related to comfort in automated driving, such as physical comfort, design expectations, and pleasantness. Several aspects of discomfort were also identified, which differ from those associated with comfort. The study further led to the development of a conceptual framework. The framework explains how AVs' driving styles, as well as other non-driving-related factors, affect user comfort in automated driving. It incorporates a range of concepts, such as trust, naturalness, expectations, and privacy concerns.

This thesis contributes to a better understanding of user comfort in automated driving, empirically and theoretically. It clarifies the effect of driving styles on user comfort from both subjective and objective perspectives. Moreover, it reveals the multifaceted nature of the concept of user comfort in automated driving. The implications drawn from this work provide design guidelines to assist in the development of more comfortable, pleasant, and acceptable automated vehicles for users.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

A number of abbreviations and acronyms are used throughout this thesis. They are listed here for reference in alphabetical order.

ACC	Adaptive Cruise Control
ADS	Automated Driving System
AISS	Arnett's Inventory of Sensation Seeking
ARTS	Automated Road Transport Systems
AVs	Automated Vehicles
BIC	Bayesian Information Criterion
CG	Centre of Gravity
DDT	Dynamic Driving Tasks
EDA	Electrodermal Activity
EMG	Electromyography
GEE	Generalised Estimating Equation
HMIs	Human Machine Interfaces
HR	Heart Rate
IQR	Interquartile Range
ISO	International Organisation for Standardisation
LOA	Levels of Automation
LoDA	Levels Of Driving Automation
LRT	Light Rail Transit
MEM	Mixed Effect Model
ML	Machine Learning
NDRAs	Non-Driving Related Activities
ODD	Operational Design Domain
OLS	Ordinary Least Squares
OR	Odds Ratio
RCNN	Recurrent Convolutional Neural Network
SAE	Society of Automotive Engineers
SCRs	Skin Conductance Responses
SS	Sensation Seeking
SSSV	Zuckerman's Sensation Seeking Scale Form V
TAM	Technology Acceptance Model

UoLDS	University of Leeds Driving Simulator
UTAUT	Unified Theory of Acceptance and Use of Technology Model
VIF	Variance Inflation Factors

CHAPTER 1

Introduction

1.1. Background

The concept of vehicle automation broadly refers to replacing some or all of the human labour of driving with electronic or mechanical devices (Shladover, 2018). Automated vehicles (AVs) are classified based on the system's capabilities and the human's involvement in driving tasks (NHTSA, 2013; SAE, 2021). The classifications range from manual driving, where the human is in charge of all driving tasks, to fully automated driving, where the vehicle can drive itself. According to the SAE levels of automation, highly automated driving (Level 4) does not require driver intervention under specific conditions, and fully automated driving (Level 5) enables the vehicle to drive itself anywhere under any conditions (SAE, 2021).

Level 4 and 5 AVs are expected to bring a plethora of benefits to users, transport, and society. For example, as these vehicles can operate independently without human input, the mobility of the elderly and disabled could be enhanced (Faber & van Lierop, 2020; Fagnant & Kockelman, 2015). With an intelligent system in control, this eliminates concerns about the degradation of human drivers' performance over time (Kyriakidis et al., 2019). Moreover, drivers are freed from the driving task to engage in other non-driving related activities (NDRAs), such as resting, working, and watching movies (Fagnant & Kockelman, 2015; Hecht et al., 2019; Kyriakidis et al., 2019). However, several challenges remain that could impede the adoption of AVs. For example, adverse weather conditions (e.g., snow, rain, and fog) could limit AV's operation by affecting their sensor perception (Zang et al., 2019). Moreover, with the priority of safety considerations, AVs might drive in an overly cautious way, such as unnecessarily slowing down or braking for nearby pedestrians who are not on their route (Brooks, 2017). Other road users could take advantage of this cautious behaviour and "bully" AVs (Liu et al., 2020).

While Level 5 vehicles are decades away, Level 4 vehicles have been operating on the road in the real world. For example, the automated driving technology company Waymo has been providing ride-hailing services in certain areas in the U.S., and these vehicles do not require a human driver (Waymo, 2023). Another example is the automated shuttle providing shared rides in specific areas (e.g., campuses), like the pod-like shuttle investigated in the European CityMobil2 project (Alessandrini et al., 2014; Madigan et al., 2017). The discussions in this thesis mainly focus on Level 4 AVs.

With the current AVs, taking an automated ride may not be comfortable for users, which can be attributed to several potential reasons. First, a cautious AV typically follows the road centre strictly and frequently adjusts for deviations, which differs from human drivers' flexibility and might give users a rigid and robotic feeling (Wei et al., 2019). The unnecessarily frequent braking for low-risk objects exhibits jerky movements, which are associated with negative experiences (Sinha et al., 2020). Second, it is predicted that AVs will increase the incidence and severity of motion sickness for users (Diels & Bos, 2015). This may be attributed to the fact that passive passengers are more susceptible to motion sickness than active drivers, due to the lack of anticipation (Kuiper et al., 2020). Looking away from the road and engaging in NDRAs further creates more sensory conflicts between visual and vestibular (motion) perceptions, which exacerbates motion sickness (Bles et al., 1998; Diels & Bos, 2015; Reason, 1978). Third, users who have a lower trust level in AVs might feel uncomfortable and thus demand more information about the vehicle (Hartwich et al., 2021). With a lack of comfortable experiences, users are likely to resist using AVs (Dichabeng et al., 2021; Motamedi et al., 2020; Siebert et al., 2013). This negative influence of discomfort on user acceptance and uptake will, in turn, limit the potential benefits that AVs provide.

AV's driving styles have been considered an important element in shaping user comfort in recent years. An automated driving style involves the vehicle's kinematics (such as its speed, acceleration, and deceleration). It is also associated with proxemics, such as how the vehicle keeps and adjusts its distance to other on-road and road-side objects. Moreover, it extends to how the vehicle negotiates various road geometries (Bellem et al., 2016; Dettmann et al., 2021; Hajiseyedjavadi et al., 2022; Hartwich et al., 2018). Existing studies suggest that driving styles have various effects on users' experience and evaluations of AVs, in terms of perceived safety, trust, familiarity/naturalness, enjoyment, and comfort (Hartwich et al., 2018; He et al., 2022; J. Lee et al., 2019; Oliveira et al., 2019). However, knowledge of the nexus between subjective evaluations and objective driving styles remains limited. For example, previous studies have shown mixed results on whether AV's driving styles similar to the user's own (i.e., human-like driving styles) are considered natural and comfortable (Griesche et al., 2016; Hajiseyedjavadi et al., 2022; Hartwich et al., 2018). Another notable issue is the lack of a commonly agreed definition for comfort in such evaluations. Cross-study comparisons are challenging due to the various descriptions and measurements used for assessing comfort.

This thesis investigates user comfort in automated driving, particularly from the perspective of driving styles. Based on the current gap in the research, it is hoped that the present thesis will facilitate a more accurate and comprehensive conceptualisation of user comfort. This is also expected to enhance the design and development of more comfortable, pleasant, and acceptable driving styles for future AVs. For a better understanding of this research topic, the next section of this chapter provides an overview of the automated driving context and human factor challenges. Then, a literature review of studies conducted in the area is provided. The literature review is from two perspectives: understanding the concept of user comfort and using automated driving styles to improve user comfort. This is followed by a summary of research gaps and the research questions addressed.

1.2. Automated driving and onboard users

1.2.1. Definitions of automated driving

The concept of "*automation*" indicates the use of machines to complete operations or functions that are typically carried out by humans (Bainbridge, 1983; Parasuraman & Riley, 1997). It was popularised in the 1940s after Ford Motor Company formed its first automation department (Hounshell, 1995). With machines taking over "doing" tasks, humans are responsible for intellectual and cognitive tasks, such as diagnosis, planning, and problem-solving (Z.-G. Wei et al., 1998). Automation systems can be designed in a manner that ensures a best fit considering the strengths and limitations of both humans and machines. For human-machine interaction, Levels of Automation (LOA) are used to specify the extent to which a task is automated, varying from fully manual to fully automated (Vagia et al., 2016).

For automated vehicles, a variety of taxonomies on levels of driving automation (LoDA) have been proposed by several institutions. For example, the U.S. Department of Transportation's National Highway Traffic Safety Administration defined five levels of vehicle automation (NHTSA, 2013), the German Federal Highway Institute defined five vehicle automation degrees (BASt, 2012; Gasser & Westhoff, 2012), and the Society for Automotive Engineers defined six levels of driving automation (SAE, 2014, 2021). These taxonomies illustrate the roles of users and the automation system in terms of driving tasks, such as longitudinal control, lateral control, and monitoring, which vary across automation levels. Among these, the most popular definition for levels of driving automation is perhaps the one introduced by SAE J3016 standards. The six levels of driving automation include Level 0 (No Driving Automation), Level 1 (Driver Assistance), Level 2 (Partial Driving Automation), Level 3 (Conditional Driving Automation), Level 4 (High Driving Automation), and Level 5 (Full Driving automation) (SAE, 2021). The categorisation of SAE LoDA is based on how dynamic driving tasks (DDT) and DDT fallback after a system failure are allocated between the automation system and the user. Here, DDT refers to all the operational and tactical functions involved with driving and navigating a vehicle on the road. This includes actions like steering, braking, accelerating, monitoring the driving environment, and responding to road conditions. DDT fallback is in response to a system failure. It refers to the process of bringing a vehicle to a minimum risk condition, which usually is a stable, stopped state with a low risk of crash. As shown in Figure 1.1, Levels 1 and 2 are labelled as "driver support" features, in which drivers execute part of the DDT while the driving automation system is active. Levels 3 to 5 are termed "automated driving" features, in which the automated driving system (ADS) consistently handles the entire DDT when activated. Together with LoDA, the operational design domain (ODD) is crucial to accurately describe an automation system. ODD defines the specific conditions under which a given LoDA can operate, including factors such as geographic location, types of roads, speed range, and environmental conditions like weather and lighting. In short, LoDA shows the range of what the system can do, while ODD specifies the circumstances and locations in which the system can operate. SAE's definitions for LoDA have been widely adopted. This thesis also adheres to the definitions of SAE LoDA.

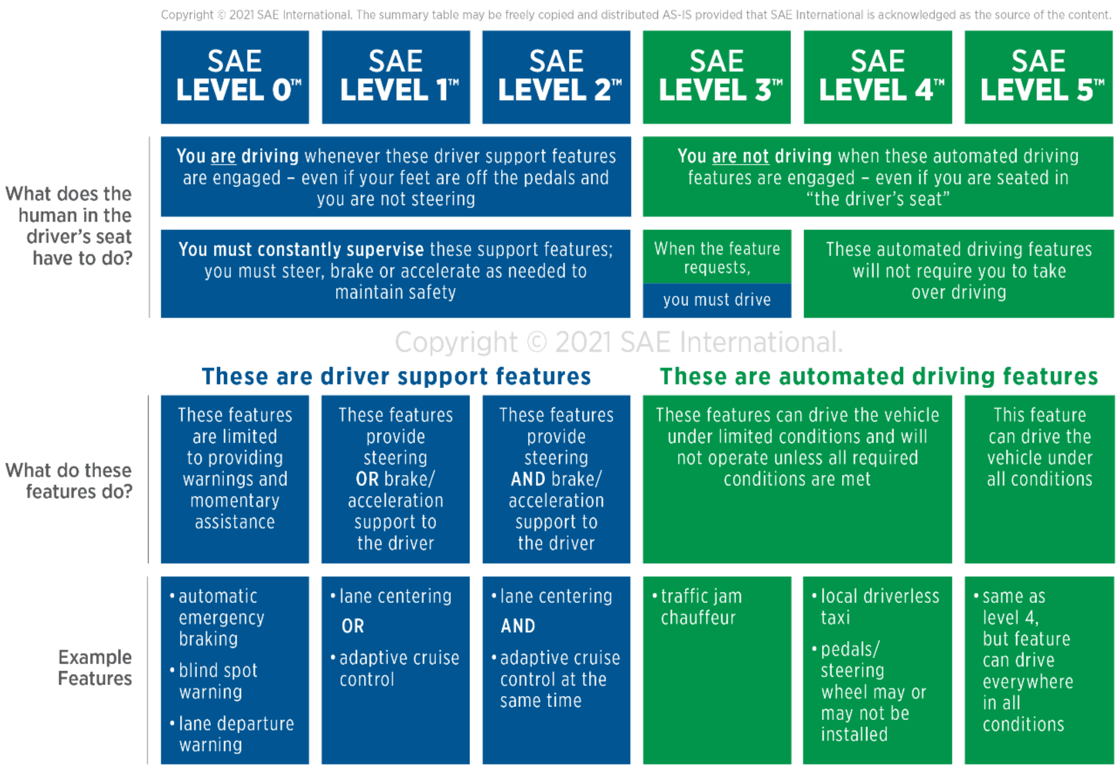


Figure 1.1. Descriptions for the five levels of driving automation defined by SAE J3016 (SAE, 2021).

Among Levels 3 to 5, Level 4 AVs are seen as more "tractable" than Level 3 (Shladover, 2016). This is because the typically short response time for take-overs in Level 3 driving often results in increased stress and workload for users (Inagaki & Sheridan, 2019; Kyriakidis et al., 2019; Merat et al., 2014; Reimer et al., 2016). Thus, Level 3 driving is considered complicated and challenging for users (Shladover, 2016). In comparison, Level 4 vehicles, which do not require operations from users, can be deployed on designated routes and are subject to specific conditions. They are suitable for particular uses, such as operating in restricted areas, on highways, for public transport, and delivering goods (Kyriakidis et al., 2019). Apart from privately owned vehicles and automated taxis, Level 4 vehicles also include automated pod-like vehicles. These vehicles are considered a complement to the public transport system, providing first-/last-mile connectivity between major transport hubs and final destinations (Madigan et al., 2017). Examples of such vehicles include the CityMobil2 Automated Road Transport Systems (ARTS) (Madigan et al., 2017), WEpods vehicle (Homem De Almeida Rodriguez Correia, 2016), and CAPRI shuttle (Paddeu et al., 2020). In comparison, Level 5 AVs are thought to be decades away, or even a "utopia" (automobile utopia), due to their unlimited ODD (Hancock et al., 2020; Shladover, 2016). This thesis mainly focuses on user comfort in Level 4 AVs, while the findings of this thesis will also be relevant to Level 5 driving.

1.2.2. Users of automated vehicles and human factors challenges

Automated driving faces several human factors challenges. A wide range of concerns are associated with Level 2 and 3 driving, such as drivers' overreliance on system performance, failure to adequately monitor the system, increased mental workload, reduced situation awareness, and deteriorated driving skills (Kim et al., 2022; Kyriakidis et al., 2019; Merat et al., 2014; Nordhoff et al., 2023; Saffarian et al., 2012).

Additional human factors challenges, such as trust in automation, acceptance, and comfort, are not only relevant to lower levels of automation, but also play a key role in Level 4 and 5 driving. Trust is defined as "*the attitude that an agent will help achieve an individual's goals in a situation characterised by uncertainty and vulnerability*" (Lee & See, 2004. p.54). Trust largely affects users' reliance on and intention to use these automation systems (Parasuraman et al., 2008), including highly and fully automated vehicles (Manchon et al., 2021; Payre et al., 2016). Acceptance is *"the degree to which an individual incorporates the system in his/her driving, or, if the system is not available, intends to use it"* (Nilsson, 2014; Xu et al., 2018). Public acceptance plays a critical role in the adoption and deployment of AVs, because the success of AVs depends not only on their technical advancement but also on human willingness to use them (Ma & Zhang, 2021; Madigan et al., 2017; Merat et al., 2017; Motamedi et al., 2020; Nordhoff et al., 2021). Both trust and acceptance have been widely researched in the field of automated driving.

Comfort is another critical factor for users to accept a product, including an automated vehicle, and it further affects their willingness to use and purchase such products (Horberry, 2014; Madigan et al., 2017; Payre et al., 2014). In automated driving, many factors challenge user comfort. For example, imperfect AV controllers can generate uncomfortable motion and trajectories (Wei et al., 2019). The switch of control can make users less aware of vehicle manoeuvres, reducing their ability to predict upcoming movements (Hartwich et al., 2018; Kuiper et al., 2020). Engaging in NDRAs while looking down in the moving vehicle may aggravate motion sickness (Sivak & Schoettle, 2015; Smyth et al., 2019). Moreover, sharing the road with other conventional vehicles and vulnerable road users presents additional challenges to the user's comfortable experience in an AV (Diels et al., 2017). Compared with other human factors issues, comfort is underexplored in automated driving. One potential reason is that Level 4 driving just emerged in recent years and is not widely available on the market. Most Level 4 vehicles on the road are prototype or test vehicles running in specific areas. For example, automated pod-like vehicles were tested in the Lake District National Park in the U.K. from 2019 to 2021 (Lake District National Park, 2020). Even the commercialised Waymo automated taxis currently operate in limited areas of particular U.S. cities (Waymo, 2023). Understanding user comfort and their evaluation of a ride requires hands-on experience with such vehicles. The limited access to Level 4 vehicles hinders a better understanding of the concept of user comfort.

The following section reviews the current understanding of user comfort, summarising definitions, measurements, and conceptual models.

1.3. Understanding user comfort: definitions, measurements, models

1.3.1. Definitions

Broadly speaking, the concept of user comfort has been investigated in terms of vehicle environment and ergonomic designs. These investigations include how temperature, ventilation, vibration, noises, vehicle interior design, and seat structure affect comfort (Ahmadpour & Lindgaard, 2014; Bryan et al., 1978; Hertzberg, 1958; Oborne, 1978; Qatu, 2012; Shen & Vértiz, 1997). Over the years, a number of definitions have been proposed for comfort. For example, in a broad sense, Slater (1985) described comfort as: "*a generic term for a pleasant state of psychological, physiological, and physical harmony between a human being and the environment*". Shen & Vértiz (1997) defined physical comfort of vehicle seats as "*the physiological and psychological state perceived during the autonomic process of relieving physical discomfort and achieving corporeal homeostasis*". Branton (1969) focused on seat comfort, suggesting that comfort is simply *the absence of discomfort*. The author further argued that comfort does not necessarily involve the presence of pleasure, because extreme feelings of positive affect might not arise from sitting in chairs. However, these definitions of comfort do not reach a common agreement. Terms and concepts are used differently, sometimes even contradictorily. This is especially the case regarding the relationship between physical, psychological, and physiological aspects of comfort. Building on these varied definitions, De Looze et al. (2003) identified three commonalities in characterising comfort: 1) comfort is a subjective and personal construct; 2) comfort is influenced by a range of physical, physiological, and psychological factors; and 3) comfort results from user interactions with the environment. However, these general summaries are not precise enough to characterise the concept of comfort. The important question of how comfort relates to discomfort remained unanswered. These summaries also do not clarify whether comfort involves positive affect or is merely a neutral state of "corporeal homeostasis". Due to their generality, specific factors affecting comfort and the types of interactions between users and the environment are not detailed.

To better characterise comfort, it is essential to understand the relationship between comfort and discomfort. Hertzberg (1958) suggested that the two concepts are two discrete states: either comfort or discomfort. In comparison, many researchers have treated comfort and discomfort as two opposite extremes on a continuous scale, which ranges from an extremely uncomfortable state to an extremely comfortable state (Richards et al., 1978). Different from these two opinions, Zhang et al. (1996) suggested that comfort and discomfort are two independent constructs and are influenced by different factors. The authors explained that discomfort is related to biomechanical factors that produce pain, soreness, stiffness, etc., whereas comfort is associated with feeling relaxed and well-being (Figure 1.2). Transitions between the two states can happen; for example, comfort will decrease when discomfort increases. Moreover, discomfort is considered to play a dominant role in the overall experience. In other words, comfort sharply diminishes once discomfort is perceived (Helander & Zhang, 1997). However, research that explicitly investigates the relationship between comfort and discomfort primarily focuses on user interaction with products like chairs (e.g., De Looze et al., 2003; Helander & Zhang, 1997). The experience of sitting on a chair in an office largely differs from that of riding in an AV in various aspects. For example, differences in body posture and the duration of maintaining the same posture, especially during a long trip, are notable. Moreover, sitting in a static room versus sitting in a moving vehicle can result in users engaging in different activities, which further leads to different postures. Within these different contexts, the factors related to comfort and discomfort can vary largely. Therefore, it remains unclear whether the relationship between comfort and discomfort, as established in product design research, can be generalised and applied to user comfort in automated driving. Understanding this is important for conceptualising user comfort. Particularly, whether it is adequate to treat comfort as the opposite of discomfort, and if not, which factors should be considered.

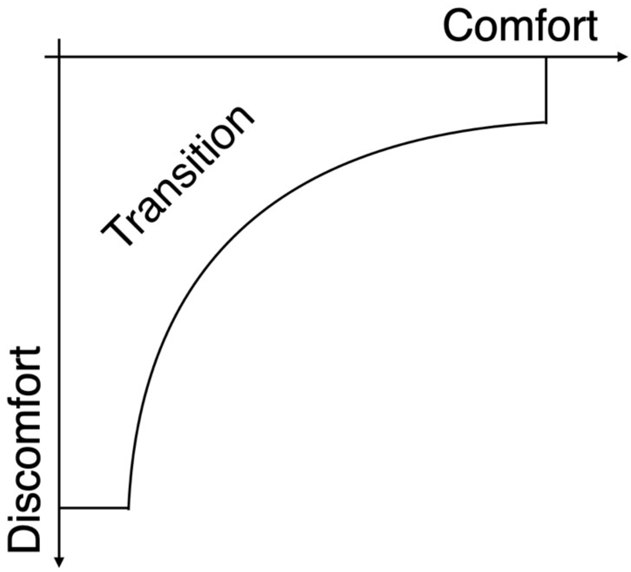


Figure 1.2. A conceptual model of sitting comfort and discomfort. Redrawn from Helander & Zhang (1997).

For manually driven vehicles, the term “ride comfort” or “ride quality” has been frequently used in the vehicle control engineering area. Ride comfort refers to the degree to which a vehicle prevents its occupants from discomfort caused by the road surface and vehicle motion (Deubel et al., 2023). Such research concerns minimising vibrations and noise levels via, for example, suspension system design and tire characteristics (Deubel et al., 2023; ISO, 1997; Jayachandran & Krishnapillai, 2013; Uys et al., 2007). It is specifically associated with the physical aspects of comfort, which can also apply to AV designs. However, solely considering physical perspective is insufficient to characterise comfort when users interact with the novel automated driving system, where multiple factors might play a role.

For automated driving, several definitions of comfort build upon concepts from ergonomic designs, while some integrate features specific to AVs, such as the experience of riding in a vehicle. Bellem et al. (2016) followed a general definition: “*Comfort is a state which is achieved by the removal or absence of uneasiness and* *distress*". This description emphasises the absence of discomfort but does not explicitly address the differences in the physical, psychological, and physiological aspects. Wasser et al. (2017) defined comfort as "*a pleasant state of well-being, ease, and physical, physiological and psychological harmony between a person and the environment*". This definition emphasises the positive aspects and mixes the physical, physiological, and psychological elements of comfort. Carsten & Martens (2018) focused more on psychological comfort and described it as "*the subjective feeling of pleasantness of driving/riding in a vehicle in the absence of both physiological and psychological stress*". This definition combines both positive aspects and the absence of negative factors. It considers the impact of both physiological and psychological factors on comfort. Taken together, these definitions use terms such as uneasiness, distress, and stress interchangeably. However, semantic differences exist among these terms; for example, stress may imply a more intense experience than uneasiness. This interchangeable use of terms could lead to inconsistencies in understanding comfort. Some definitions combine physical, physiological, and psychological perspectives. However, as indicated by sitting comfort research (Zhang et al., 1996), these perspectives likely relate to different factors. Such a combined approach makes it challenging to identify the specific impacts of each perspective on comfort. Moreover, the interaction with the environment is a key factor in characterising comfort. However, most definitions do not adequately adapt to the context of automated driving, failing to specify the role of the AV environment in determining comfort. This environment varies largely, ranging from vehicle interior designs and ambient conditions to interactions with other road users. Adapting sufficiently to the context can integrate specific factors to comfort in automated driving. This will lead to a more precise description compared to comfort in a broad sense.

1.3.2. Measurements

Measurements of comfort vary across studies and contexts. For example, assessing comfort of a chair involves both objective and subjective evaluations. Objective measures include examining the chair's support for different body parts, analysing the distribution of pressure, and evaluating the alignment of the user's spine (Hiemstra-van Mastrigt et al., 2017; Motavalli & Ahmad, 1993). These measures relate to the biomechanical aspects of the human body, such as the muscle contractions and stress exerted on the spine in response to body posture. One method to objectively measure such body activities is through electromyography (EMG), which can capture back muscle activities in a sitting posture (Motavalli & Ahmad, 1993). Subjective measures are frequently used for evaluating seating comfort. For example, Helander & Zhang (1997) asked participants to assess the comfort of chairs three times during a workday using a Chair Evaluation Checklist (Figure 1.3). Participants provided ratings for several comfort descriptors, such as feeling relaxed and feeling soft, and discomfort descriptors, such as sore muscles and uneven pressure from the seat back. While these methods provide valuable insights, their applicability to the dynamic environment of automated driving is limited. In AVs, although users remain seated, the continuously changing vehicle motions and surrounding traffic conditions introduce new factors affecting comfort. Therefore, simply measuring muscle activities or using descriptors designed for static seating scenarios is not sufficient to capture the broader range of factors that affect comfort in automated driving.

	Not at all	Moderately	Extremely		Not at all	Moderately	Extremely
I have sore muscles	1 2 3	4 5 6 7	8 9	I feel relaxed	1 2 3	4 5 6 7	8 9
I have heavy legs	1 2 3	4 5 6 7	8 9	I feel refreshed	1 2 3	4 5 6 7	8 9
I feel uneven pressure from sear pan or seat back	1 2 3	4 5 6 7	8 9	The chair feels soft	1 2 3	4 5 6 7	8 9
I feel stiff	1 2 3	4 5 6 7	8 9	The chair is spacious	1 2 3	4 5 6 7	8 9
I feel restless	1 2 3	4 5 6 7	8 9	The chair looks nice	1 2 3	4 5 6 7	8 9
I feel tired	1 2 3	4 5 6 7	8 9	I like the chair	1 2 3	4 5 6 7	8 9
I feel uncomfortable	1 2 3	4 5 6 7	8 9	I feel comfortable	1 2 3	4 5 6 7	8 9

Figure 1.3. Chair evaluation checklist. Redrawn from Helander & Zhang (1997).

For automated driving, a variety of measurements have been used, including subjective evaluations (Bellem et al., 2017; Cramer & Klohr, 2019; Hajiseyedjavadi et al., 2022; Hartwich et al., 2018; Yusof et al., 2016) and objective physiological measures (Beggiato et al., 2019; Dillen et al., 2020; Radhakrishnan et al., 2020;

Smyth et al., 2021). In terms of subjective evaluations, single-item or multiple-item scales are frequently used, where participants indicate their level of agreement or disagreement on a continuous scale. Regarding single-item scales, Yusof et al. (2016) used a single item with a five-point Likert scale ranging from 1 (very comfortable) to 5 (very uncomfortable). Rossner & Bullinger (2020) asked participants about their driving comfort using a single item, on an 11-point Likert scale with values from 0 (very low) to 10 (very high). Paddeu et al. (2020) employed an 11-point single-item scale ranging from 0 (completely uncomfortable) to 10 (completely comfortable). Hartwich et al. (2018) used a 100-point scale to measure discomfort using a handset (Figure 1.4). During an automated ride, participants pressed a button on the handset to indicate their current level of discomfort on a scale ranging from 0 (comfortable) to 100 (uncomfortable), as a stronger press indicates higher discomfort. However, these single-item scales may oversimplify the concept of comfort, potentially overlooking multiple factors that affect user comfort. With such a combined scale, the aspects of comfort that users evaluate might vary across individuals. Moreover, these scales differ in their explanations for numbers (e.g., 0 – very low versus 0 – completely uncomfortable) and scale length (e.g., five versus eleven). This variation raises questions about the comparability between different scales. For example, whether a three on a 1-5 scale is equivalent to a 50 on a 0-100 scale in cross-study comparisons.

Figure 1.4. Handset used for the online assessment of comfort during automated driving in a driving simulator (Dettmann et al., 2021; Hartwich et al., 2018).

In terms of multi-item scales, Paddeu et al. (2020) adapted a comfort checklist from the research about chair comfort by Zhang et al. (1996) for automated driving. The adapted checklist includes six attributes of comfort: seating, noise, acceleration/deceleration, vibration, temperature, and personal space. While this approach covers more aspects, these factors primarily focus on physical comfort. In contrast, with a focus on psychological comfort, Hartwich et al. (2018) used a 32-item questionnaire to measure four dimensions, including convenience (or comfort) and joy (or enjoyment), as well as their negative states – lack of convenience and joy. However, the equivalence of convenience to comfort was not clearly justified. The lack of detailed questions in English limits further discussion on this approach. Taken together, the application of multi-item scales for measuring comfort in automated driving is still limited and lacks validation. These attempts in previous studies sometimes show a bias towards certain aspects, like physical factors. A comprehensive measure incorporating physical and psychological perspectives is missing. Moreover, ironically, both of these studies that applied multi-item scales also employed single-item scales, as mentioned. This might be contradictory regarding the nature of comfort - whether it is multi-dimensional or single-dimensional.

Many studies measuring comfort fail to provide participants with a clear definition of comfort, often treating it as an umbrella term that includes various user experiences. For example, Hajiseyedjavadi et al. (2022) asked participants to respond with a simple “yes” or “no” to whether they found the AV controller’s behaviour “safe/natural/comfortable” using two buttons on a handset (Figure 1.5). This approach assumes a uniform understanding of these concepts among participants and their ability to report experiences effectively. However, there are potential problems associated with this method. While these three concepts are all positive user experiences and might be closely related to each other, participants, as non-experts, could interpret these terms differently. For example, their evaluation might skew toward feeling safe, which possibly is easier to evaluate than other aspects. As a result, the collected responses could contain a broader range of concepts than solely comfort, which might affect the accuracy of the findings.

Figure 1.5. Participants held a handset device to provide real-time feedback in a driving simulator (Hajiseyedjavadi et al., 2022).

In terms of objective measures, physiological metrics are expected to reflect the real-time status of users in an automated ride (Beggiato et al., 2018). Examples of physiological metrics include cardiovascular, electrodermal, and pupillometry measures. As a cardiovascular measure, Heart rate (HR), the number of heartbeats per minute, decreased in uncomfortable situations, such as when the AV approached an intersection and entered a highway (Beggiato et al., 2019). Electrodermal activity (EDA) is the variation in the electrical characteristics of the skin caused by sweat gland activity (Boucsein, 2012). Skin conductance responses (SCRs), as an EDA metric, were found to be more sensitive to capturing discomfort in the continuously changing driving environment, than HR-based measures (Radhakrishnan et al., 2020). While the authors did not provide further explanations, one potential reason for the sensitivity is that SCRs associated with emotional arousal are better correlated with discomfort, compared with HR related to general stress levels. In contrast, no significant association between EDA and discomfort was found in a study by Beggiato et al. (2019). However, the insignificance might be due to the data collection tools. The smart band used by Beggiato et al. applies to the wrist, while the more precise devices like Biopac (used by Radhakrishnan et al., 2020) and Shimmer (used by Dillen et al., 2020) apply electrodes to two fingers. The latter devices could ensure tighter contact of the sensors with the skin, and fingers have more sweat glands than wrist for better electrical signal collection. Regarding pupillometry measures, it was found that pupil diameter increased and eye blink rate decreased with a higher level of discomfort in automated driving (Beggiato et al., 2019). However, from a practical perspective, in AVs, motions caused by the user's body movement, vehicle motion, interaction with HMIs, and engagement in NDRAs, can easily create artefacts in these physiological measures (Bent et al., 2020; Hossain et al., 2021; Reis et al., 2014). Such artefacts can lead to inaccuracy in comfort/discomfort measurement. In terms of conceptual understanding, these physiological measures all aim to establish a correlation with discomfort, assuming discomfort includes a range of cognitive and emotional states such as stress, cognitive load, emotional arousal, and fatigue. The approach of mixing a variety of concepts already challenges the accurate understanding of factors that affect discomfort. Moreover, these studies also had to measure a ground truth to correlate with discomfort, using subject rating. However, these subjective measurements also vary across studies, adding extra challenges to drawing clear conclusions from different studies. In addition, as the relationship between comfort and discomfort is inconclusive, translating findings that focus on discomfort to understanding factors that contribute to comfort is difficult.

1.3.3. Conceptual models

Several conceptual models have been proposed to understand the factors that contribute to user comfort or discomfort. De Looze et al. (2003) presented a framework for conceptualising sitting comfort and discomfort. As shown in Figure 1.6, the left side of the model concerns discomfort, which is primarily associated with physical factors. The author suggested that factors affect discomfort on three levels: human, seat, and context. For example, the task that the user engages in (i.e., human), the physical characteristics of a seat (i.e., seat), and the environment (i.e., context) have impacts on users' internal states, such as forces and pressure on the body and joints. Then, users may experience muscle activation, increased skin temperature, and intradiscal pressure when remaining seated. Accordingly, users may perceive discomfort. The right side of the model explains how the factors on the three levels of human, seat, and context affect comfort. Here, these factors are more than physical features; for example, individual expectations (i.e., human), the aesthetic design of a seat (i.e., seat), and psycho-social factors like the user's job satisfaction (i.e., context) also affect comfort. The arrows pointing from discomfort to comfort indicate the dominant effect of discomfort. This theoretical model shows the hypothetical relationship between comfort and discomfort, and includes a range of factors that affect the two states. It specifically focuses on factors related to seating, which is insightful for AV seat designs. However, directly applying this model to automated driving is insufficient, because more potential factors are involved in AVs. For example, on the "seat" level, the authors specified the physical features and designs of a seat. When "seat" is replaced by "AV", it becomes a more complicated system involving the system-generated motion, interfaces, the presence of a potential safety driver or remote operator, etc. Features of these components need further specification for automated driving.

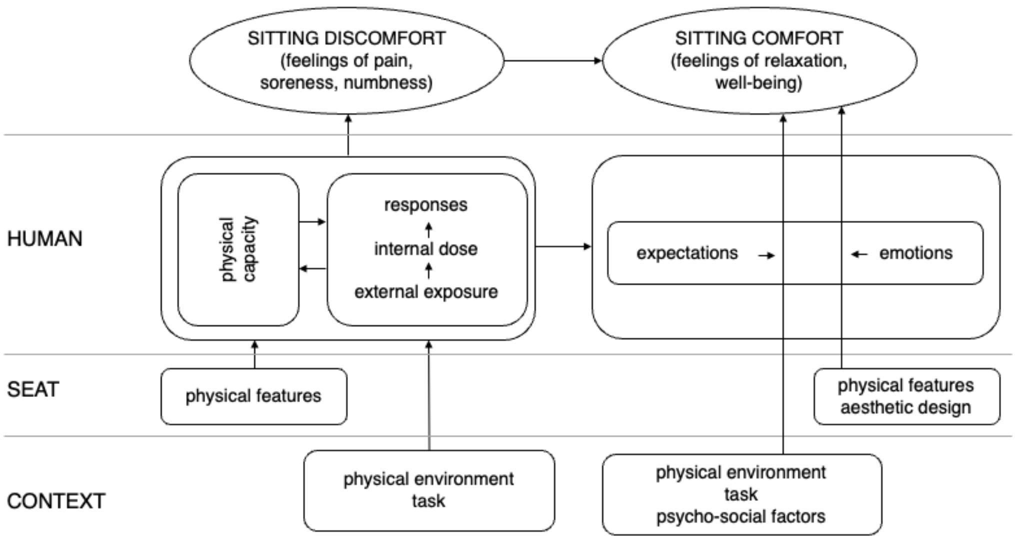


Figure 1.6. Theoretical model of comfort and discomfort and its underlying factors at the human, seat and context level. Redrawn from De Looze et al. (2003). 'Exposure' refers to external factors the user is subject to, such as material of the seat and environmental conditions. 'Dose' refers to the extent or magnitude of exposure. 'Response' refers to the body's reaction to dose and exposure. 'Capacity' refers to the person's ability to withstand exposure and dose.

Going beyond seating comfort, the conceptual model proposed by Ahmadpour & Lindgaard (2014) explains passenger comfort in the aircraft cabin (Figure 1.7). This model identifies eight factors influencing comfort. For each comfort-related factor, there is a corresponding concern on the discomfort side. The authors suggested that the level and aspect that users experience comfort depends on whether certain concerns are solved (or if discomfort is eliminated). From most to least important, *peace of mind* is related to a state of psychological ease and is associated with fewer concerns like security. *Physical wellbeing* is related to physical aspects such as bodily support. *Proxemics* involves reducing concerns about autonomy, control, and privacy within one's limited seating area. *Satisfaction* describes the gratification from solving concerns like accessibility and high-quality design. *Pleasure* refers to a joyful experience influenced by cabin ambience and exceeded expectations. *Social* refers to interpersonal interactions, such as tolerance for other passengers' behaviour. *Aesthetics* refers to pleasantness about the neatness and style of the cabin. The last factor, *association,* relates to familiar memories and symbolism. This model captures a wide range of factors affecting comfort, which includes more aspects than solely the seats. The authors also suggested that comfort and discomfort are the two extremes on the same scale, as they are affected by the same set of factors, which is in contrast with the model of De Looze et al. (2003). However, it can be argued that aircraft cabins differ from AVs, and comfort is likely perceived differently by users in these two contexts. In terms of motions, aircraft have more dimensions of movement compared to AV running on the ground, for example, moving in the vertical direction. Yet, apart from taking off and landing, aircraft mostly cruise at a constant speed, where passengers get less affected by acceleration/deceleration. In comparison, an AV has to adjust its speed frequently in response to changes in road geometries and traffic conditions. Moreover, with professional pilots in charge, aircraft passengers may barely be concerned about aircraft controls and focus more on other activities. AV users may have such concerns with or without the presence of a safety driver and pay more attention to the road. These differences between the two transport modes limit the transferability of this model to AVs.

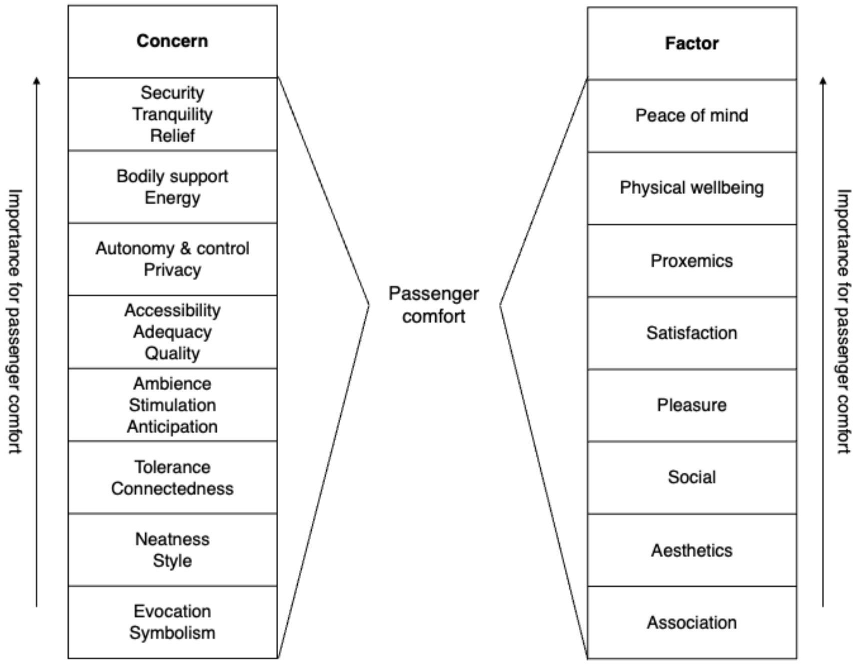


Figure 1.7. An overview of the eight factors of passenger comfort in relation to their concerns. Redrawn from Ahmadpour et al. (2016).

Focusing on the underlying process of user discomfort, Cohen-Lazry et al. (2022) explained how discomfort develops in a broad sense, combining external factors and each individual's needs (Figure 1.8). The authors also provided an example of how this discomfort model can be applied to automated driving. This model shows that users form wishes based on their needs and expectations, such as the desire for a sense of safety in AVs. In the meantime, users perceive external factors, such as acceleration and vibrations of the AV, while such perceptions can differ between individuals. These subjective wishes are then compared with their experience (i.e., perceived external factors); for example, users might expect an AV to drive at a high speed on a highway. The gaps between these wishes and actual experiences are evaluated. Those gaps are located along "comfort envelopes", which depend on specific contexts. The envelope accounts for various dimensions of comfort and discomfort. For AVs, the authors gave an example of a comfort envelope formed in terms of apparent safety (i.e., feeling safe) and avoidance of pain (i.e., avoiding any negative experiences). Here, users feel comfortable only if they feel safe and experience limited negative experiences, which falls in a comfort zone. The gaps between wishes and actual experiences are assessed on multiple dimensions, such as physical, psychological, and physiological aspects. Finally, discomfort on multiple dimensions is summed up, which results in the overall feeling of discomfort. However, the limitation of this work is that it is not tailored to automated driving. The authors indeed provided an example explaining how it can be applied to automated driving. Yet, the example includes only two factors that affect user comfort in AVs, both of which are associated with psychological aspects of comfort. Due to the focus and scope of this model, a more comprehensive list of relevant factors specific to automated driving is lacking.

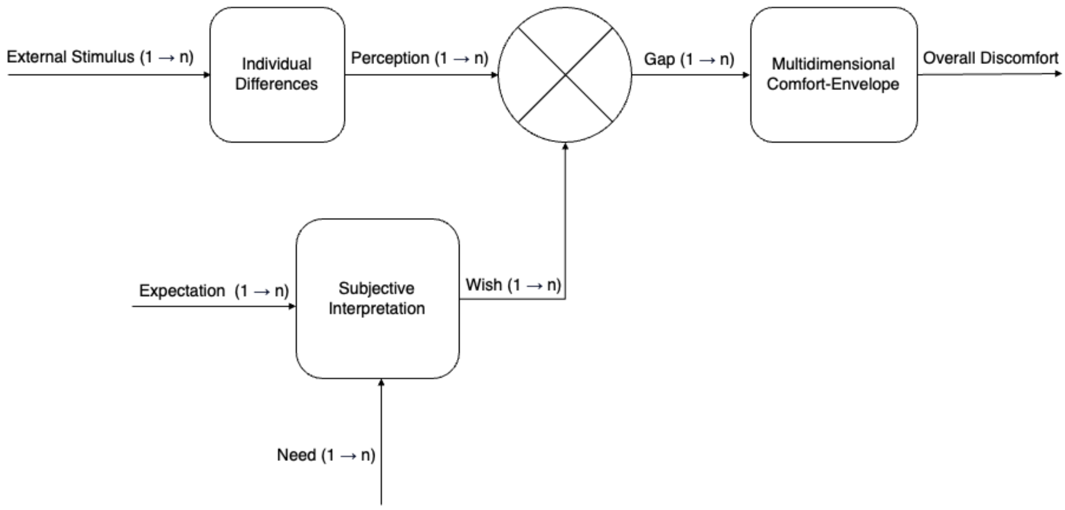


Figure 1.8. A model of discomfort. Redrawn from Cohen-Lazry et al. (2022).

Particularly for driving, Elbanhawi et al. (2015) recognised that the shift of control from manually driven vehicles to AVs requires further evaluation of what constitutes occupants' comfort. The authors reviewed comfort-related factors in traditional vehicles and added new factors specific to automated driving. As shown in Figure 1.9, traditional factors include *air quality*, *sound and noise*, *temperature*, and *vibrations*, which are also relevant to AVs. The authors also highlighted four key factors to consider in automated driving: *naturality*, *disturbances*, *apparent safety*, and *motion sickness*. *Naturality* refers to how natural or familiar the vehicle's movements feel to users. Unnatural or unexpected movements can cause discomfort, especially in a vehicle where users are not in control and cannot predict the vehicle's movements. *Disturbances* result from vehicle control (e.g., braking, acceleration, and turning) and road-vehicle interaction (e.g., uneven road resultant vibrations); disturbances are associated with vehicles' behaviours and mechanical designs of vehicles. Minimising disturbances is thought to be crucial to improving ride quality and ensuring a smooth ride. *Apparent safety* refers to users' perception of safety within the vehicle, which may differ from actual safety. *Motion sickness* in AVs can arise from the mismatch between visual and vestibular (motion) feedback. However, this framework mainly makes a list of relevant factors without considering the relationships between them. For example, reducing disturbances caused by frequent braking may also make the ride feel more natural and safer for users. Moreover, this framework considers user comfort primarily from the perspective of vehicle control and trajectory planning, while other aspects like individual and contextual influences are ignored. For example, the authors suggest that apparent safety can be achieved by maintaining a proper distance with regard to other vehicles and obstacles, as well as providing smooth movements. Yet, a comfortable distance might vary across individuals, while dense traffic conditions might not allow enough distance to be kept. Despite these limitations, this framework emphasises that AV's driving styles might be an effective way to improve user comfort.

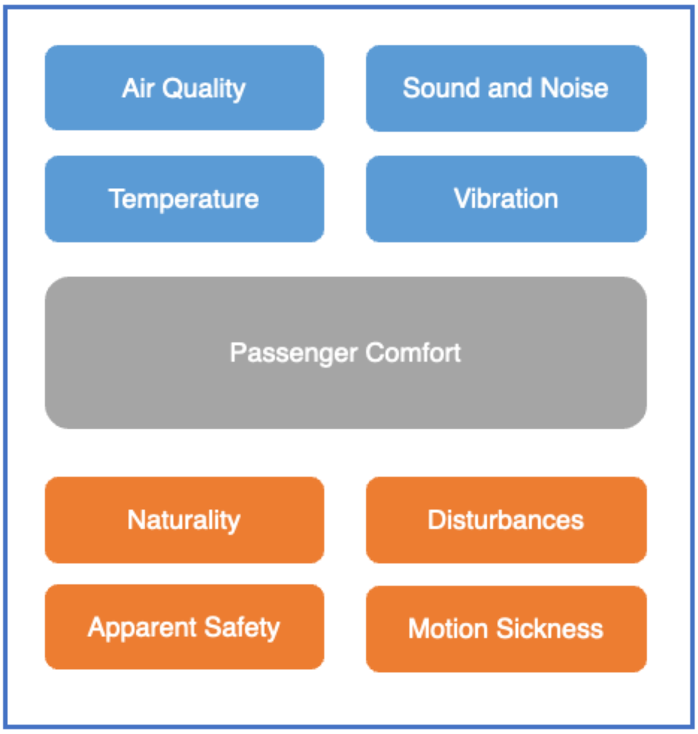


Figure 1.9. Factors influencing ride comfort in traditional (blue) and automated (orange) vehicles. Redrawn from Elbanhawi et al. (2015).

1.4. Improving user comfort via the AV's driving styles

This section introduces the process of how an AV drives and the current AV's driving styles. Then, an introduction to manual driving styles and their implications for AV driving styles is provided. This section then reviews studies that investigate the effect of automated driving styles on user experiences, including comfort.

1.4.1. Current AV's driving styles

According to Paden et al. (2016), the AV's decision-making process consists of several steps. First, a *route planner* generates a route through the road network based on the user's specified destination. Following this, a *behavioural layer* analyses the environment and generates a motion specification to navigate the chosen route. This involves assessing current traffic situations, road conditions, and behaviours of other road users. Then, a *motion planner* develops a feasible motion strategy. This involves planning a path or trajectory that the vehicle can follow, considering the vehicle dynamics and the environment. The final phase involves a *feedback control system*, which adjusts actuation variables, such as steering, acceleration, and braking. This adjustment is to correct any deviations from the planned path by the motion planner and adapt appropriately to any changes in the environment. In this process, the motion planning phase plays a key role in determining a trajectory that is safe, comfortable, and dynamically feasible.

A number of motion planning algorithms have been developed (González et al., 2016; Paden et al., 2016; Song et al., 2023). These algorithms are based on computational models, with a primary focus on solving the challenges of navigating an AV through an environment, considering factors such as obstacle avoidance and path efficiency. In this case, the vehicle might make decisions that, while computationally and technically optimal, could feel robotic and unintuitive to its users. As the algorithms always prioritise safety and strictly follow traffic rules, the vehicle's behaviours might feel rigid to users, especially in scenarios where human drivers might be more flexible (e.g., slightly going over the speed limit). Some algorithms take comfort into consideration by minimising sudden accelerations, decelerations, and turns (Aledhari et al., 2023). However, such considerations are generally implemented through objective parameters and functions, rather than through direct subjective evaluations or feedback from users. Apart from the potentially robotic and rigid perception of the computational motion planners, there are additional challenges to user comfort in AVs. One is related to loss of control in Level 4 and 5 vehicles; without active control over the pedals and steering wheel, users are unable to predict the upcoming manoeuvres generated by the systems. The lack of anticipation leads to the discrepancy between expected and experienced motion, which can cause motion sickness (Kuiper et al., 2020; Rolnick & Lubow, 1991). Moreover, when engaging in NDRAs, for example, reading texts or watching a video, the visual feedback of static text or dynamic video does not match the vestibular feedback of the vehicle's motion (Diels & Bos, 2015). This can aggravate discomfort or motion sickness. Therefore, it is crucial to understand users' subjective perceptions and evaluations of automated driving.

1.4.2. Insights from manual driving styles

Before looking into how users like to be driven by AVs, understanding how users drive when they are in control can provide valuable insights for developing automated driving styles. In manual driving, the term "driving styles" refers to a set of habits that a driver develops over time, including preferences for driving speed, overtaking distance, distance kept with regards to other surrounding vehicles, and the tendency to violate traffic regulations (Elander et al., 1993). One aim of classifying manual driving styles is to improve road safety by providing interventions, such as driver training (Sagberg et al., 2015; Taubman-Ben-Ari et al., 2004). Taubman-Ben-Ari et al. (2004) identified eight types of driving styles, based on a factor analysis of self-reported driving behaviours. These included *dissociative*, *anxious*, *risky*, *angry*, *high-velocity, distress-reducti*on, *patient*, and *careful*. Manual driving styles are typically classified on a range from aggressive to defensive, representing the two ends of the risky–safe spectrum (Sagberg et al., 2015).

Manual driving styles are associated with drivers' demographic characteristics like age and gender, as well as their personality traits such as sensation seeking, desire for control, and extraversion (Taubman-Ben-Ari et al., 2004). In terms of demographic features, older drivers were found to be more likely to drive carefully and defensively than younger drivers, such as changing lanes less frequently (Boyce & Geller, 2002; Reimer et al., 2013). Sagberg et al. (2015) suggested that females are more likely to exhibit patient and careful driving styles than males. In terms of personality traits, sensation seeking (SS) is characterised as "*the need for varied, novel, and complex sensations and experiences, and the willingness to take physical and social risks for the sake of such experience*" (Zuckerman, 1979, p. 10). Desire for control taps into the need for control in daily life (Burger & Cooper, 1979). Extraverted people usually do not take hardships and difficulties in life too seriously (Eysenck & Eysenck, 1975). Sensation seeking has been associated with risk-taking behaviours in manual driving (Taubman-Ben-Ari et al., 2004; Zuckerman & Neeb, 1980). For example, drivers with higher sensation seeking scores were found to tend to drive fast (Louw et al., 2019; Riendeau et al., 2018). According to Taubman-Ben-Ari et al. (2004), drivers who had a high need for control either tended to drive more carefully or exhibited angry driving when frustrated with little or no control. Extraverted drivers were less likely to drive in a dissociative or anxious way.

Manual driving styles are also affected by road environments, such as road geometries, posted speed limits, and roadside furniture. For example, in a simulator study by Calvi (2015), drivers were found to significantly reduce speed and drive closer to the centreline of the road with the presence of trees, especially when trees were close to the road edge. This was particularly the case for sharp curves. With smaller space between trees, drivers were found to keep more distance from the road edge. Goralzik & Vollrath (2017) found that for a higher speed limit of 50km/h, narrower lanes and sharper curves significantly reduced drivers' speed. This effect was not found for a lower speed limit of 30km/h. Moreover, Ben-Bassat & Shinar (2011) suggested that with wider road shoulders and the presence of guardrails, drivers increased their speed. In terms of lateral position, drivers drove away from the road centre with a narrower road shoulder (0.5 m wide) compared with a wider road shoulder (3 m wide). With the presence of a guardrail, drivers drove farther from it than without a guardrail.

In summary, individuals with different characteristics can exhibit a wide range of driving styles when they act as active drivers, and their driving styles are affected by the road environment. In comparison, an AV has the necessity to prioritise safety for its passengers and other road users. Such safety considerations might lead to an overly cautious driving style for AVs; for example, an automated shuttle running at an average speed of 8km/h on real roads was complained of as too slow for daily trips (Nordhoff et al., 2018, 2019). Therefore, differences lie between users' manual driving styles, their expectations about an AV's driving style, and its actual driving styles. To reduce these differences and help users better anticipate AVs' behaviours, some researchers suggest adopting human-like driving styles for AVs that align with users' manual driving styles (Hasenjäger & Wersing, 2017; Li et al., 2022; Wei et al., 2019). For example, to mitigate the potential rigid and overly cautious feelings caused by precisely following the road centre line, Wei et al. (2019) created a “safety corridor” for AV controllers. This approach created a range of AVs’ lateral deviation with regards to the road centre, by incorporating drivers’ manual driving data. In simulations, the authors showed that such AV controllers could respond to road geometries and other objects in a more human-like way, in terms of avoiding sharp turns and not always following the centre lane. However, this method was based on aggregated driving data, without considering the effect of individual characteristics on the safety corridor. It is possible that some users might feel uncomfortable when they are driven by this AV, which learns from a combination of distinct drivers. Yet, even if an AV could be further personalised and mimic individuals’ driving styles (e.g., Zhao et al., 2022), it remains unclear whether users, being passive passengers rather than active drivers, feel comfortable in AVs that resemble their own manual driving styles. The following section reviews research that examined users’ subjective perceptions and evaluations of AVs’ driving styles.

1.4.3. Users’ evaluations of an AV’s driving styles

To understand how users like to “be driven” by AVs, recent studies have investigated the effect of the AV’s driving styles on users’ experiences. These investigations have focused on subjective evaluations, in terms of comfort, feeling safe, trust, enjoyment, and self-reported preference. For such evaluations, kinematics and proxemics, as two fundamental factors of a driving style, are varied to characterise distinct driving styles. It is notable that individual characteristics and environmental factors also play a role in these subjective evaluations.

Effect of vehicle factors

In terms of the effect of vehicle factors on user comfort, Bellem et al. (2018) focused on specific manoeuvres in a moving-based simulator study. They examined users’ preferences for variations of three common highway manoeuvres: lane change, acceleration, and deceleration behind a vehicle. The authors created three variations for each manoeuvre, by adjusting longitudinal or lateral jerk (i.e., the changes in acceleration rate), based on recorded manual driving. For lane change, variations included differences in the magnitude of the first and second peaks in lateral acceleration, and how early the first peak occurred during the manoeuvre. Acceleration was varied by changing jerk during the initial and final stages of acceleration. For deceleration, one variation used a similar approach to the acceleration manipulation, another used a smaller jerk, and a third applied a human-like method. This human-like variation of deceleration involved starting with a strong and rapid braking, and then gradually reducing the intensity as the vehicle approached an object. Participants in this study expressed their preference for every two out of three variations for each manoeuvre. Results showed a preference for lane change variation with a strong initial lateral jerk, providing an early perceivable action. For both acceleration and deceleration manoeuvres, minimising jerk was preferred. Particularly, the human-like deceleration method was least preferred; this finding led the authors to suggest that users do not necessarily like a human-like driving style in AVs. However, this study did not include a baseline condition, such as the original manual driving recordings, for comparison. As a result, participants could only compare the human-modified variations relative to each other. Their perceptions might be skewed; for example, a preference for a particular variation over another might be because it is better in comparison, not necessarily because it is closer to a comfortable driving experience. The absence of a baseline might limit the generalisability of their findings. Moreover, the evaluation was solely based on subjective preferences without specifying any aspects, while the authors proposed that these results could inform improvements in driving comfort. In other words, “preference” was considered the same as “comfort” in this study, although participants were not instructed to rate preference based on any specific criteria. Thus, the findings might reflect other user experiences rather than user comfort. It was also not mentioned how long each drive lasted, which could affect user experience. For example, a short exposure to a manoeuvre (e.g., 10 sec) is less naturalistic compared with a longer duration of driving (e.g., 10 minutes). Adequate exposure to automated driving might help users provide more reliable evaluations.

Apart from the manoeuvre-based approach, research that investigates the impact of AV's driving styles on subjective evaluations defines driving styles in various ways. The term "driving style" is broadly used in research, with descriptors such as "defensive" and "aggressive" commonly employed. However, the objective vehicle metrics defining these styles vary largely across studies. For example, in the study of Hartwich et al. (2018), the familiarity of an automated driving style compared to a participant's manual driving style was quantified by calculating the sum of speed differences at each point along the drive (Figure 1.10). Here, a larger difference in speed between the two driving styles indicates less familiarity. Dillen et al. (2020) took a different approach, varying the thresholds for acceleration and car-following distance to create four distinct driving styles (see details in Table 1.1). In contrast, Basu et al. (2017) defined the defensiveness of a driving style by incorporating a range of longitudinal vehicle features, such as the distance to other cars, time to brake, and speed. For example, a larger distance indicated more defensive driving. Variations in lateral changes were smoothed to make their recorded driving less "instantly recognisable". As a result, even if two driving styles can be both named "defensive" in two studies, they could drive in different ways in terms of speed choice, lateral acceleration, and distance kept with regards to other vehicles. Then, users in the two studies are likely to perceive and evaluate these driving styles differently. To cope with such challenges in defining and categorising automated driving styles, standardising vehicle metrics that are associated with user comfort is needed. With this understanding, different studies could choose relatively consistent vehicle metrics to modify and create AV's driving styles.

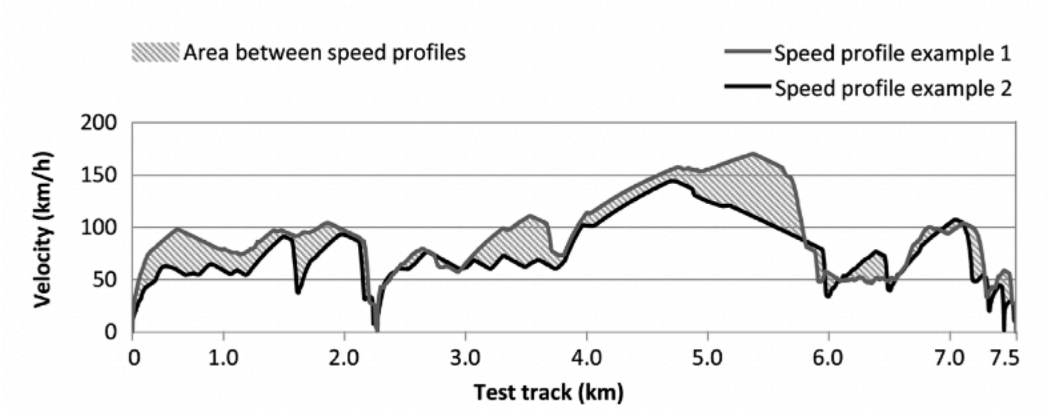


Figure 1.10. The distance between two driving styles was defined by the area between the speed profiles (Hartwich et al., 2018).

Table 1.1. The varied thresholds for the lateral and longitudinal components of acceleration and distance (Dillen et al., 2020).

Parameter	Less aggressive		More aggressive	
	Longitudinal	Lateral	Longitudinal	Lateral
Acceleration (m/s^2)	2.5	2	4	4
Distance (m)	10	4.5	7.5	2

Effect of individual characteristics

Individual characteristics are expected to affect users' subjective evaluations of automated driving, as individuals are likely to have different preferences. While personalisation to individuals might be unrealistic, adapting driving styles to different groups of users has been considered. Individual characteristics, such as users' personality traits and demographic factors, are considered in their evaluations of AV's driving styles.

Several studies have considered sensation seeking to group users during analysis when examining whether users desire an AV that mimics their manual driving style. However, these studies have not presented conclusive results.

In a Wizard-of-Oz study, Yusof et al. (2016) examined user preferences in terms of comfort, pleasantness, and safety for three driving styles – defensive, assertive, and light rail transit (LRT). Defensive driving was characterised by lower acceleration profiles, while assertive driving features higher acceleration profiles in the longitudinal, lateral, and vertical directions. LRT accelerated and decelerated slower than human participants' driving. Four scenarios during the ride on real roads on a university campus were selected to create differences between these driving styles, including a speed hump, leaving and approaching a junction, and navigating a curve. Subjective ratings were collected after the vehicle drove through each scenario. To understand the relationship between users' manual driving styles and automated driving styles, participants were asked to provide ratings about whether they felt the vehicle drove similarly to themselves. Moreover, users' sensation seeking scores (Zuckerman et al., 1978) were used to categorise them as assertive or defensive drivers. Assertive drivers were those with higher scores (10-20), while defensive drivers were those with lower scores (0-9). Results showed that the defensive driving style was favoured by both defensive and assertive drivers in all scenarios, in terms of comfort, pleasantness, and safety. The authors thus suggested that comfortable automated driving styles do not necessarily match users' own driving styles, especially for assertive drivers. Yet, it was also found that some assertive drivers felt familiar with the defensive, not the assertive, driving style. The authors speculated that this might be because the simulated assertive driving style had too high accelerations to match assertive drivers' style. However, with a small number of participants (N = 12) who were all younger than 49 years, the differences in their defensiveness/assertiveness might be small. For example, two participants might score similarly in sensation seeking, like 9 and 10, but were assigned to two groups. This means these participants categorised as assertive and defensive drivers might not be different enough to show distinct preferences for these driving styles. Moreover, this study ran on a short (440m) track on a university campus where low-speed limits usually apply. This limitation could reduce the actual and perceived differences between these driving styles.

In contrast, Hajiseyedjavadi et al. (2022) found variation in evaluations of different driving styles by different sensation seekers. In a motion-based driving simulator study, the authors compared four automated driving styles: fast, slow, conventional, and replay. The fast and slow styles, controlled by model-based human-like controllers, were designed to maintain specific boundaries in terms of speed and lateral position, with the fast controller operating at higher speeds and keeping a larger distance from the road centre. The conventional controller, a non-human-like system, rigidly tracked the centre of the lane. The replay was a playback of each participant's own driving. For evaluations, participants pressed one of the two buttons on a handset to indicate a positive or negative evaluation, combining safe, natural, and comfortable experiences. Results showed that the slow driving style was found to be preferred by participants in terms of an overall positive experience. However, the reliance on a binary button-press method and the mixture of concepts (see also Figure 1.5) may have oversimplified the evaluations. It remains unclear whether the positive evaluations of the slow controller were more due to feeling safe, natural, or comfortable. In terms of sensation seeking, the 23 participants in this study were divided into four groups (or quantiles) based on their scores on the Arnett inventory of sensation seeking questionnaire (Arnett, 1994). Significant results were found for the two extreme groups; low sensation seekers in quantile one had an average score of 40.7, and high sensation seekers in quantile four had an average score of 61.4. Results showed that low sensation seekers tended to prefer the more cautious and slower controller, as they provided more negative evaluations for the fast controller than the slow controller. High sensation seekers generally provided less negative feedback for the fast controller compared to the slow controller, although this trend was not statistically significant. Therefore, the authors suggested that individuals' sensation seeking traits are associated with their preferences for automated driving styles. However, the discovered association was only significant for low sensation seekers, while no significance was found for the rest of the three groups. This indicates that users with medium sensation seeking tendencies might not be affected by varying driving styles. Yet, dividing 23 participants into four groups means each group included no more than six people, and only two groups were included in the statistical test. Using a small sample might make the results more susceptible to being influenced by individual participants and less representative of the larger population (Button et al., 2013).

For studies involving sensation seeking measurement, it is worth mentioning that different questionnaires were used: Zuckerman's sensation seeking scale Form V (SSSV; Zuckerman et al., 1978) and Arnett's inventory of sensation seeking (AISS; Arnett, 1994). Moreover, thrill and adventure seeking, as a sub-scale of SSSV, was used by Bellem et al. (2018). The authors found no significant association between participants' preferences for different AV manoeuvres and their sensation seeking traits. While both questionnaires tap into sensation seeking, they are based on different conceptualisations of this trait. Zuckerman considers sensation seeking as a need for novel and complex stimuli, while Arnett considers it to include novelty and intensity as two sub-dimensions (Arnett, 1994; Haynes et al., 2000; Zuckerman et al., 1978). These questionnaires also included different questions. Therefore, the differences in the association between sensation seeking and evaluations of driving styles might be attributed to the different scales. Moreover, those studies mostly categorised their participants at the time of analysis, which might lead to relatively small differences in their sensation seeking scores. To further examine this effect, a pre-selection of participants with extreme sensation seeking scores might be needed.

Age, as a demographic factor, has been considered in evaluating user experiences in automated driving. The older generation is likely to benefit more from driving automation due to the decline in their perceptual, cognitive, and physical abilities (Haghzare et al., 2021; Hartwich et al., 2018; Huang et al., 2022). Thus, it is important to understand older users' needs and further ensure their comfort and other experiences in AVs. In a fixed-based driving simulator study, Hartwich et al. (2018) investigated the effect of familiarity with driving styles and age on user experiences, in terms of comfort, enjoyment, and acceptance. Three driving styles were compared: one familiar drive, which was a replay of the participant's manual drive, and two unfamiliar drives, each randomly chosen from replays of other drivers' manual drives. Although automation increased comfort for both younger

(25-35 years) and older (65-84 years) users, it decreased enjoyment for younger users. The authors suggested that this was perhaps because watching the AV's drive was boring. In terms of familiarity, younger users were found to report higher comfort, enjoyment, and acceptance of the familiar automated driving styles. In contrast, older drivers preferred unfamiliar driving styles that were faster than their manual styles. According to the authors, this preference among older drivers was linked to their desire to experience driving styles that were not limited by age-related compensatory strategies (e.g., slower speed). This study suggested that mimicking the users' manual driving styles is not always beneficial to user comfort and enjoyment, especially for older demographics. There are potential concerns about the methodology. One issue is that individuals were assumed to find their own driving styles familiar. However, familiarity is subjective, and participants' perceived familiarity with their driving styles might not fully align with the automated replication of their manual driving. Moreover, the approach to defining "unfamiliar" driving styles has potential issues. These styles were randomly chosen from a pool of 16 other participants' drives, which might not truly represent unfamiliarity. For example, a participant who usually drives defensively might feel familiar with a randomly selected, defensive, driving style. Therefore, results might be biased by confounds such as users' manual driving styles. Moreover, without directly measuring participants' perceived familiarity, it is challenging to confirm the intended manipulation of familiarity was successful, which should be considered in future studies.

Effect of environmental factors

While manual driving styles, such as speed choice and lateral position, are affected by the road environment (Section 1.4.2), automated driving styles also vary in response to road features. How an AV negotiates roads could further affect the comfortable feelings of users. While the road environment is a necessary element in such research, few studies have explicitly investigated the impact of environmental factors on subjective evaluations of AVs. One notable example is the aforementioned simulator study by Hajiseyedjavadi et al. (2022), in which four automated driving controllers were compared. These included two human-like driving styles, travelling either at a faster or slower speed, a robotic, conventional controller, and a replay of the user's manual drive. This study involved several road environments with varying road geometries (e.g., various curvature radii, curve direction, and road width) and roadside furniture (e.g., hedges, parked cars, work zones). These AV controllers navigated the same road differently, in terms of speed and lateral deviations from the road centre. Users provided real-time binary ratings by pressing one of two buttons on a handset: a positive rating to indicate that the driving behaviour was safe/natural/comfortable, and a negative rating to express disagreement with the assessment. Regarding the effect of road environment, the study found that road curvature and road furniture significantly affected subjective evaluations of these automated driving styles. Users provided more negative ratings for the fast and slow controllers on roads with sharper curves; this might be due to the curve-cutting behaviour of the two controllers, according to the authors. Particularly, the fast controller received negative evaluations in scenarios involving narrow roads with high hedges. The authors suggested that this was possibly due to the unpleasant visual feedback from the combination of higher speeds, sharper and narrower roads, and high hedges. To be specific, when a vehicle moves fast, especially in environments with close, high hedges, it creates a visually overwhelming or unpleasant experience due to the rapid movement of these hedges in the users' peripheral vision (Godley et al., 2004; Pretto & Chatziastros, 2006). Moreover, it can be argued that the AV controllers' motion around the sharp curves might have been uncomfortable, as narrow and curved roads are challenging. Such roads usually require more careful manoeuvres, such as slower speed and more cautious steering. This study focused more on static features, including road geometries (e.g., curves), on-road obstacles (e.g., parked cars), and roadside furniture (e.g., curbs and hedges). These provide valuable insights for developing AV controllers on highways and roads in rural areas. However, real-world roads also involve dynamic features, such as upcoming cars, pedestrians, and cyclists sharing the same road. While existing investigations are very rare, more research is needed to understand how users feel when AVs negotiate roads with more complicated features.

Overall remarks

Taken together, several challenges lie in the comparison across studies, and thus, concluding design strategies for comfortable driving styles is difficult. First, many studies evaluate multiple, closely related concepts, such as safety, comfort, and naturalness together, making it difficult for participants to distinguish between them. This overlap makes the extent to which automated driving styles can enhance user comfort remain unclear. Second, even when studies use similar terms like "defensive/slow" and "aggressive/assertive/fast", the interpretation of these styles can vary due to differences in objective vehicle metrics and implementation methods (e.g. apparatus and driving environments). A range of equipment has been used to simulate automated driving, such as fixed-based driving simulators, motion-based simulators, Wizard-of-Oz vehicles, and pre-programmed vehicles. Simulators can replicate various road environments, such as urban and highway roads, but may focus more on visual aspects like distance to other cars, neglecting kinematic features like acceleration (particularly in fixed-based simulators). Moreover, simulation sickness, although irrelative to driving styles, can negatively affect user comfort. In tests using real vehicles, factors like the presence of a safety driver, the constraints of a test track environment (e.g., obstacles, surrounding cars, and pedestrians), and uncontrolled weather, can also affect the generalisation of results. Therefore, the variations in experimental environments and methodologies also introduce significant challenges in drawing comprehensive conclusions about comfortable driving styles.

1.5. Research gaps

Creating a comfortable automated driving experience is crucial to user acceptance. To achieve it, a deep understanding of user comfort in relation to AVs' driving styles is needed. Despite growing interest in and research into user experiences with AVs, there is still limited knowledge about user comfort in automated driving. This thesis points out three notable research gaps based on previous studies.

- ***Gap 1:*** *Understanding user preferences for automated driving styles, which range from non-human-like to various human-like styles, in terms of perceived naturalness and comfort.*

While numerous studies have explored user preferences for a range of driving styles, there is no clear and consistent way of characterising, differentiating, and comparing these driving styles, such as aggressive versus defensive or natural versus unnatural (familiar versus unfamiliar). Drivers exhibit various manual driving styles, which are affected by individual characteristics and environmental factors. However, when being driven by AVs, it remains largely unexplored whether users prefer AVs to drive similarly to their manual driving styles or operate in a more machine-like manner. Moreover, it is unclear how users perceive various driving styles exhibited by AVs, either human-like or non-human-like, as natural (or familiar). This situation further limits our understanding of how individual characteristics and external environments influence user comfort in automated driving.

- ***Gap 2:*** *Identifying the relationship between various objective vehicle metrics and subjective comfort evaluations of automated driving style, to enhance the standardised characterisation of automated driving styles across studies.*

Another research gap is the absence of standardised metrics for defining driving styles, which makes it difficult to determine what constitutes a comfortable driving style. Although previous studies have used a range of longitudinal and lateral metrics to characterise driving styles for AVs, the naming conventions (e.g., “defensive”) vary. This introduces inconsistencies when comparing user preferences and evaluations across studies. Moreover, different methods used to demonstrate and simulate driving styles - such as fixed-based simulators versus real vehicles, and simulated scenarios versus test tracks – add further uncertainties in identifying which objective metrics are vital in defining comfortable driving styles. In short, the relationship between objective vehicle metrics and subjective user evaluation of comfort is not fully understood, necessitating research into the roles of different objective metrics in user comfort. In addition, understanding the relationship between vehicle metrics and perceived naturalness of driving styles is important. Establishing this relationship helps us understand how users perceive and evaluate aspects of automated driving compared with their own driving styles, and how this further affects their comfortable experiences.

- ***Gap 3:*** *Conceptualising user comfort in automated driving, by investigating factors that underlie user comfort and developing a conceptual framework to explain how AV's driving styles, along with non-driving-related factors, affect user comfort.*

While user comfort in automated driving is considered important, our understanding of this concept remains limited. Studies that explore improving user comfort via driving styles of AVs either provide widely varying definitions or provide no definition at all. These studies employ a number of distinct methods to measure comfort. The lack of commonly agreed definitions and measurements makes it challenging to compare results from different studies. Moreover, a conceptual framework dedicated to the context of automated driving is missing. Numerous studies have investigated the effect of driving styles on various concepts such as enjoyment, naturalness, and feeling safe. However, the intersection of these concepts with comfort – often described interchangeably with aforementioned concepts – remains inadequately explored. A detailed conceptual framework that incorporates these, closely related, concepts to explain how automated driving styles affect user comfort, is needed.

1.6. Research questions

In order to narrow down the identified research gaps, this thesis looks into understanding and improving user comfort in automated driving, from the perspective of driving styles. The investigations include subjective evaluations, objective vehicle metrics, and conceptual development. The central research question of this thesis is: *How do the AV's driving styles affect and enhance user comfort in automated driving?* To be specific, this research aims to answer three research questions, as outlined below, which will be addressed in Chapters 2 to 4.

- ***RQ 1:*** *How comfortable and natural do users perceive and evaluate human-like and non-human-like automated driving styles, considering the influences of users' sensation seeking propensities and environmental factors?*

Research question RQ 1 focuses on subjective evaluations of different driving styles (human-like vs non-human-like) in terms of comfort and naturalness and is addressed in Chapter 2. By providing clear definitions and using real-time subjective ratings, this investigation aims to further understand whether users perceive human-like driving styles as natural and comfortable, as two separate concepts. The considerations of diverse road environments and sensation seeking traits are expected to make such understanding more comprehensive.

- ***RQ 2:*** *How do vehicle metrics (i.e., kinematics and proxemics) influence subjective evaluations of automated rides in terms of comfort and naturalness, considering the interplay between an individual's manual driving style and the automated vehicle's driving style?*

Research question RQ 2 looks into the relationship between subjective evaluations and objective vehicle metrics, in terms of the relative importance of a wide range of kinematic and proxemic factors. It also considers the objective similarities, characterised by vehicle metrics, between users' manual driving styles and automated driving styles to depict the relationship between objective similarities and subjective familiarities/naturalness as well as comfort. This is addressed in Chapter 3.

- ***RQ3:*** *How can a conceptual framework be developed to comprehensively explain the influence of an automated vehicle's driving style on user comfort, by identifying and contrasting terms describing comfort and discomfort, and clarifying the relationships among various related concepts?*

Research question RQ 3 studies the definition and influencing factors of user comfort and discomfort in automated driving. Chapter 4 addresses RQ 3 and develops a conceptual framework to provide an explanation for how driving styles affect user comfort and how other psychological concepts are involved in this process. Addressing RQ 3 is expected to improve our understanding of the concept of user comfort in automated driving, and further facilitate more accurate measurement and better cross-study comparisons.

1.7. Thesis outline

This thesis comprises three empirical papers, with each chapter of the thesis organised based on one paper which is either published or under review for peer-reviewed journals.

Chapter 2 looks into users' subjective evaluations of three automated driving styles (two human-like and one non-human-like) in terms of comfort and naturalness, when the controllers negotiated UK-roads in a high-fidelity, moving-based, driving simulator. It is worth mentioning that this study was based on the follow-up experiment of the work by Hajiseyedjavadi et al. (2022), and both were part of the UK-funded HumanDrive project. Main differences and improvements in this experiment included: a) providing definitions of comfort and naturalness for participants and separating these evaluations in different drives, rather than mixing concepts; b) offering more options, i.e., a 10-point Likert scale, for participants, to capture more subtle differences in their evaluations, compared with the binary option offered by Hajiseyedjavadi et al. (2022); c) using replays of representative human drives to demonstrate AVs' human-like driving styles, rather than developing model-based controllers; and d) replicating a real UK road stretch to enable driving experiences in line with real-world driving.

Chapter 3 investigates the relationship between objective vehicle metrics, including kinematics and proxemics, and subjective evaluations of comfort and naturalness, using the extended driving simulator data from Chapter 2. While Chapter 2 focused on subjective evaluations, Chapter 3 extended this to the associations between subjective evaluations and vehicle metrics. With this shifted focus, both automated driving data and participants' manual driving data were explored, some of which were visualised in Chapter 2 without further quantification.

Chapter 4 explores definitions of comfort and discomfort in currently available transport modes, and contrasts these with the context of automated driving. Moreover, a conceptual framework is developed and refined to explain how driving styles affect user comfort in AVs.

Chapter 5 highlights the principal findings of this thesis, summarises theoretical, methodological, and practical contributions, reflects on the research limitations, and provides suggestions for future studies.

1.8. References

Ahmadpour, N., & Lindgaard, G. (2014). *Impact of the Seat on Aircraft Passenger Comfort Experience in the Cabin Interior. July*, 4830–4837.

Ahmadpour, N., Robert, J. M., & Lindgaard, G. (2016). Aircraft passenger comfort experience: Underlying factors and differentiation from discomfort. *Applied Ergonomics*, *52*, 301–308. https://doi.org/10.1016/j.apergo.2015.07.029

Aledhari, M., Rahouti, M., Qadir, J., Qolomany, B., Guizani, M., & Al-Fuqaha, A. (2023). *Motion Comfort Optimization for Autonomous Vehicles: Concepts, Methods, and Techniques* (arXiv:2306.09462). arXiv. https://doi.org/10.48550/arXiv.2306.09462

Alessandrini, A., Cattivera, A., Holguin, C., & Stam, D. (2014). CityMobil2: Challenges and Opportunities of Fully Automated Mobility. In G. Meyer & S. Beiker (Eds.), *Road Vehicle Automation* (pp. 169–184). Springer International Publishing. https://doi.org/10.1007/978-3-319-05990-7_15

Arnett, J. (1994). Sensation seeking: A new conceptualization and a new scale. *Personality and Individual Differences*, *16*(2), 289–296.

Bainbridge, L. (1983). IRONIES OF AUTOMATION. In G. Johannsen & J. E. Rijnsdorp (Eds.), *Analysis, Design and Evaluation of Man–Machine Systems* (pp. 129–135). Pergamon. https://doi.org/10.1016/B978-0-08-029348-6.50026-9

BASt. (2012). *Legal consequences of an increase in vehicle automation: Consolidated final report of the project group; Part 1.* https://bast.opus.hbz-nrw.de/frontdoor/index/index/year/2013/docId/689

Basu, C., Yang, Q., Hungerman, D., Singhal, M., & Dragan, A. D. (2017). Do You Want Your Autonomous Car to Drive Like You? *ACM/IEEE International Conference on Human-Robot Interaction*, *Part F1271*, 417–425. https://doi.org/10.1145/2909824.3020250

Beggiato, M., Hartwich, F., & Krems, J. (2018). Using Smartbands, Pupillometry and Body Motion to Detect Discomfort in Automated Driving. *Frontiers in*

Human Neuroscience, *12*(September), 1–12. https://doi.org/10.3389/fnhum.2018.00338

Beggiato, M., Hartwich, F., & Krems, J. (2019). Physiological correlates of discomfort in automated driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, *66*, 445–458. https://doi.org/10.1016/j.trf.2019.09.018

Bellem, H., Klüver, M., Schrauf, M., Schöner, H. P., Hecht, H., & Krems, J. F. (2017). Can We Study Autonomous Driving Comfort in Moving-Base Driving Simulators? A Validation Study. *Human Factors*, *59*(3), 442–456. https://doi.org/10.1177/0018720816682647

Bellem, H., Schönenberg, T., Krems, J. F., & Schrauf, M. (2016). Objective metrics of comfort: Developing a driving style for highly automated vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, *41*, 45–54. https://doi.org/10.1016/j.trf.2016.05.005

Bellem, H., Thiel, B., Schrauf, M., & Krems, J. F. (2018). Comfort in automated driving: An analysis of preferences for different automated driving styles and their dependence on personality traits. *Transportation Research Part F: Traffic Psychology and Behaviour*, *55*, 90–100. https://doi.org/10.1016/j.trf.2018.02.036

Ben-Bassat, T., & Shinar, D. (2011). Effect of shoulder width, guardrail and roadway geometry on driver perception and behavior. *Accident Analysis & Prevention*, *43*(6), 2142–2152. https://doi.org/10.1016/j.aap.2011.06.004

Bent, B., Goldstein, B. A., Kibbe, W. A., & Dunn, J. P. (2020). Investigating sources of inaccuracy in wearable optical heart rate sensors. *Npj Digital Medicine*, *3*(1), Article 1. https://doi.org/10.1038/s41746-020-0226-6

Bles, W., Bos, J. E., de Graaf, B., Groen, E., & Wertheim, A. H. (1998). Motion sickness: Only one provocative conflict? *Brain Research Bulletin*, *47*(5), 481–487. https://doi.org/10.1016/S0361-9230(98)00115-4

Boucsein, W. (2012). *Electrodermal Activity*. Springer Science & Business Media.

Boyce, T. E., & Geller, E. S. (2002). An instrumented vehicle assessment of problem behavior and driving style: Do younger males really take more risks?

Accident Analysis & Prevention, *34*(1), 51–64. https://doi.org/10.1016/S0001-4575(00)00102-0

Branton, P. (1969). Behaviour, Body Mechanics and Discomfort. *Ergonomics*, *12*(2), 316–327. https://doi.org/10.1080/00140136908931055

Brooks, R. (2017). *The Big Problem With Self-Driving Cars Is People*. IEEE Spectrum. https://spectrum.ieee.org/the-big-problem-with-selfdriving-cars-is-people

Bryan, M. E., Tempest, W., & Williams, D. (1978). Vehicle noise and the passenger. *Applied Ergonomics*, *9*(3), 151–154. https://doi.org/10.1016/0003-6870(78)90005-4

Burger, J. M., & Cooper, H. M. (1979). The desirability of control. *Motivation and Emotion*, *3*(4), 381–393. https://doi.org/10.1007/BF00994052

Button, K. S., Ioannidis, J. P. A., Mokrysz, C., Nosek, B. A., Flint, J., Robinson, E. S. J., & Munafò, M. R. (2013). Power failure: Why small sample size undermines the reliability of neuroscience. *Nature Reviews Neuroscience*, *14*(5), Article 5. https://doi.org/10.1038/nrn3475

Calvi, A. (2015). Does roadside vegetation affect driving performance? Driving simulator study on the effects of trees on drivers' speed and lateral position. *Transportation Research Record*, *2518*, 1–8. https://doi.org/10.3141/2518-01

Carsten, O., & Martens, M. H. (2018). How can humans understand their automated cars? HMI principles, problems and solutions. *Cognition, Technology and Work*, *21*(1), 3–20. https://doi.org/10.1007/s10111-018-0484-0

Cohen-Lazry, G., Degani, A., Oron-Gilad, T., & Hancock, P. A. (2022). Discomfort: An assessment and a model. *Theoretical Issues in Ergonomics Science*, 1–24. https://doi.org/10.1080/1463922X.2022.2103201

Cramer, S., & Klohr, J. (2019). Announcing Automated Lane Changes: Active Vehicle Roll Motions as Feedback for the Driver. *International Journal of Human-Computer Interaction*, *35*(11), 980–995. https://doi.org/10.1080/10447318.2018.1561790

De Looze, M. P., Kuijt-Evers, L. F. M., & Van Dieën, J. (2003). Sitting comfort and discomfort and the relationships with objective measures. *Ergonomics*, *46*(10), 985–997. https://doi.org/10.1080/0014013031000121977

Dettmann, A., Hartwich, F., Roßner, P., Beggiato, M., Felbel, K., Krems, J., & Bullinger, A. C. (2021). Comfort or Not? Automated Driving Style and User Characteristics Causing Human Discomfort in Automated Driving. *International Journal of Human-Computer Interaction*, *37*(4), 331–339. https://doi.org/10.1080/10447318.2020.1860518

Deubel, C., Ernst, S., & Prokop, G. (2023). Objective evaluation methods of vehicle ride comfort—A literature review. *Journal of Sound and Vibration*, *548*, 117515. https://doi.org/10.1016/j.jsv.2022.117515

Dichabeng, P., Merat, N., & Markkula, G. (2021). Factors that influence the acceptance of future shared automated vehicles – A focus group study with United Kingdom drivers. *Transportation Research Part F: Traffic Psychology and Behaviour*, *82*(December 2020), 121–140. https://doi.org/10.1016/j.trf.2021.08.009

Diels, C., & Bos, J. E. (2015). Self-driving carsickness. *Applied Ergonomics*, *53*, 374–382. https://doi.org/10.1016/j.apergo.2015.09.009

Diels, C., Erol, T., Kukova, M., Wasser, J., Cieslak, M., Miglani, A., Mansfield, N., Hodder, S., & Bos, J. (2017). Designing for Comfort in Shared and Automated Vehicles (SAV): A Conceptual Framework. *Loughborough University Institutional Repository*, *June*, 1–8.

Dillen, N., Ilievski, M., Law, E., Nacke, L. E., Czarnecki, K., & Schneider, O. (2020). *Keep Calm and Ride Along: Passenger Comfort and Anxiety as Physiological Responses to Autonomous Driving Styles*. 1–13. https://doi.org/10.1145/3313831.3376247

Elander, J., West, R., & French, D. (1993). Behavioral Correlates of Individual Differences in Road-Traffic Crash Risk: An Examination of Methods and Findings. *Psychological Bulletin*, *113*(2), 279–294. https://doi.org/10.1037/0033-2909.113.2.279

Elbanhawi, M., Simic, M., & Jazar, R. (2015). In the Passenger Seat: Investigating Ride Comfort Measures in Autonomous Cars. *IEEE Intelligent Transportation Systems Magazine*, *7*(3), 4–17. https://doi.org/10.1109/MITS.2015.2405571

Eysenck, H. J., & Eysenck, S. B. G. (1975). *Manual of the Eysenck Personality Questionnaire (Junior and Adult)*.

Faber, K., & van Lierop, D. (2020). How will older adults use automated vehicles? Assessing the role of AVs in overcoming perceived mobility barriers. *Transportation Research Part A: Policy and Practice*, *133*, 353–363. https://doi.org/10.1016/j.tra.2020.01.022

Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, *77*, 167–181. https://doi.org/10.1016/j.tra.2015.04.003

Gasser, T. M., & Westhoff, D. (2012). *BASt-study: Definitions of Automation and Legal Issues in Germany*.

Godley, S. T., Triggs, T. J., & Fildes, B. N. (2004). Perceptual lane width, wide perceptual road centre markings and driving speeds. *Ergonomics*, *47*(3), 237–256. https://doi.org/10.1080/00140130310001629711

González, D., Pérez, J., Milanés, V., & Nashashibi, F. (2016). A Review of Motion Planning Techniques for Automated Vehicles. *IEEE Transactions on Intelligent Transportation Systems*, *17*(4), 1135–1145. https://doi.org/10.1109/TITS.2015.2498841

Goralzik, A., & Vollrath, M. (2017). The effects of road, driver, and passenger presence on drivers' choice of speed: A driving simulator study. *Transportation Research Procedia*, *25*, 2061–2075. https://doi.org/10.1016/j.trpro.2017.05.400

Griesche, S., Nicolay, E., Assmann, D., Dotzauer, M., & Käthner, D. (2016). Should my car drive as I do? What kind of driving style do drivers prefer for the design of automated driving functions?. *Braunschweiger Symposium Automatisierungssysteme, Assistenzsysteme Und Eingebettete Systeme Für*

Transportmittel (AAET), *February*, 185–204. https://www.researchgate.net/publication/294087276

Haghzare, S., Campos, J. L., Bak, K., & Mihailidis, A. (2021). Older adults' acceptance of fully automated vehicles: Effects of exposure, driving style, age, and driving conditions. *Accident Analysis & Prevention*, *150*, 105919. https://doi.org/10.1016/j.aap.2020.105919

Hajiseyedjavadi, F., Boer, E. R., Romano, R., Paschalidis, E., Wei, C., Solernou, A., Forster, D., & Merat, N. (2022). Effect of environmental factors and individual differences on subjective evaluation of human-like and conventional automated vehicle controllers. *Transportation Research Part F: Traffic Psychology and Behaviour*, *90*, 1–14. https://doi.org/10.1016/j.trf.2022.07.018

Hancock, P. A., Kajaks, T., Caird, J. K., Chignell, M. H., Mizobuchi, S., Burns, P. C., Feng, J., Fernie, G. R., Lavallière, M., Noy, I. Y., Redelmeier, D. A., & Vrkljan, B. H. (2020). Challenges to Human Drivers in Increasingly Automated Vehicles. *Human Factors*, *62*(2), 310–328. https://doi.org/10.1177/0018720819900402

Hartwich, F., Beggiato, M., & Krems, J. F. (2018). Driving comfort, enjoyment and acceptance of automated driving–effects of drivers' age and driving style familiarity. *Ergonomics*, *61*(8), 1017–1032. https://doi.org/10.1080/00140139.2018.1441448

Hartwich, F., Hollander, C., Johannmeyer, D., & Krems, J. F. (2021). Improving Passenger Experience and Trust in Automated Vehicles Through User-Adaptive HMIs: "The More the Better" Does Not Apply to Everyone. *Frontiers in Human Dynamics*, *3*(June). https://doi.org/10.3389/fhumd.2021.669030

Hasenjäger, M., & Wersing, H. (2017). Personalization in advanced driver assistance systems and autonomous vehicles: A review. *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*, 1–7. https://doi.org/10.1109/ITSC.2017.8317803

Haynes, C. A., Miles, J. N. V., & Clements, K. (2000). A confirmatory factor analysis of two models of sensation seeking. *Personality and Individual Differences*, *29*(5), 823–839. https://doi.org/10.1016/S0191-8869(99)00235-4

He, X., Stapel, J., Wang, M., & Happee, R. (2022). Modelling perceived risk and trust in driving automation reacting to merging and braking vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, *86*(January), 178–195. https://doi.org/10.1016/j.trf.2022.02.016

Hecht, T., Darlagiannis, E., & Bengler, K. (2019). Non-driving Related Activities in Automated Driving – An Online Survey Investigating User Needs. *International Conference on Human Systems Engineering and Design: Future Trends and Applications*, *1026*, 182–188.

Helander, M. G., & Zhang, L. (1997). *Field studies of comfort and discomfort in sitting*. *0139*(1997). https://doi.org/10.1080/001401397187739

Hertzberg, H. T. E. (1958). Seat comfort. In R. Hansen, D. R. Cnrnog, & H. T. E. Hertzberg (Eds.), *Annotated Bibliography of Applied Physical Anthropology in Human Engineering* (pp. 297–300). WADC Technical report.

Hiemstra-van Mastrigt, S., Groenesteijn, L., Vink, P., & Kuijt-Evers, L. F. M. (2017). Predicting passenger seat comfort and discomfort on the basis of human, context and seat characteristics: A literature review. *Ergonomics*, *60*(7), 889–911. https://doi.org/10.1080/00140139.2016.1233356

Homem De Almeida Rodriguez Correia, G. (2016). WEpods project: Finding the potential for automated road public transport. *Fly over, 25 (2), 2016*. https://repository.tudelft.nl/islandora/object/uuid%3A5f3f6982-c35b-4edc-bdfd-095f35200e48

Horberry, M. A. R., Alan Stevens, Tim. (2014). Driver Acceptance of New Technology: Overview. In *Driver Acceptance of New Technology*. CRC Press.

Hossain, M.-B., Posada-Quintero, H. F., Kong, Y., McNaboe, R., & Chon, K. H. (2021). A Preliminary Study on Automatic Motion Artifact Detection in Electrodermal Activity Data Using Machine Learning. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International*

Conference, *2021*, 6920–6923. https://doi.org/10.1109/EMBC46164.2021.9629513

Hounshell, D. A. (1995). Ford Automates: Technology and Organization in Theory and Practice. *Business and Economic History, 24*(1), 59–71.

Huang, G., Hung, Y.-H., Proctor, R. W., & Pitts, B. J. (2022). Age is more than just a number: The relationship among age, non-chronological age factors, self-perceived driving abilities, and autonomous vehicle acceptance. *Accident Analysis & Prevention*, *178*, 106850. https://doi.org/10.1016/j.aap.2022.106850

Inagaki, T., & Sheridan, T. B. (2019). A critique of the SAE conditional driving automation definition, and analyses of options for improvement. *Cognition, Technology & Work*, *21*(4), 569–578. https://doi.org/10.1007/s10111-018-0471-5

ISO. (1997). *Mechanical vibration and shock—Evaluation of human exposure to whole-body vibration—Part 1: General requirements*. https://www.iso.org/standard/7612.html

Jayachandran, R., & Krishnapillai, S. (2013). Modeling and optimization of passive and semi-active suspension systems for passenger cars to improve ride comfort and isolate engine vibration. *Journal of Vibration and Control*, *19*(10), 1471–1479. https://doi.org/10.1177/1077546312445199

Kim, H., Song, M., & Doerzaph, Z. (2022). Is Driving Automation Used as Intended? Real-World Use of Partially Automated Driving Systems and their Safety Consequences. *Transportation Research Record*, *2676*(1), 30–37. https://doi.org/10.1177/03611981211027150

Kuiper, O. X., Bos, J. E., Schmidt, E. A., Diels, C., & Wolter, S. (2020). Knowing What's Coming: Unpredictable Motion Causes More Motion Sickness. *Human Factors*, *62*(8), 1339–1348. https://doi.org/10.1177/0018720819876139

Kyriakidis, M., de Winter, J. C. F., Stanton, N., Bellet, T., van Arem, B., Brookhuis, K., Martens, M. H., Bengler, K., Andersson, J., Merat, N., Reed, N., Flament, M., Hagenzieker, M., & Happee, R. (2019). A human factors perspective on automated driving. *Theoretical Issues in Ergonomics Science*, *20*(3), 223–249. https://doi.org/10.1080/1463922X.2017.1293187

Lake District National Park. (2020, March 31). *Driverless Pods*. Lake District National Park: hq@lakedistrict.gov.uk. https://www.lakedistrict.gov.uk/caringfor/smarter-travel/driverless-pods

Lee, J. D., & See, K. A. (2004). *Trust in Automation: Designing for Appropriate Reliance*. *46*(1), 50–80.

Lee, J., Liu, S. Y., Domeyer, J., & DinparastDjadid, A. (2019). Assessing Drivers' Trust of Automated Vehicle Driving Styles With a Two-Part Mixed Model of Intervention Tendency and Magnitude. *Human Factors*. https://doi.org/10.1177/0018720819880363

Li, P., Pei, X., Chen, Z., Zhou, X., & Xu, J. (2022). Human-like motion planning of autonomous vehicle based on probabilistic trajectory prediction. *Applied Soft Computing*, *118*, 108499. https://doi.org/10.1016/j.asoc.2022.108499

Liu, P., Du, Y., Wang, L., & Da Young, J. (2020). Ready to bully automated vehicles on public roads? *Accident Analysis & Prevention*, *137*, 105457. https://doi.org/10.1016/j.aap.2020.105457

Louw, T., Hajiseyedjavadi, F. H., Jamson, H., Romano, R., Boer, E., & Merat, N. (2019). *The Relationship between Sensation Seeking and Speed Choice in Road Environments with Different Levels of Risk*. *April*, 29–35. https://doi.org/10.17077/drivingassessment.1671

Ma, Z., & Zhang, Y. (2021). Drivers trust, acceptance, and takeover behaviors in fully automated vehicles: Effects of automated driving styles and driver's driving styles. *Accident Analysis & Prevention*, *159*, 106238. https://doi.org/10.1016/j.aap.2021.106238

Madigan, R., Louw, T., Wilbrink, M., Schieben, A., & Merat, N. (2017). What influences the decision to use automated public transport? Using UTAUT to understand public acceptance of automated road transport systems. *Transportation Research Part F: Traffic Psychology and Behaviour*, *50*, 55–64. https://doi.org/10.1016/j.trf.2017.07.007

Manchon, J. B., Bueno, M., & Navarro, J. (2021). From manual to automated driving: How does trust evolve? *Theoretical Issues in Ergonomics Science*, *22*(5), 528–554. https://doi.org/10.1080/1463922X.2020.1830450

Merat, N., Jamson, A. H., Lai, F. C. H., Daly, M., & Carsten, O. M. J. (2014). Transition to manual: Driver behaviour when resuming control from a highly automated vehicle. *Transportation Research Part F: Traffic Psychology and Behaviour*, *27*, 274–282. https://doi.org/10.1016/j.trf.2014.09.005

Merat, N., Madigan, R., & Nordhoff, S. (2017). Human Factors, User Requirements, and User Acceptance of Ride-Sharing in Automated Vehicles. *International Transport Forum*, *10*(February), 1–30.

Motamedi, S., Wang, P., Zhang, T., & Chan, C.-Y. (2020). Acceptance of Full Driving Automation: Personally Owned and Shared-Use Concepts. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *62*(2), 288–309. https://doi.org/10.1177/0018720819870658

Motavalli, S., & Ahmad, F. (1993). Measurement of seating comfort. *Computers & Industrial Engineering*, *25*(1), 419–422. https://doi.org/10.1016/0360-8352(93)90310-T

NHTSA. (2013). *Preliminary statement of policy concerning automated vehicles*. US National Highway Traffic Safety Administration.

Nilsson, E. A., András Várhelyi, Lena. (2014). The Definition of Acceptance and Acceptability. In *Driver Acceptance of New Technology*. CRC Press.

Nordhoff, S., de Winter, J., Madigan, R., Merat, N., van Arem, B., & Happee, R. (2018). User acceptance of automated shuttles in Berlin-Schöneberg: A questionnaire study. *Transportation Research Part F: Traffic Psychology and Behaviour*, *58*, 843–854. https://doi.org/10.1016/j.trf.2018.06.024

Nordhoff, S., de Winter, J., Payre, W., van Arem, B., & Happee, R. (2019). What impressions do users have after a ride in an automated shuttle? An interview study. *Transportation Research Part F: Traffic Psychology and Behaviour*, *63*(May), 252–269. https://doi.org/10.1016/j.trf.2019.04.009

Nordhoff, S., Lee, J. D., Calvert, S. C., Berge, S., Hagenzieker, M., & Happee, R. (2023). (Mis-)use of standard Autopilot and Full Self-Driving (FSD) Beta: Results from interviews with users of Tesla's FSD Beta. *Frontiers in Psychology*, *14*. https://www.frontiersin.org/articles/10.3389/fpsyg.2023.1101520

Nordhoff, S., Malmsten, V., van Arem, B., Liu, P., & Happee, R. (2021). A structural equation modeling approach for the acceptance of driverless automated shuttles based on constructs from the Unified Theory of Acceptance and Use of Technology and the Diffusion of Innovation Theory. *Transportation Research Part F: Traffic Psychology and Behaviour*, *78*, 58–73. https://doi.org/10.1016/j.trf.2021.01.001

Oborne, D. J. (1978). Vibration and passenger comfort: Can data from subjects be used to predict passenger comfort? *Applied Ergonomics*, *9*(3), 155–161. https://doi.org/10.1016/0003-6870(78)90006-6

Oliveira, L., Proctor, K., Burns, C. G., & Birrell, S. (2019). Driving style: How should an automated vehicle behave? *Information (Switzerland)*, *10*(6), 1–20. https://doi.org/10.3390/INFO10060219

Paddeu, D., Parkhurst, G., & Shergold, I. (2020). Passenger comfort and trust on first-time use of a shared autonomous shuttle vehicle. *Transportation Research Part C*, *115*(March), 102604. https://doi.org/10.1016/j.trc.2020.02.026

Paden, B., Čáp, M., Yong, S. Z., Yershov, D., & Frazzoli, E. (2016). A Survey of Motion Planning and Control Techniques for Self-Driving Urban Vehicles. *IEEE Transactions on Intelligent Vehicles*, *1*(1), 33–55. https://doi.org/10.1109/TIV.2016.2578706

Parasuraman, R., & Riley, V. (1997). Humans and Automation: Use, Misuse, Disuse, Abuse. *Human Factors*, *39*(2), 230–253. https://doi.org/10.1518/001872097778543886

Parasuraman, R., Sheridan, T., & Wickens, C. (2008). Situation Awareness, Mental Workload, and Trust in Automation: Viable, Empirically Supported

Cognitive Engineering Constructs. *Journal of Cognitive Engineering and Decision Making*, *2*, 140–160. https://doi.org/10.1518/155534308X284417

Payre, W., Cestac, J., & Delhomme, P. (2014). Intention to use a fully automated car: Attitudes and a priori acceptability. *Transportation Research Part F: Traffic Psychology and Behaviour*, *27*, 252–263. https://doi.org/10.1016/j.trf.2014.04.009

Payre, W., Cestac, J., & Delhomme, P. (2016). Fully Automated Driving: Impact of Trust and Practice on Manual Control Recovery. *Human Factors*, *58*(2), 229–241. https://doi.org/10.1177/0018720815612319

Pretto, P., & Chatziastros, A. (2006, October 1). *Changes in optic flow and scene contrast affect the driving speed*. https://www.semanticscholar.org/paper/Changes-in-optic-flow-and-scene-contrast-affect-the-Pretto-Chatziastros/ad688474d1b7d502f330d0d3a4d2df3470a9c8e8

Qatu, M. S. (2012). Recent research on vehicle noise and vibration. *International Journal of Vehicle Noise and Vibration*, *8*(4), 289–301. https://doi.org/10.1504/IJVNV.2012.051536

Radhakrishnan, V., Merat, N., Louw, T., Lenné, M. G., Romano, R., Paschalidis, E., Hajiseyedjavadi, F., Wei, C., & Boer, E. R. (2020). Measuring drivers' physiological response to different vehicle controllers in highly automated driving (HAD): Opportunities for establishing real-time values of driver discomfort. *Information (Switzerland)*, *11*(8), 1–14. https://doi.org/10.3390/INFO11080390

Reason, J. T. (1978). Motion Sickness Adaptation: A Neural Mismatch Model. *Journal of the Royal Society of Medicine*, *71*(11), 819–829. https://doi.org/10.1177/014107687807101109

Reimer, B., Donmez, B., Lavallière, M., Mehler, B., Coughlin, J. F., & Teasdale, N. (2013). Impact of age and cognitive demand on lane choice and changing under actual highway conditions. *Accident Analysis & Prevention*, *52*, 125–132. https://doi.org/10.1016/j.aap.2012.12.008

Reimer, B., Pettinato, A., Fridman, L., Lee, J., Mehler, B., Seppelt, B., Park, J., & Iagnemma, K. (2016). Behavioral Impact of Drivers' Roles in Automated Driving. *Proceedings of the 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 217–224. https://doi.org/10.1145/3003715.3005411

Reis, P. M. R., Hebenstreit, F., Gabsteiger, F., von Tscharner, V., & Lochmann, M. (2014). Methodological aspects of EEG and body dynamics measurements during motion. *Frontiers in Human Neuroscience*, *8*, 156. https://doi.org/10.3389/fnhum.2014.00156

Richards, L. G., Jacobson, I. D., & Kuhlthau, A. R. (1978). What the passenger contributes to passenger comfort. *Applied Ergonomics*, *9*(3), 137–142. https://doi.org/10.1016/0003-6870(78)90003-0

Riendeau, J., Stinchcombe, A., Weaver, B., & Bédard, M. (2018). Personality factors are associated with simulated driving outcomes across the driving lifespan. *Transportation Research Part F: Traffic Psychology and Behaviour*, *54*, 171–187. https://doi.org/10.1016/j.trf.2018.01.022

Rolnick, A., & Lubow, R. E. (1991). Why is the driver rarely motion sick? The role of controllability in motion sickness. *Ergonomics*, *34*(7), 867–879. https://doi.org/10.1080/00140139108964831

Rossner, P., & Bullinger, A. C. (2020). How Do You Want to be Driven? Investigation of Different Highly-Automated Driving Styles on a Highway Scenario. *Advances in Intelligent Systems and Computing*, *964*, 36–43. https://doi.org/10.1007/978-3-030-20503-4_4

SAE. (2014). *Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems*. https://www.sae.org/standards/content/j3016_201401/

SAE. (2021). *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles*.

Saffarian, M., De Winter, J. C. F., & Happee, R. (2012). Automated driving: Human-factors issues and design solutions. *Proceedings of the Human Factors and Ergonomics Society*, 2296–2300. https://doi.org/10.1177/1071181312561483

Sagberg, F., Selpi, Bianchi Piccinini, G. F., & Engström, J. (2015). A Review of Research on Driving Styles and Road Safety. *Human Factors*, *57*(7), 1248–1275. https://doi.org/10.1177/0018720815591313

Shen, W., & Vértiz, A. M. (1997). *Redefining Seat Comfort*. 970597. https://doi.org/10.4271/970597

Shladover, S. E. (2016). The Truth About "Self-Driving" Cars. *Scientific American*, *314*(6), 52–57.

Shladover, S. E. (2018). Connected and automated vehicle systems: Introduction and overview. *Journal of Intelligent Transportation Systems*, *22*(3), 190–200. https://doi.org/10.1080/15472450.2017.1336053

Siebert, F. W., Oehl, M., Höger, R., & Pfister, H. R. (2013). Discomfort in Automated Driving—The Disco-Scale. *Communications in Computer and Information Science*, *374*(PART II), 337–341. https://doi.org/10.1007/978-3-642-39476-8_69

Sinha, S., Shivanand Swamy, H. M., & Modi, K. (2020). User Perceptions of Public Transport Service Quality. *Transportation Research Procedia*, *48*, 3310–3323. https://doi.org/10.1016/j.trpro.2020.08.121

Sivak, M., & Schoettle, B. (2015). *Motion sickness in self-driving vehicles* (Issue April). https://deepblue.lib.umich.edu/handle/2027.42/111747

Slater, K. (1985). *Human Comfort* (Vol. 2). Charles C Thomas Pub Ltd. https://doi.org/10.2307/2071632

Smyth, J., Birrell, S., Woodman, R., & Jennings, P. (2021). Exploring the utility of EDA and skin temperature as individual physiological correlates of motion sickness. *Applied Ergonomics*, *92*(January 2020), 103315. https://doi.org/10.1016/j.apergo.2020.103315

Smyth, J., Jennings, P., & Birrell, S. (2019). *Are you Sitting Comfortably? How Current Self-Driving Car Concepts Overlook Motion Sickness , and the Impact it has on Comfort and Productivity. An Introduction to Motion Sickness*. *964*. https://doi.org/10.1007/978-3-030-20503-4_36

Song, X., Gao, H., Ding, T., Gu, Y., Liu, J., & Tian, K. (2023). A Review of the Motion Planning and Control Methods for Automated Vehicles. *Sensors*, *23*(13), Article 13. https://doi.org/10.3390/s23136140

Taubman-Ben-Ari, O., Mikulincer, M., & Gillath, O. (2004). The multidimensional driving style inventory—Scale construct and validation. *Accident Analysis and Prevention*, *36*(3), 323–332. https://doi.org/10.1016/S0001-4575(03)00010-1

Uys, P. E., Els, P. S., & Thoresson, M. (2007). Suspension settings for optimal ride comfort of off-road vehicles travelling on roads with different roughness and speeds. *Journal of Terramechanics*, *44*(2), 163–175. https://doi.org/10.1016/j.jterra.2006.05.002

Vagia, M., Transeth, A. A., & Fjerdingen, S. A. (2016). A literature review on the levels of automation during the years. What are the different taxonomies that have been proposed? *Applied Ergonomics*, *53*, 190–202. https://doi.org/10.1016/j.apergo.2015.09.013

Vink, P., & Hallbeck, S. (2012). Editorial: Comfort and discomfort studies demonstrate the need for a new model. *Applied Ergonomics*, *43*(2), 271–276. https://doi.org/10.1016/j.apergo.2011.06.001

Wasser, J., Diels, C., Baxendale, A., & Tovey, M. (2017). Driverless pods: From technology demonstrators to desirable mobility solutions. In N. Stanton (Ed.), *Advances in Human Aspects of Transportation. AHFE 2017. Advances in Intelligent Systems and Computing* (Vol. 597, pp. 538–550). Springer, Cham. https://doi.org/10.1007/978-3-319-60441-1_53

Waymo. (2023). *Waymo Driver*. Waymo. https://waymo.com/waymo-driver/

Wei, C., Romano, R., Hajiseyedjavadi, F., Merat, N., & Boer, E. (2019). Driver-centred Autonomous Vehicle Motion Control within A Blended Corridor. *IFAC-PapersOnLine*, 52(5), 212–217. https://doi.org/10.1016/J.IFACOL.2019.09.034

Wei, C., Romano, R., Merat, N., Wang, Y., Hu, C., Taghavifar, H., Hajiseyedjavadi, F., & Boer, E. R. (2019). Risk-based autonomous vehicle motion control with considering human driver's behaviour. *Transportation Research Part C:*

Emerging Technologies, *107*(August), 1–14. https://doi.org/10.1016/j.trc.2019.08.003

Wei, Z.-G., Macwan, A. P., & Wieringa, P. A. (1998). A Quantitative Measure for Degree of Automation and Its Relation to System Performance and Mental Load. *Human Factors*, *40*(2), 277–295. https://doi.org/10.1518/001872098779480406

Xu, Z., Zhang, K., Min, H., Wang, Z., Zhao, X., & Liu, P. (2018). What drives people to accept automated vehicles? Findings from a fi eld experiment. *Transportation Research Part C*, *95*(June), 320–334. https://doi.org/10.1016/j.trc.2018.07.024

Yusof, N. M., Karjanto, J., Terken, J., Delbressine, F., Hassan, M. Z., & Rauterberg, M. (2016). The exploration of autonomous vehicle driving styles: Preferred longitudinal, lateral, and vertical accelerations. *AutomotiveUI 2016 - 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, Proceedings*, 245–252. https://doi.org/10.1145/3003715.3005455

Zang, S., Ding, M., Smith, D., Tyler, P., Rakotoarivelo, T., & Kaafar, M. A. (2019). The Impact of Adverse Weather Conditions on Autonomous Vehicles: How Rain, Snow, Fog, and Hail Affect the Performance of a Self-Driving Car. *IEEE Vehicular Technology Magazine*, *14*(2), 103–111. https://doi.org/10.1109/MVT.2019.2892497

Zhang, L., Helander, M. G., & Drury, C. G. (1996). Identifying Factors of Comfort and Discomfort in Sitting. *Human Factors, 38*(3), 377–389. https://doi.org/10.1518/001872096778701962

Zhao, Z., Wang, Z., Han, K., Gupta, R., Tiwari, P., Wu, G., & Barth, M. J. (2022). Personalized Car Following for Autonomous Driving with Inverse Reinforcement Learning. *2022 International Conference on Robotics and Automation (ICRA)*, 2891–2897. https://doi.org/10.1109/ICRA46639.2022.9812446

Zuckerman, M. (1979). *Sensation Seeking: Beyond the Optimal Level of Arousal*. L. Erlbaum Associates.

Zuckerman, M., Eysenck, S. B., & Eysenck, H. J. (1978). Sensation seeking in England and America: Cross-cultural, age, and sex comparisons. *Journal of Consulting and Clinical Psychology*, *46*(1), 139–149. https://doi.org/10.1037/0022-006X.46.1.139

Zuckerman, M., & Neeb, M. (1980). Demographic influences in sensation seeking and expressions of sensation seeking in religion, smoking and driving habits. *Personality and Individual Differences*, *1*(3), 197–206. https://doi.org/10.1016/0191-8869(80)90051-3

CHAPTER 2

Drivers' evaluation of different automated driving styles: Is it both comfortable and natural?

Abstract

Objective: This study investigated users' subjective evaluation of three highly automated driving styles, in terms of comfort and naturalness, when negotiating a UK road in a high-fidelity, motion-based, driving simulator.

Background: Comfort and naturalness are thought to play an important role in contributing to users' acceptance and trust of automated vehicles (AVs), although not much is understood about the types of driving style which are considered comfortable or natural.

Method: A driving simulator study, simulating roads with different road geometries and speed limits, was conducted. Twenty-four participants experienced three highly automated driving styles, two of which were recordings from human drivers, and the other was based on a machine learning (ML) algorithm, termed Defensive, Aggressive, and Turner, respectively. Participants evaluated comfort or naturalness of each driving style, for each road segment, and completed a Sensation Seeking (SS) questionnaire, which assessed their risk-taking propensity.

Results: Participants regarded both human-like driving styles as more comfortable and natural, compared with the less human-like, ML-based, driving controller. Particularly, between the two human-like controllers, the Defensive style was considered more comfortable, especially for the more challenging road environments. Differences in preference for controller by driver trait were also observed, with the Aggressive driving style evaluated as more natural by the high sensation seekers.

Conclusion: Participants were able to distinguish between human- and machine-like AV controllers. A range of psychological concepts must be considered for the subjective evaluation of controllers.

Application: Insights into how different driver groups evaluate automated vehicle controllers are important in designing more acceptable systems in the future.

Keywords: highly automated driving, driving style, comfort, naturalness, sensation seeking

2.1. Introduction

With higher SAE level AVs (SAE International, 2016), drivers will inevitably lose the controllability of the vehicle, and the role of human drivers will shift from active controllers of the vehicle, towards passive observers and passengers (Elbanhawi et al., 2015; Kaber & Endsley, 2004). There are several subsequent concerns that might hinder the deployment of these vehicles, such as users' experience of comfort inside the AV (Elbanhawi et al., 2015). Comfort is crucial for an AV's implementation, as it is found to be correlated with trust and acceptance (Paddeu et al., 2020; Siebert et al., 2013), important elements for encouraging public uptake of these new forms of mobility (Madigan et al., 2016).

Although there is currently no commonly agreed definition for comfort in this context, some suggestions exist. Under the context of automated driving, Hartwich et al. (2018) summarised driving comfort as '*a subjective, pleasant state of relaxation given by confidence and an apparently safe vehicle operation, which is achieved by the removal or absence of uneasiness and distress*' (p. 1019).

For automated vehicles, however, comfort is not simply limited to physical aspects of the vehicle, such as good seat design (Ebe & Griffin, 2001), or acceptable levels of engine noise, and vehicle vibrations (Qatu, 2012). These features are mentioned in studies of traditional, manually operated, road vehicles, and also in other domains, for example, cabin noise in aircraft (Pennig et al., 2012). Since the vehicle is no longer controlled by a human, it is important that its "driving behaviour", and how it negotiates different road geometries, and traffic conditions, is considered pleasant, and rated positively by the user, ensuring it feels comfortable and safe (Elbanhawi et al., 2015; Summala, 2007). Other, more psychological, terms and concepts used in this context include ensuring the AV is considered reliable, and familiar, avoiding any sudden surprise behaviours, which are shown to enhance the acceptance, satisfaction and perceived safety of AVs (Carsten & Martens, 2018; Ramm et al., 2014).

One, relatively unexplored, concept in this context is "naturalness" of the AV's driving behaviour, which has been linked to the familiarity of the AV's manoeuvres, for the user. Here, the familiarity of AV movements, rendered by mimicking human-like vehicle controls, is expected to fulfil human users' anticipation of an AV's behaviours, and result in positive subjective feedback (Butakov & Ioannou, 2015; Hartwich et al., 2018). Moreover, Elbanhawi et al. (2015) suggest that naturalness of automated driving is an important determinant of comfort. However, some empirical studies have shown that familiar automated driving manoeuvres do not always lead to higher subjective comfort (Hartwich et al., 2018), which suggests that more knowledge is needed on the link between these two concepts, since they will likely contribute to acceptance of future AVs.

From a technical perspective, there are a large number of automated driving styles that could be generated for such investigations. Taking motion planning as an example, the generated driving behaviour of AVs could be robotic, with algorithm-optimised trajectories, based solely on sensory information provided by lasers, radars and cameras, to adapt to the environment (e.g., Urmson et al., 2008). Alternatively, these may mimic a human driver's average behavioural patterns, by training models, based on real human driving data (e.g., Hajiseyedjavadi et al., 2022; Rehder et al., 2017; Wei et al., 2019). Personalisation of driving styles can also be achieved by using users' own driving style in the model development loop (e.g., Menner et al., 2019).

Studies on manual driving suggest that participants' reported levels of comfort are also linked to the vehicle's "driving style" (Ellinghaus & Schlag, 2001, cited in Bellem et al., 2018), which is defined as the driving habits of the driver, such as their preferred speed, threshold for overtaking, headway distance, and tendency to violate traffic regulations (Elander et al., 1993). In highly automated vehicles, the use of such driving styles has been reported to enhance driving comfort of passive users (Bellem et al., 2018).

Research has revealed the existence of several driving styles, associated with different character traits of human drivers, loosely linked to defensive (less sudden acceleration and deceleration) and aggressive (higher acceleration and more sudden braking) driving behaviours (Murphey et al., 2009). Results also suggest that different automated driving styles are sometimes found to be preferred by different groups of users, when evaluated in terms of comfort, safety and pleasantness, although findings are inconclusive. For example, a more defensive driving style, with slower lane changing features, and lower acceleration, was favoured by most participants, when compared with a higher-acceleration, more assertive, driving style (Rossner & Bullinger, 2020). Moreover, Hartwich et al. (2018) found that familiar driving styles (a replay of participants' own driving) were more favoured by younger drivers (25-35 years), while faster and unfamiliar automated driving styles (that of the younger drivers) were preferred by older drivers (65-84 years). Therefore, Hartwich et al. (2018) suggest that solely mimicking drivers' personal manual driving habits may not be suitable for all age groups. Using a more comprehensive set of vehicle kinematics, Bellem et al. (2018) manipulated the initiation time and strength of acceleration and jerk of three manoeuvres on the highway (i.e., lane changes, accelerations and decelerations). These authors recommend a number of configurations for comfortable driving experiences, such as minimising jerk for acceleration and deceleration manoeuvres, lowering acceleration, and providing action feedback, which is when maximum acceleration is applied at the early stages of a lane change manoeuvre.

As outlined above, most of the existing studies considering users' responses to different driving styles of AVs have compared different replays of drivers' manual driving performance. To date, there has been little comparison of user preferences for machine- versus human-like AV driving styles. An important consideration here is the balance between what is expected from users about the acceptable driving style of an AV, compared to that of a human driver. For example, studies have shown that an AV controller that precisely follows the lane centre, is considered more competent, compared to those with less accurate lane-tracking and more lateral drifts from the centre lane (Price et al., 2016). Therefore, from a human factors perspective, more research is warranted to understand what types of driving styles and behaviours of machine- and human-like driving are considered more comfortable and natural, and whether these are linked to the particular driving environment being negotiated by the AV.

Users' perception of an AV's driving style is known to be influenced by both objective and subjective factors. For example, road furniture and geometry are known to influence ratings of safety and comfort (Hajiseyedjavadi et al., 2022) and physiological response (Beggiato et al., 2019; Radhakrishnan et al., 2020), while a number of studies have shown a correlation between personality traits such as Sensation Seeking (Arnett, 1994) and preferred driving style. For example, in manual driving; drivers with high sensation seeking scores are found to drive in a riskier and more aggressive manner and at higher speeds, while low sensation seekers have a tendency to drive more slowly (Louw et al., 2019; Taubman-Ben-Ari et al., 2004; Zuckerman & Neeb, 1980). However, results are mixed regarding preferences for AV-driving styles. For example, Yusof et al. (2016) reported that both assertive and defensive drivers, characterised by higher and lower sensation seeking scores, respectively, showed a consistent preference for a defensive (and not assertive) AV driving style. Therefore, in addition to considering user response to two human-like and one machine-like AV controller, this study assessed the effect of road geometries and users' sensation seeking scores on such evaluations.

2.1.1. Current study

This study is based on data collected from a driving simulator study within the UK-funded HumanDrive project (TS/P012035/1); the main purpose of which was to develop, and evaluate, advanced AV-controllers, imitating natural, human-like, driving styles. Two representative human-like driving styles were recorded, and replayed to participants. Response to these was compared to a machine-like, machine learning (ML)-built, driving style (Solernou et al., 2020).

The following research questions were addressed in the present study:

1. Are the three driving styles rated differently in terms of perceived comfort and naturalness?
2. Do environmental settings influence the comfort and naturalness of the three driving styles?
3. Do users' sensation seeking propensities affect their ratings of comfort and naturalness towards the three driving styles?
4. Is a natural driving style also a comfortable driving style?

2.2. Methods

2.2.1. Participants

Twenty-four participants (12 male, 12 female) aged between 20 and 49 years (M = 35.7, SD = 7.1) were recruited. All participants held a valid UK driving licence, with experience ranging from 2 to 27 years (M = 14.7, SD = 7.8). Reported annual driving distance ranged from 500 to 18000 miles (M = 7554.2, SD = 3982.7).

All participants were recruited by using the University of Leeds Driving Simulator database, and all provided informed consent to take part in the study. Each participant was compensated £30 for taking part in the study. This study was approved by the University of Leeds Ethics Committee (LTTRAN-086).

2.2.2. Apparatus

The high-fidelity, motion-based University of Leeds Driving Simulator (UoLDS) was used in the experiment. The simulator's vehicle cab is based around a 2006 Jaguar S-type, housed within a 4m diameter, spherical projection dome. There are eight visual channels rendered at 60 frames/s, predominantly at a resolution of 1920×1200, providing a horizontal forward field of view of 270°. The simulator also incorporates an eight degree-of-freedom electrical motion system. The generated range of acceleration of the motion system is ±5.0 m/s^2 (Jamson et al., 2007)

2.2.3. Experimental Design

A fully within-participant experimental design was used in this study to investigate participants' subjective evaluation of three different automated vehicle driving styles, described below. Participants were asked to use an eleven-point, Likert-type, scale, to rate how "comfortable" and "natural" each automated drive felt, as it negotiated the same stretch of road, in six separate drives, completed over two days.

2.2.3.1. Driving styles

A machine learning (ML) based controller, and two human-driven controllers were developed for evaluation in this study. These controllers are described further below, and a diagram presenting the development procedure is shown in Figure 2.1.

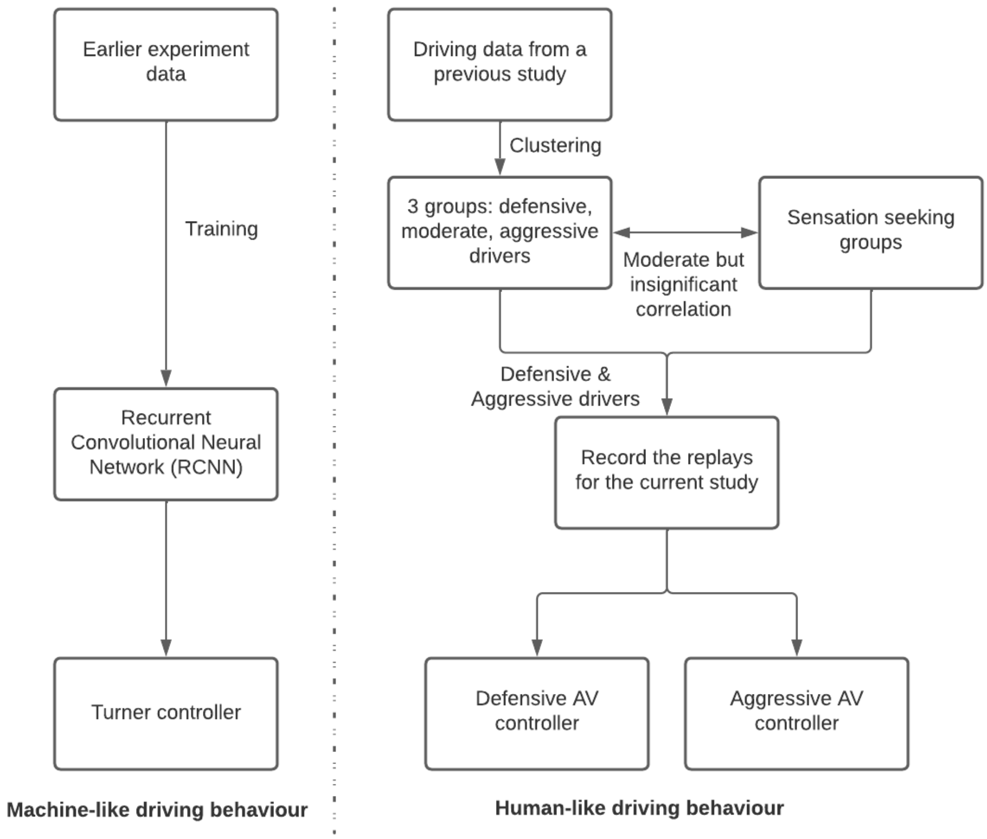


Figure 2.1. Overview of the development of the three AV controllers

<u>The ML-built controller (Turner)</u>

The ML controller was calibrated using a Recurrent Convolutional Neural Network (RCNN) that was capable of imitating the human driving behaviour, in terms of future yaw rate and speed demands. The RCNN was trained from data of 10 participants, from an earlier experiment of the project (see Solernou et al., 2020). This controller will be called the Turner controller from here on.

<u>The human-like controllers (Termed Aggressive and Defensive controllers)</u>

The two human-like controllers were recorded drives of human participants, collected before the main study took place, which were then replayed to participants of this study. Previous studies have shown a positive correlation between speed choice and sensation seeking (Louw et al., 2019) as well as risk-taking behaviour in manual driving (Ge et al., 2014; Oppenheim et al., 2016;

Riendeau et al., 2018; Ulleberg & Rundmo, 2003). To ensure that distinct differences in driving behaviour would arise between the two human-driven controllers, recruitment of participants used for the human-driven controllers was based on their sensation seeking scores.

Before recruiting participants for these replay drives, data from a previous study of the project was used to create clusters of driving behaviour (see Appendix 1). These participants were clustered into three main groups: defensive, moderate and aggressive drivers. There was a moderate, but insignificant, correlation between participants' sensation seeking scores, and cluster membership ($r(14) = .429$, $p = .143$). For example, we found that the aggressive driving cluster contained participants with higher sensation seeking scores. The absence of a significant correlation was likely due to the small sample size used in this study. Following this analysis, participants with higher sensation seeking scores from the aggressive cluster, and lower sensation seeking scores from the defensive cluster were contacted to participate in the replay recordings of the current study. In total, eight participants were recruited, four for each sensation seeking group (Table 2.1).

Table 2.1. Descriptive statistics of the participants used for the replay recording phase.

	Gender		Age		AISS score
	Male	Female	Mean	Std.	Mean
High sensation seeking	4	0	36.25	9.78	55.75
Low sensation seeking	2	2	52	6.73	45

Note. AISS scores were calculated based on drivers' responses to Arnett Inventory of Sensation Seeking (AISS; Arnett, 1994), and scores were the sum of all responses to in total of 20 questions, with a higher score means higher sensation seeking propensities.

During the recording process, each participant drove the experimental route three times. The process took approximately one hour. After the data collection, the clustering process was applied again for the new data, to confirm the obtained driving behaviours belonged to the previously identified defensive and aggressive driver groups, respectively. Out of the eight participants recorded, the manual driving data of two participants (one per sensation seeking group, with scores of 59 and 43, respectively) which was closest to the median of the defensive and aggressive clusters, were selected as the representative driving styles for our two human-like controllers. It is worth highlighting that the selected drives were also checked to ensure that no unusual or unexpected manoeuvres existed along the drive. For the rest of this paper, the higher sensation seekers' driving style will be termed Aggressive, and the lower sensation seekers' driving style will be called the Defensive driving style.

2.2.3.2. Road Environment and Scenarios

The simulated driving scene was modelled from real stretches of road around North Bedfordshire in the UK (Figure 2.2). Two loops, going North and South, were simulated, creating a virtual environment covering around 12 miles of driving. In the present work, however, only the North loop was included for the simulated drive, since it included the range of scenarios required for studying driver behaviour in response to changes in speed and geometry, and shortened the overall drive. This section of road was approximately 5 miles long, taking about 15 minutes to complete.

To understand user preferences for, and in response to, a wide range of road geometries and speed profiles, the layout of the North loop contained a combination of high-speed (60 mph) rural sections, with varying road curvature, and more built-up, village sections, at a speed limit of 40 mph (Table 2.2).

Figure 2.2. Example of the simulated (top) and real (bottom) road environments

Table 2.2. The speed limit and geometrical details of the simulated road.

Zone	Curve radius	Curve direction	Road type	Speed limit (mph)	Road context
1	300-800m	Left	Rural	60	Kerb + grass and the bridge in the middle of the area
2	Straight	Straight	Rural	60	Kerb + grass with hedge far from the road edge
3	<150m	Left	Rural	60	Kerb + grass and trees far from the road edge
4	<150m	Left	Rural	60	Kerb + grass with hedge quite far from the road edge
5	300-800m	Right	Rural	60	Kerb + grass with hedge quite far from the road edge
6	<150m	Right	Village	40	Kerb + grass and some structures far from the road edge
7	<150m	Left	Village	40	Kerb + grass
8	200-300m	Right	Village	40	Kerb + grass and hedge around 1-2m from the road edge
9	Straight	Straight	Village	40	Kerb + grass and fence quite close to the road edge
10	150-200m	Right	Village	30	Kerb + pavement and village structures far from the road edge
11	150-200m	Right	Village	30	Parked cars zone
12	300-800m	Right	Village	30	Kerb + grass and village structures
13	200-300m	Left	Rural	40	Grass, bushes and trees not close to the road edge
14	300-800m	Right	Rural	40	Grass and hedge far from the road edge
15	<150m	Right	Rural	60	Grass and trees far from the road edge
16	<150m	Left	Rural	60	Hedge at the road edge
17	150-200m	Right	Rural	60	Grass and hedge far from the road edge
18	300-800m	Left	Rural	60	Grass and bushes around 2m from the road edge
19	Straight	Straight	Rural	60	Fence around 1-2m from the road edge
20	Straight	Straight	Rural	60	Hedge at the road edge and an intersection at the end of the section
21	na	na	University	30	Mini roundabout and road markings
22	<150m	Left	University	30	Parked cars zone
23	300-800m	Left	University	30	Kerb + pavement
24	Straight	Straight	University	30	Kerb + pavement

2.2.3.3. *Variables*

The dependent variables were comfort and naturalness of the driving experience, for each controller. A search of the literature at the time of study design revealed an absence of a formal, and universally agreed, description for the two terms. To ensure that the same term was understood by all participants, we therefore used a small expert group within the project team to define the two terms, and included this information in the participant briefing sheet:

i. Comfortable driving was defined as '*a driving style that does not cause any feeling of uneasiness or discomfort*';

ii. Natural driving was defined as '*a driving style that is closest to your own driving*'.

Participants evaluated each controller, in two ways: (i) after each drive, participants were asked to provide an overall rating, based on their entire driving experience., and (ii) throughout the drive, immediately after they heard a short auditory beep, which was played via the car's speakers, corresponding to 24 relevant sections in the drive (Table 2.2). They were taught to use a Likert-type scale for guiding their responses, providing a number between -5 (Extremely Uncomfortable/Unnatural) and +5 (Extremely Comfortable/Natural) (Figure 2.3).

Participants also completed the Arnett Inventory of Sensation Seeking questionnaire (Arnett, 1994) after they finished the last drive. This questionnaire includes twenty items, and four response options for each item, ranging from 1 (does not describe me at all) to 4 (describes me very well). Reverse-worded items were further reverse-coded. We used the sum score of these items to characterise sensation seeking tendency, with a higher score indicating a higher sensation seeking tendency.

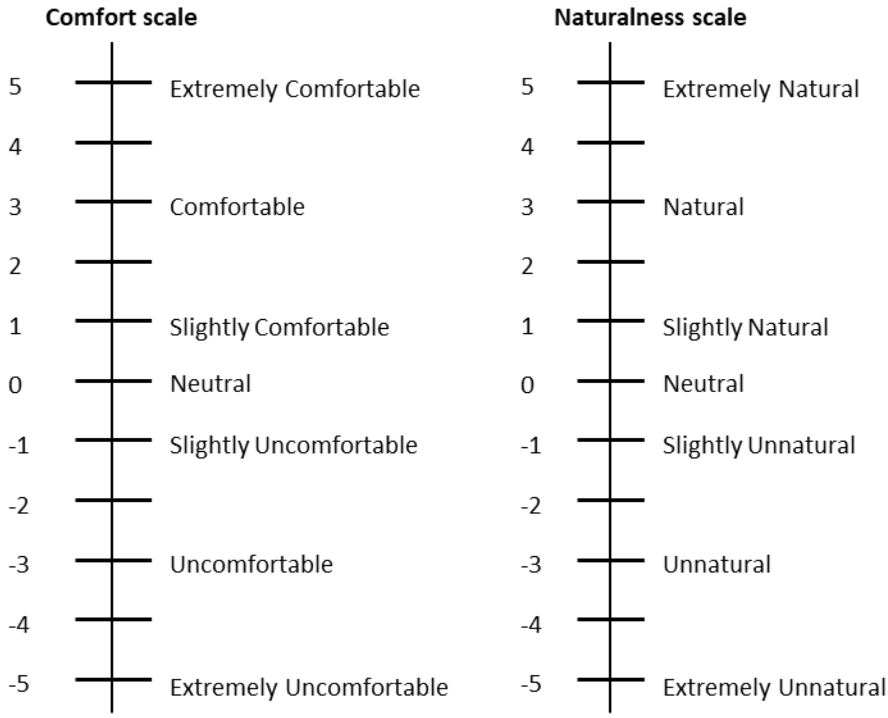


Figure 2.3. The Comfort and Naturalness scales used in the study.

2.2.4. Procedure

To reduce the effect of fatigue on participants, the study was conducted over two separate days (M=6.75 days apart, SD=2.17), with data collection lasting about 1.5 hours on each day. Participants evaluated the three driving styles twice: once in terms of comfort, and once in terms of naturalness, with half of the participants evaluating in terms of comfort on day 1, and the other half on day 2 (Figure 2.4).

Upon arrival on the first day, each participant received a written and verbal briefing of the study, including how to use the subjective scale, and provided their written consent to take part in the experiment. They then started the simulator experiment with a practice drive in manual driving, followed by a practice ride in an automated driving mode. A researcher accompanied participants during the practice session, which lasted 20-30 minutes. Following the practice drive, the researcher left the simulator dome, and the participant started the first of three experimental drives, one for each controller. The order of the three automated driving styles was counterbalanced across participants, and participants left the simulator dome after each drive, to reduce fatigue effects. After the second day's experiment, participants were asked to complete a set of questionnaires, including the sensation seeking questionnaire. The data from the other questionnaires is not reported here.

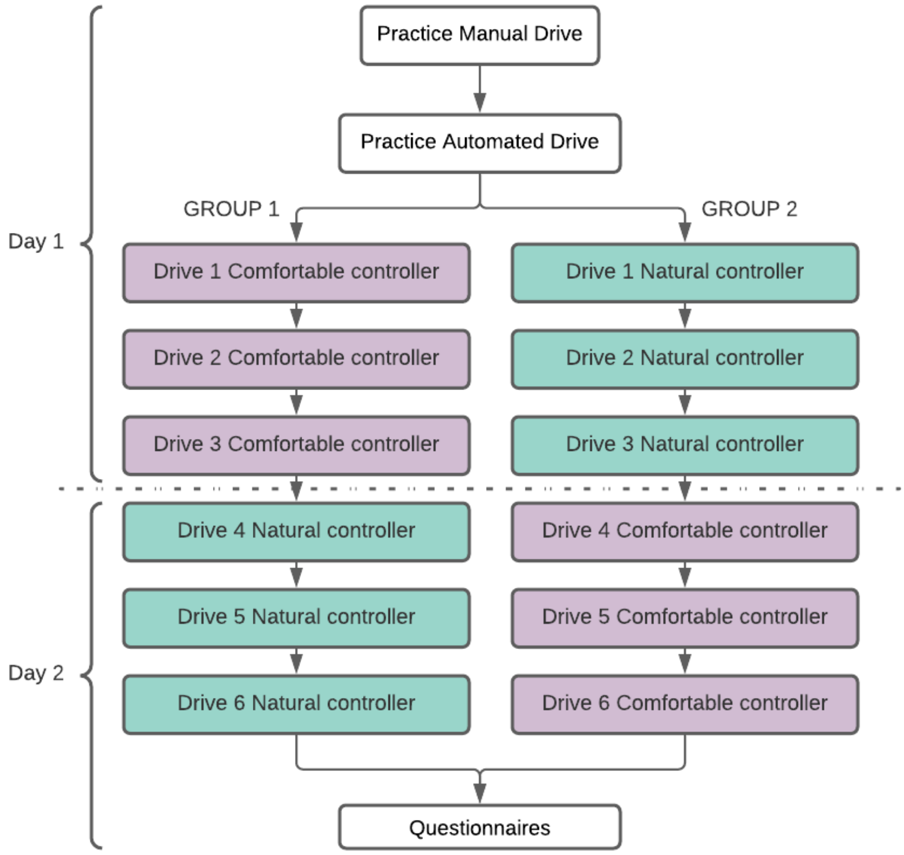


Figure 2.4. The overall experimental procedure, including the order of drives.

2.3. Results

The main aim of the analyses was to assess users' evaluation of the three automated controllers, in terms of comfort and naturalness. Participants' subjective feedback about the driving styles adopted by the controllers was provided in two ways: (i) an overall evaluation of the controller, after finishing the entire drive, and (ii) 24 responses, based on the 24 auditory beeps throughout each drive, which prompted a response for each of the different driving zones. Two statistical tests were used: the Wilcoxon signed-rank test was used for the overall evaluation provided at the end of each drive, and the Generalised Estimating Equation (GEE) (Liang & Zeger, 1986) was used for the 24 individual evaluations provided during the drive (see configurations of GEE in Appendix 2).

2.3.1. Subjective evaluations of the driving styles

Table 2.3 shows results of the Wilcoxon signed-ranks test on matched-pairs, and Figure 2.5 shows box plots of overall comfort and naturalness evaluation of the three driving styles.

Regarding overall comfort, the Wilcoxon test showed significantly higher evaluation for the Defensive controller, compared to the Aggressive and the Turner controllers (both $p < .001$). There was no significant difference between the Aggressive and Turner controllers ($p = .49$). Regarding overall naturalness, the Wilcoxon test showed a significantly higher evaluation for the Defensive controller, compared to the Turner ($p < .001$), and a higher evaluation than the Aggressive controller ($p = .02$). A significantly lower score for the Turner than the Aggressive controller ($p = .01$) was also revealed.

Figure 2.5 shows that the evaluation of the Defensive driving style was relatively consistent across participants. By contrast, the evaluation for the Aggressive and Turner controllers was more variable, with a bimodal pattern observed in response to naturalness of the Aggressive, and the comfort and naturalness of the Turner. To understand this further, we conducted additional analyses by taking participants' personality trait into account.

Table 2.3. Wilcoxon signed-rank test results for overall comfort and naturalness.

Comfort (overall)			
Driving style	z	p	r
Defensive vs Turner	4.27	0.000*	0.87
Defensive vs Aggressive	4.11	0.000*	0.84
Aggressive vs Turner	0.70	0.490	0.14
Naturalness (overall)			
Driving style	z	p	r
Defensive vs Turner	3.67	0.001*	0.75
Aggressive vs Turner	2.44	0.010*	0.50
Defensive vs Aggressive	2.25	0.020*	0.46

Note. * p < .05. Orders of paired comparison are based on z values.

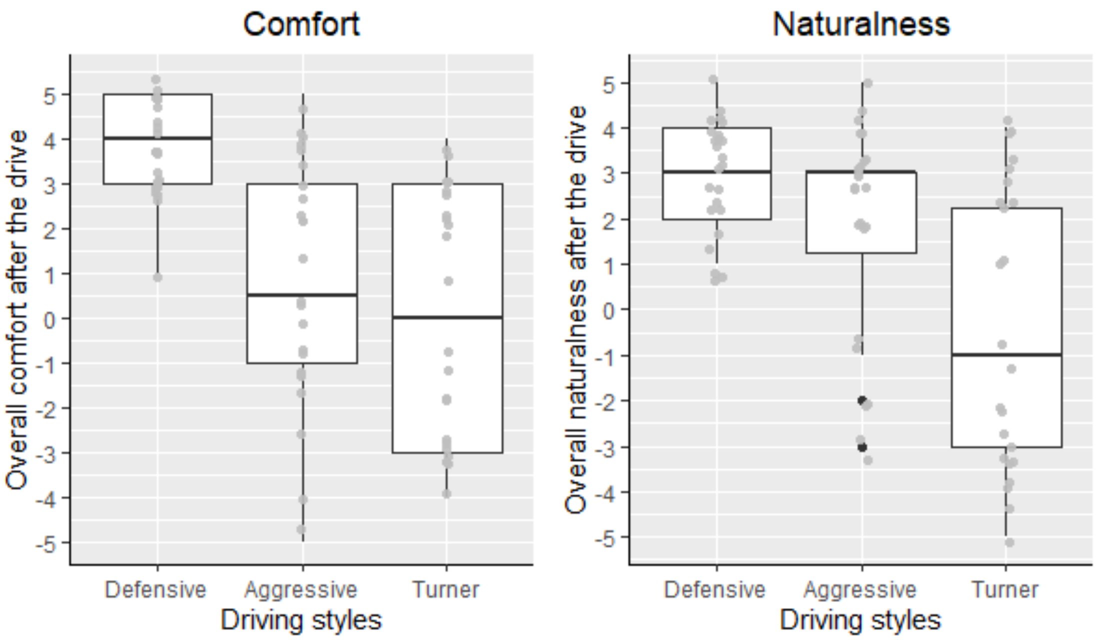


Figure 2.5. Evaluation of each controllers' driving style, in terms of its overall comfort (left) and overall naturalness (right). Horizontal lines inside each box represent the median values. Whiskers denote a distance of 1.5 times interquartile range (IQR) above the upper quantile up to the largest observation, or below the lower quartiles up to the smallest value. Grey dots represent data points (with small variations added to the position to avoid overlapping), while black points represent outliers.

Table 2.4 presents the GEE results for the repeated ratings of comfort and naturalness. Regarding comfort, the probability of reporting high levels of comfort was significantly higher for the Defensive controller, compared to both the Turner (OR = 7.21, p < .001), and Aggressive controllers (OR = 4.01, p < .001). Comfort ratings were also slightly higher for the Aggressive, than the Turner, controller (OR = 1.80, p = .04). Regarding naturalness, both the Defensive, and Aggressive controllers were more likely to be rated more natural, when compared to the Turner controller (OR = 4.98, p < .001; OR = 2.59, p = .002). The Defensive controller also had a higher probability of being assessed as more natural than the Aggressive driving style (OR = 1.92, p = .01).

Table 2.4. GEE model parameter estimates and odds ratios for repeatedly reported comfort and naturalness

Comfort					
Driving style	Coefficient	SE	Wald	Sig	Odds ratio (OR)
Defensive vs Turner	1.975	0.238	68.847	0.000*	7.206
Defensive vs Aggressive	1.388	0.234	35.111	0.000*	4.007
Aggressive vs Turner	0.587	0.285	4.258	0.039*	1.799
Naturalness					
Driving style	Coefficient	SE	Wald	Sig	Odds ratio (OR)
Defensive vs Turner	1.606	0.232	48.113	0.000*	4.980
Aggressive vs Turner	0.953	0.305	9.745	0.002*	2.593
Defensive vs Aggressive	0.653	0.255	6.560	0.010*	1.921

Note. * p < .05. Orders of paired comparison are based on the odds ratios.

To further understand whether subjective evaluation was due to any differences in the driving styles of the controllers, the vehicle kinematics, including the speed and lateral offsets of all three controllers, were inspected (Figure 2.6 and Figure 2.7). The interpretations provided in this section were based on visual observations of the controllers' kinematic characteristics only, and no formal analyses were conducted. Figure 2.6 shows that, overall, speed was higher in the Aggressive driving style, compared to the other two controllers. The Defensive and Turner controllers had similar increasing or decreasing trends in speed, for the same road sections, with smoother patterns (i.e., less frequent and gentler fluctuations in speed) seen for the Defensive controller. There was not much difference in the observed lateral offset of the three controllers (Figure 2.7).

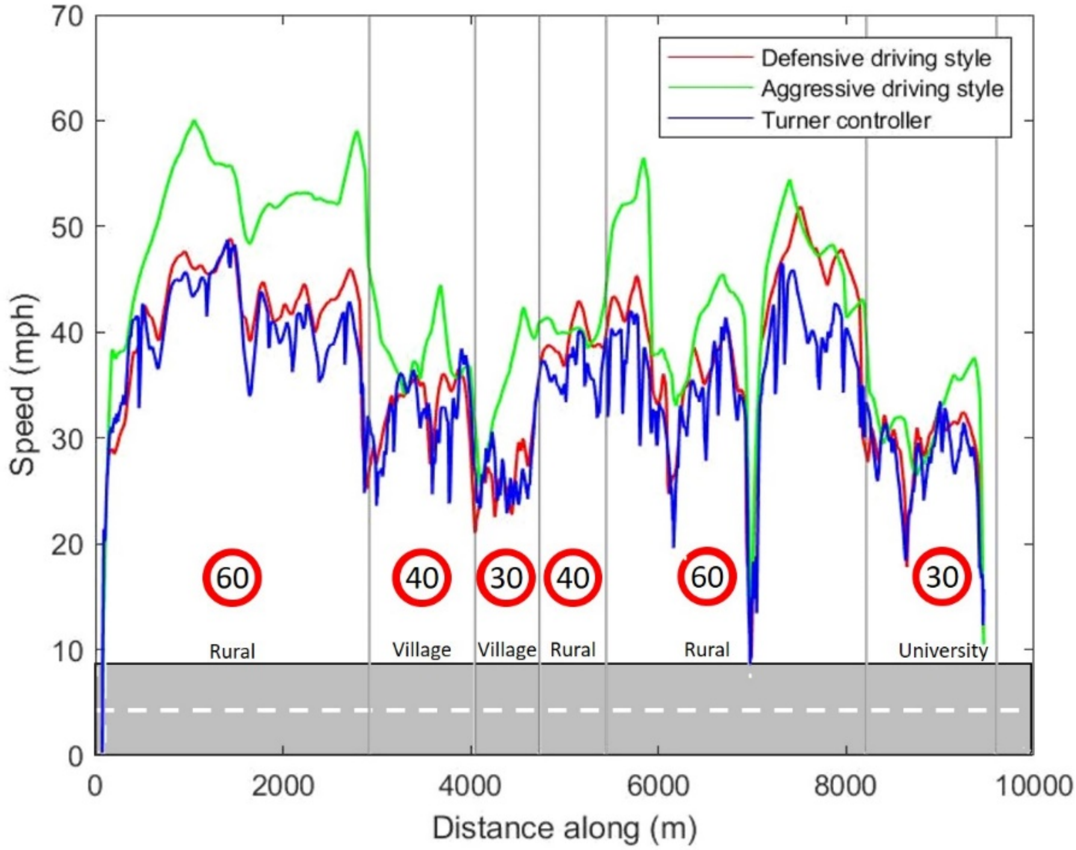


Figure 2.6. The speed profiles of the controllers.

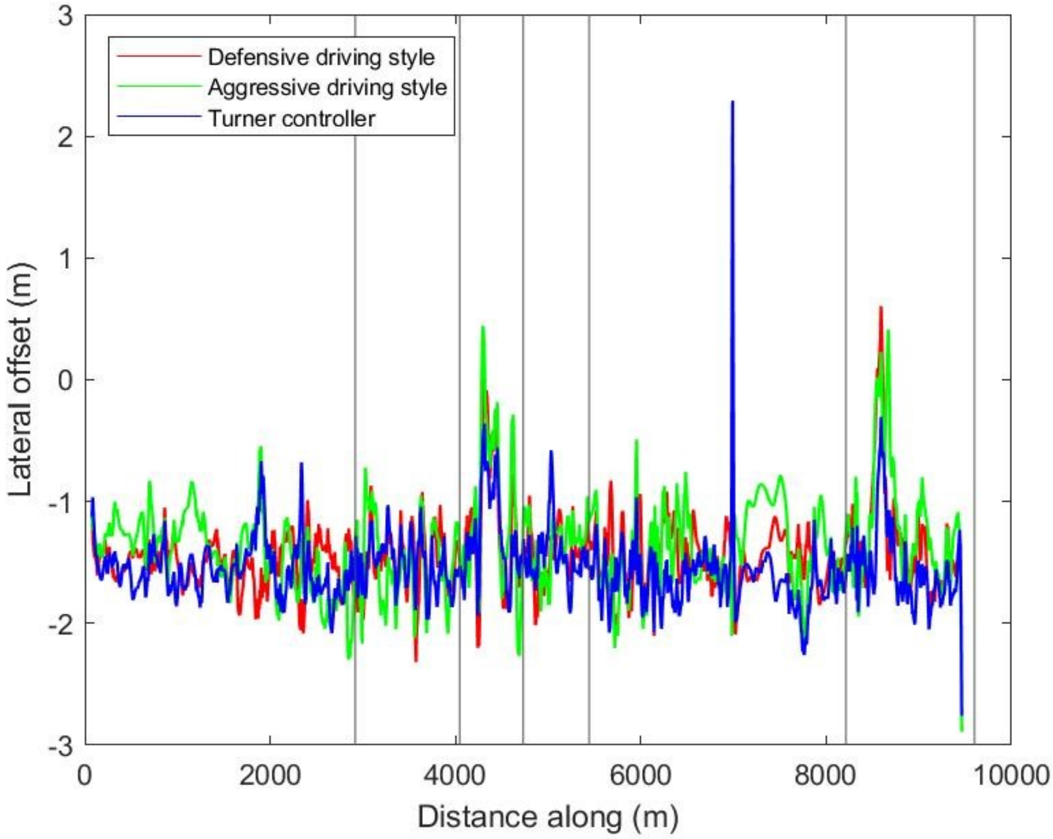


Figure 2.7. The lateral offset profiles of the controllers

2.3.2. The effect of road environment on subjective evaluation

As shown in Table 2.2, the simulated road included a range of road environments divided into five main categories: (i) road type, (ii) speed limit, (iii) road context, (iv) curve direction, and (v) curve radius. For simplicity, only two categories were included in this analysis, as follows:

i. road type (rural and village), which differed by posted speed limit (60 mph vs 40 mph), and roadside furniture (see Table 2.2);

ii. curve radius (five levels, varying from straight sections to curves of less than 150m).

Road type was included as the representative of speed limit and road context, supported by the strong ($r = 0.88$, $p < .001$) and medium ($r = -0.05$, $p < .001$) correlation between road type and the two categories (speed limit, road context), respectively. The University road type was excluded from analysis, due to the small number of sections falling into this category. The direction of a curve was also not included as a factor, as it was not expected to have a significant influence on results. It is worth mentioning that the number of road sections in each level outlined above was not equal, since the road was a replication of the real world.

Figure 2.8 shows the average comfort and naturalness ratings for the three driving styles, for the different road sections. An overall pattern was observed, such that, with increasing curve radius, there was a mild reduction in both comfort and naturalness ratings for all controllers, especially in the Rural areas. This pattern was not apparent in the Village areas, apart from two unexpected fluctuations. Inspection of the vehicle-based metrics showed a high speed for the Aggressive controller in the 200-300 Curve Radius section, and a suddenly changing speed of the Turner in the 300-800 Curve Radius section (for further evaluation of these, see Appendix 3).

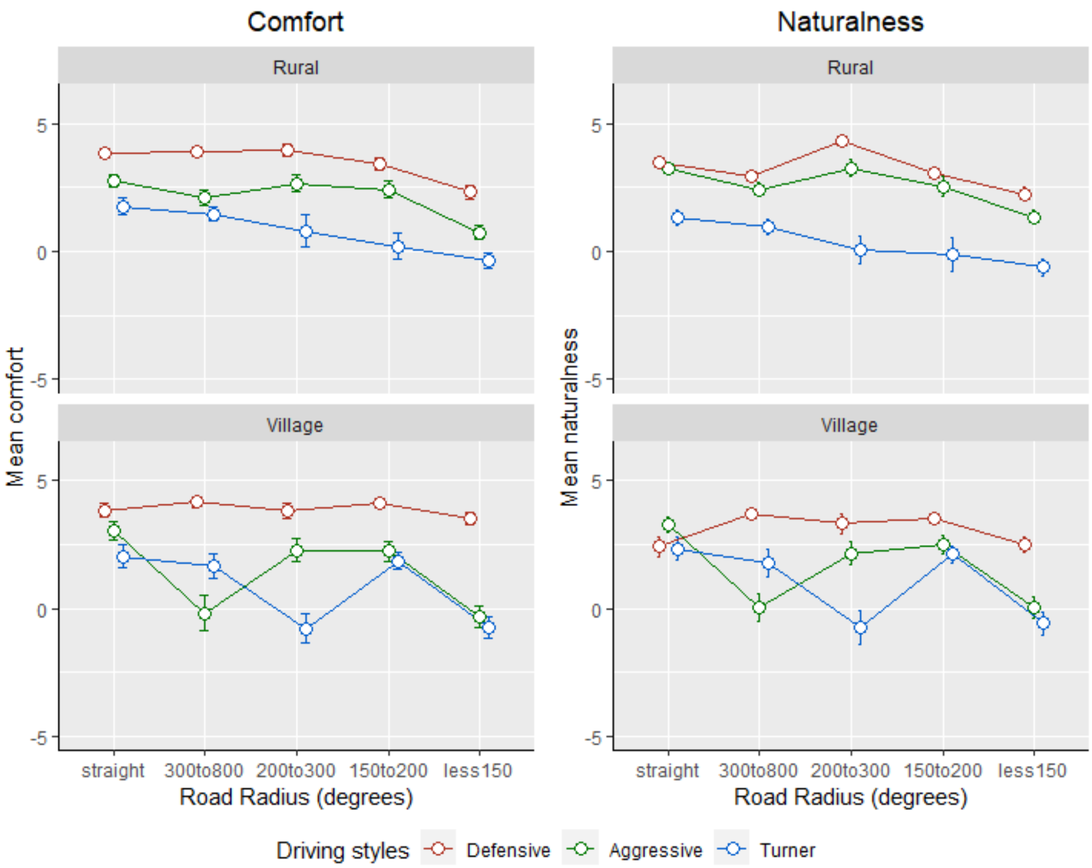


Figure 2.8. Mean evaluation scores for comfort (left) and naturalness (right) for each driving style, for the different road environments. Error bars indicate standard error of the data.

Table 2.5 shows the results of the GEE models, which showed that the effect of driving style, on comfort and naturalness ratings, was significant for both the Rural and Village road sections (all $p < .001$). In the Rural sections, which had a generally higher speed limit than the Village sections, there was less difference in odds ratios between the Aggressive and the Turner controllers for the gentler roads (i.e., Straight and Curve Radius 300-800), but this difference was more prominent for the shaper road sections (i.e., Curve Radius 150-200, and 200-300). It is also worth highlighting the preference for the Defensive controller over the Turner, where the odds ratios are seen to be larger with increasing road curvatures. However, these differences in controllers were not observed for the sharpest Rural section (i.e., less than 150).

In the Village sections, where the controllers negotiated the road at a lower speed, the observed pattern with curvature outlined above, was not as apparent. This may be because all controllers negotiated the curves at a relatively low speed, thus reducing the effect of Curve Radius. Overall, the Defensive controller remained the most comfortable and natural, compared to the Aggressive and Turner controllers, indicated by the odds ratios for all Village sections. In contrast, not much difference was seen in the evaluation for comfort and naturalness between the Aggressive and Turner controllers, for the Village sections.

Table 2.5. The GEE model parameter estimates and odds ratios, for comfort and naturalness in rural and village roads with different curvatures.

		Comfort						Naturalness					
Environment	**Curvature**	**N**	**Driving style**	**Coefficient**	**SE**	**Sig**	**OR**	**N**	**Driving styles**	**Coefficient**	**SE**	**Sig**	**OR**
Rural	Straight	216	Defensive vs Turner	1.662	0.326	0.000*	5.270	215[b]	Defensive vs Turner	1.709	0.347	0.000*	5.522
			Defensive vs Aggressive	0.969	0.293	0.001*	2.636		Aggressive vs Turner	1.569	0.365	0.000*	4.801
			Aggressive vs Turner	0.693	0.366	0.058	1.999		Defensive vs Aggressive	0.140	0.253	0.580	1.150
	300to800	288	Defensive vs Turner	1.926	0.289	0.000*	6.860	288	Defensive vs Turner	1.316	0.307	0.000*	3.727
			Defensive vs Aggressive	1.350	0.290	0.000*	3.856		Aggressive vs Turner	1.141	0.342	0.001*	3.129
			Aggressive vs Turner	0.576	0.310	0.063	1.779		Defensive vs Aggressive	0.175	0.301	0.561	1.191
	200to300	72	Defensive vs Turner	2.812	0.483	0.000*	16.650	72	Defensive vs Turner	4.067	0.624	0.000*	58.356
			Aggressive vs Turner	1.422	0.506	0.005*	4.146		Aggressive vs Turner	2.441	0.667	0.000*	11.486
			Defensive vs Aggressive	1.390	0.411	0.001*	4.016		Defensive vs Aggressive	1.625	0.453	0.000*	5.081
	150to200	72	Defensive vs Turner	2.800	0.496	0.000*	16.446	72	Aggressive vs Turner	2.728	0.677	0.000*	15.295
			Aggressive vs Turner	1.561	0.522	0.003*	4.764		Defensive vs Turner	2.670	0.458	0.000*	14.439
			Defensive vs Aggressive	1.239	0.488	0.011*	3.452		Defensive vs Aggressive	-0.058	0.547	0.916	0.944
	less150	288	Defensive vs Turner	1.667	0.252	0.000*	5.295	287[c]	Defensive vs Turner	1.784	0.303	0.000*	5.955
			Defensive vs Aggressive	0.966	0.277	0.000*	2.627		Aggressive vs Turner	1.159	0.415	0.005*	3.185
			Aggressive vs Turner	0.701	0.269	0.009*	2.016		Defensive vs Aggressive	0.626	0.265	0.018*	1.869

	Straight	72	Defensive vs Turner	1.859	0.459	0.000*	6.415	72	Aggressive vs Turner	0.958	0.410	0.020*	2.607
			Defensive vs Aggressive	1.342	0.441	0.002*	3.828		Defensive vs Turner	0.083	0.5525	0.880	1.087
			Aggressive vs Turner	0.516	0.427	0.227	1.676		Defensive vs Aggressive	-0.875	0.508	0.085	0.417
	300to800	72	Defensive vs Aggressive	2.934	0.767	0.000*	18.796	72	Defensive vs Aggressive	3.667	0.542	0.000*	39.121
			Defensive vs Turner	2.480	0.425	0.000*	11.936		Defensive vs Turner	1.917	0.513	0.000*	6.798
			Aggressive vs Turner	-0.454	0.554	0.412	0.635		Aggressive vs Turner	-1.75	0.800	0.029*	0.174
Village [d]	200to300	71[a]	Defensive vs Turner	3.591	0.514	0.000*	36.255	72	Defensive vs Turner	3.917	0.692	0.000*	50.233
			Aggressive vs Turner	2.159	0.529	0.000*	8.662		Aggressive vs Turner	2.75	0.660	0.000*	15.643
			Defensive vs Aggressive	1.432	0.552	0.009*	4.186		Defensive vs Aggressive	1.167	0.631	0.064	3.211
	150to200	144	Defensive vs Turner	2.191	0.380	0.000*	8.948	144	Defensive vs Turner	1.396	0.410	0.001*	4.038
			Defensive vs Aggressive	1.649	0.440	0.000*	5.204		Defensive vs Aggressive	1.021	0.377	0.007*	2.776
			Aggressive vs Turner	0.542	0.372	0.145	1.719		Aggressive vs Turner	0.375	0.537	0.485	1.455
	less150	144	Defensive vs Turner	2.962	0.431	0.000*	19.336	144	Defensive vs Turner	3.042	0.531	0.000*	20.940
			Defensive vs Aggressive	2.943	0.529	0.000*	18.974		Defensive vs Aggressive	2.438	0.726	0.001*	11.444
			Aggressive vs Turner	0.238	0.303	0.432	1.268		Aggressive vs Turner	0.604	0.790	0.444	1.830

Note. * $p < .05$. Orders of comparison are based on odds ratios. [a b c] 1 observation was missing. [d] GEE with the linear link function was used for naturalness (see Appendix 2).

2.3.3. The influence of personality traits on subjective evaluation

Following data collection, participants were divided into two sub-samples, based on their average scores to the 20 AISS items. Evaluation of the controllers by the two sub-samples, providing the lowest (mean = 48.54, N = 13), and highest sensation seeking score (mean = 59.45, N = 11), was then assessed.

Table 2.6 and Figure 2.9 show that the Defensive driving style was regarded as the most comfortable, for both the high and low sensation seekers. Interesting results were observed regarding the evaluation of naturalness. Low sensation seekers evaluated the Defensive as much more natural than the other two controllers, whereas high sensation seekers rated the Aggressive and Defensive driving styles about the same, in terms of naturalness. This finding also explains the bimodal pattern of evaluations on naturalness, shown in Figure 2.5 (right).

Table 2.6. The GEE model parameter estimates and odds ratios regarding comfort and naturalness for low and high sensation seekers.

	N	Driving style	Coefficient	SE	Wald	Sig	Odds ratio (OR)
Comfort							
Low sensation seekers	934[a]	Defensive vs Turner	1.809	0.346	27.305	0.000*	6.102
		Defensive vs Aggressive	1.356	0.378	12.875	0.000*	3.881
		Aggressive vs Turner	0.452	0.436	1.075	0.300	1.572
High sensation seekers	791[b]	Defensive vs Turner	2.153	0.296	53.039	0.000*	8.607
		Defensive vs Aggressive	1.507	0.281	28.865	0.000*	4.515
		Aggressive vs Turner	0.645	0.348	3.438	0.064	1.906
Naturalness							
	N	Driving style	Coefficient	SE	Wald	Sig	Odds ratio (OR)
Low sensation seekers	936	Defensive vs Turner	1.593	0.262	37.061	0.000*	4.919
		Defensive vs Aggressive	0.949	0.368	6.666	0.010*	2.583
		Aggressive vs Turner	0.644	0.463	1.933	0.164	1.904
High sensation seekers	789[c]	Defensive vs Turner	1.652	0.379	18.98	0.000*	5.217
		Aggressive vs Turner	1.258	0.370	11.584	0.001*	3.518
		Defensive vs Aggressive	0.394	0.334	1.390	0.238	1.483

Note. * $p < .05$. [abc] observations were missing, with the number of 2, 1, and 3, respectively.

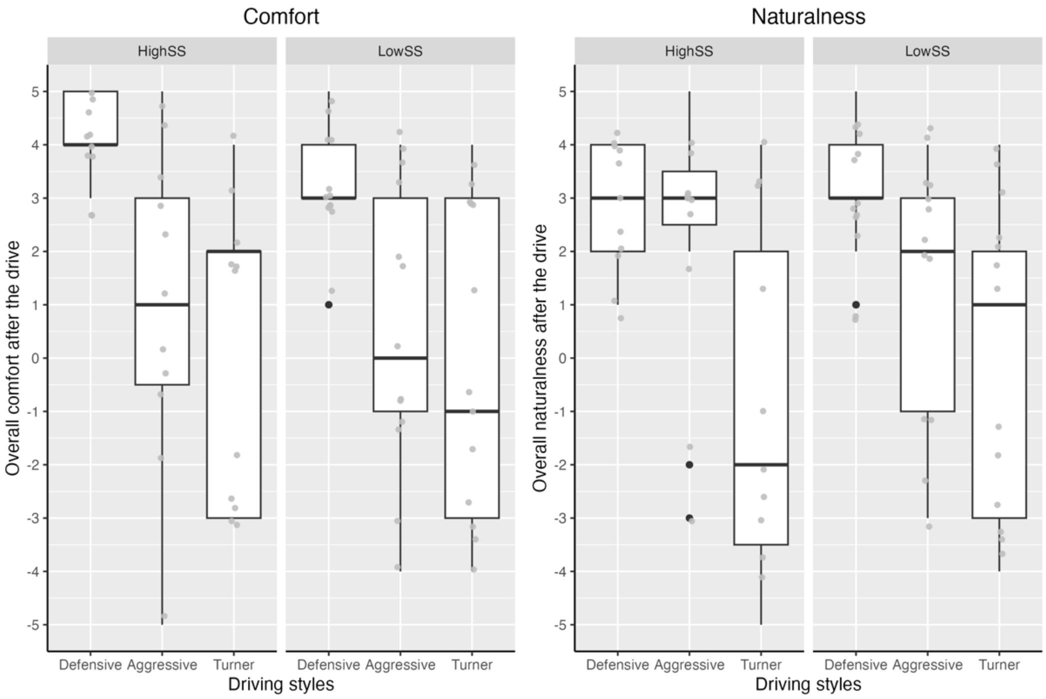


Figure 2.9. Overall comfort (left) and naturalness (right) evaluation of the driving styles from different sensation seekers.

2.4. Discussion

This driving simulator study examined users' subjective evaluation of the driving style of three AV controllers, in terms of comfort and naturalness, when negotiating a range of rural and village sections of a UK road. The link between participants' sensation seeking scores and their evaluation of these controllers was also investigated.

In terms of human- vs machine-like controllers, results showed that users preferred the two human-like AV controllers, in terms of both comfort and naturalness. Contrasting our findings with similar studies is challenging, as, at the time of writing, there are very few studies which have explicitly compared participant preferences for human-like and machine-like automated vehicle controllers. One exception is a study by Oliveira et al. (2019), who measured users' trust towards a highly automated pod, which showed either human- or machine-like driving behaviours, when crossing a T-junction. In this study, human-like behaviour was produced by demonstrating a cautious "peeking" behaviour by the pod, before it crossed the junction, while machine-like behaviour was produced by an assertive crossing, as if the road conditions were known to the automated pod. Oliveira et al. (2019) showed no difference in trust ratings for the two behaviours of the pod. There are two reasons why our study results are in contrast to those of Oliveira et al. (2019). One may be due to a difference in the concept used between our two studies: trust versus comfort and naturalness. The other may be because of the lower operating speed of the AV used in an urban road, by Oliveira et al, compared to the higher travelling speeds of our vehicle, travelling in rural road sections. This contrast in results illustrates the importance of considering the scenarios used to evaluate AV driving styles in such studies, since they vary across different road environments, based on both geometry and posted speed limit, which clearly influences any subjective assessment and evaluation (Hajiseyedjavadi et al., 2022). Further work on the influence of different scenarios on subjective appraisals of human- vs machine-like AV driving styles, should clarify this.

Overall, participants rated the Defensive controller more comfortable than the other two controllers, while both the Defensive and Aggressive controllers were assessed as more natural than the Turner. This suggests that there may be a distinction between what human evaluators consider a comfortable versus natural driving style, which is perhaps in contrast to the suggestion made by Elbanhawi et al. (2015), who regarded natural, or familiar, driving manoeuvres as one contributor to driving comfort. Our results suggest that comfort and naturalness of a controller should not be used interchangeably in such research, and that while human-like driving styles can be considered as equally more natural than a ML-based controller, they are not necessarily as equally comfortable. Therefore, factors which contribute to the comfort of a controller are not the same as those that determine its naturalness.

Regarding how road geometries and vehicle kinematics affected subjective ratings, our results show that variations in speed potentially had a greater influence on evaluation of comfort and naturalness of the controllers, when compared to differences in lateral offset. This was especially the case for the rural sections, which contained roads of tighter curvature, and higher speed. These results are in line with the work of Hajiseyedjavadi et al. (2022), who found that their model-based human-like AV driving controllers were assessed as less pleasant when negotiating narrower curves. These authors also found that a more rigid controller, which always followed the centre of the lane, received better evaluations. Together, these results suggest the influence of vehicle kinematics and road geometry on subjective evaluation of AV controllers. Moreover, our results showed little difference in lateral kinematic features of the three controllers, which was also reflected in the evaluations. Therefore, future studies need to examine the effect of more pronounced lateral offset on subjective evaluation, especially since maintaining sufficient and safe distance to road edges is thought to enhance driving comfort (Summala, 2007).

We found an interesting interaction between personality trait and evaluation of the controllers, with high sensation seekers rating the Aggressive driving style (which was a recording of another representative high sensation seeker) as natural, which was not the case for low sensation seekers. As naturalness in this study was defined as a driving style that is *"closest to your own driving"*, it is interesting to see this strong influence of personality traits on driving style and preference. The distinction between comfort and naturalness as concepts is also highlighted here, because there was no difference in the two groups, when evaluating the comfort of the Aggressive driving style. In other words, while the high sensation seekers thought the Aggressive driving style was natural, they did not find it comfortable. These results highlight the value of personalisation of automated controllers, to benefit the range of preferences by consumers with varying personality traits, notwithstanding their safety considerations.

2.4.1. Limitations

One limitation of the present study is the motion-planning performance of the Turner controller, which was developed using a small number of participants. Moreover, although the motion planner's output consists of a series of aim speeds and positions, we only used simple controllers that were manually calibrated for the automated vehicle to drive, using this data flow. Thus, a future study could use more data to train the motion planner and consider a better approach for implementing the controllers.

As with all controlled driving simulator studies, there are caveats regarding the relevance and generalisability of these findings, and their implications with respect to real-world AV controllers. Creating very realistic controllers was possible in this driving simulator study, due to its advanced motion-controller capabilities. However, future studies would benefit from evaluating these sorts of controllers in real-world settings, also assessing how such evaluation is affected by other real-world factors, such as different road surfaces, or presence of other roadside objects and road users.

2.4.2. Conclusions

Participants rated the two human-like driving styles as more natural, compared with the less human-like, ML-based, controller. Most participants also rated the Defensive driving style (gentler speed profiles) as more comfortable than the Aggressive controller (higher accelerations and more sudden braking profiles). This study shows, for the first time, that participants are able to distinguish between the natural driving manoeuvres of humans and the more machine-like negotiations of an artificial controller. In addition, we illustrate that there is a more complex relationship between concepts such as comfort and naturalness when evaluating automated vehicle controllers.

2.5. References

Arnett, J. (1994). Sensation seeking: A new conceptualization and a new scale. *Personality and Individual Differences*, *16*(2), 289–296.

Beggiato, M., Hartwich, F., & Krems, J. (2019). Physiological correlates of discomfort in automated driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, *66*, 445–458. https://doi.org/10.1016/j.trf.2019.09.018

Bellem, H., Thiel, B., Schrauf, M., & Krems, J. F. (2018). Comfort in automated driving: An analysis of preferences for different automated driving styles and their dependence on personality traits. *Transportation Research Part F: Traffic Psychology and Behaviour*, *55*, 90–100. https://doi.org/10.1016/j.trf.2018.02.036

Butakov, V., & Ioannou, P. (2015). Driving Autopilot with Personalization Feature for Improved Safety and Comfort. *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, *2015-Octob*, 387–393. https://doi.org/10.1109/ITSC.2015.72

Carsten, O., & Martens, M. H. (2018). How can humans understand their automated cars? HMI principles, problems and solutions. *Cognition, Technology and Work*, *21*(1), 3–20. https://doi.org/10.1007/s10111-018-0484-0

Ebe, K., & Griffin, M. J. (2001). Factors affecting static seat cushion comfort. *Ergonomics*, *44*(10), 901–921. https://doi.org/10.1080/00140130110064685

Elander, J., West, R., & French, D. (1993). Behavioral Correlates of Individual Differences in Road-Traffic Crash Risk: An Examination of Methods and Findings. *Psychological Bulletin*, *113*(2), 279–294. https://doi.org/10.1037/0033-2909.113.2.279

Elbanhawi, M., Simic, M., & Jazar, R. (2015). In the Passenger Seat: Investigating Ride Comfort Measures in Autonomous Cars. *IEEE Intelligent Transportation Systems Magazine*, 7(3), 4–17. https://doi.org/10.1109/MITS.2015.2405571

Ge, Y., Qu, W., Jiang, C., Du, F., Sun, X., & Zhang, K. (2014). The effect of stress and personality on dangerous driving behavior among Chinese drivers. *Accident Analysis and Prevention*, *73*, 34–40. https://doi.org/10.1016/j.aap.2014.07.024

Hajiseyedjavadi, F., Romano, R., Paschalidis, E., Wei, C., Solernou, A., Jamson, A. H., Boer, E. R., & Merat, N. (2022). Effect of environmental factors and individual differences on subjective evaluation of human-like and conventional automated vehicle controllers. *Transportation Research Part F: Traffic Psychology and Behaviour*, *90*, 1–14. https://doi.org/10.1016/j.trf.2022.07.018

Hartwich, F., Beggiato, M., & Krems, J. F. (2018). Driving comfort, enjoyment and acceptance of automated driving–effects of drivers' age and driving style familiarity. *Ergonomics*, *61*(8), 1017–1032. https://doi.org/10.1080/00140139.2018.1441448

Jamson;, A. H., Horrobin, A. J. ., & Auckland, R. A. (2007). Whatever Happened to the LADS? Design and development of the new University of Leeds Driving Simulator. *DSC 2007 North America*.

Kaber, D. B., & Endsley, M. R. (2004). The effects of level of automation and adaptive automation on human performance, situation awareness and workload in a dynamic control task. In *Theoretical Issues in Ergonomics Science* (Vol. 5, Issue 2). https://doi.org/10.1080/1463922021000054335

Liang, K. Y., & Zeger, S. L. (1986). Longitudinal data analysis using generalized linear models. *Biometrika*, *73*(1), 13–22. https://doi.org/10.1093/biomet/73.1.13

Louw, T., Hajiseyedjavadi, F. H., Jamson, H., Romano, R., Boer, E., & Merat, N. (2019). *The Relationship between Sensation Seeking and Speed Choice in Road Environments with Different Levels of Risk*. *April*, 29–35. https://doi.org/10.17077/drivingassessment.1671

Madigan, R., Louw, T., Dziennus, M., Graindorge, T., Ortega, E., Graindorge, M., & Merat, N. (2016). Acceptance of Automated Road Transport Systems (ARTS): An Adaptation of the UTAUT Model. *Transportation Research Procedia*, *14*(0), 2217–2226. https://doi.org/10.1016/j.trpro.2016.05.237

Menner, M., Berntorp, K., Zeilinger, M. N., & Di Cairano, S. (2019). Inverse Learning for Human-Adaptive Motion Planning. *Proceedings of the IEEE Conference on Decision and Control*, *2019-Decem*, 809–815. https://doi.org/10.1109/CDC40024.2019.9030020

Murphey, Y. L., Milton, R., & Kiliaris, L. (2009). Driver's style classification using jerk analysis. *2009 IEEE Workshop on Computational Intelligence in Vehicles and Vehicular Systems, CIVVS 2009 - Proceedings*, 23–28. https://doi.org/10.1109/CIVVS.2009.4938719

Oliveira, L., Proctor, K., Burns, C. G., & Birrell, S. (2019). Driving style: How should an automated vehicle behave? *Information (Switzerland)*, *10*(6), 1–20. https://doi.org/10.3390/INFO10060219

Oppenheim, I., Oron-Gilad, T., Parmet, Y., & Shinar, D. (2016). Can traffic violations be traced to gender-role, sensation seeking, demographics and driving exposure? *Transportation Research Part F: Traffic Psychology and Behaviour*, *43*, 387–395. https://doi.org/10.1016/j.trf.2016.06.027

Paddeu, D., Parkhurst, G., & Shergold, I. (2020). Passenger comfort and trust on first-time use of a shared autonomous shuttle vehicle. *Transportation Research Part C*, *115*(March), 102604. https://doi.org/10.1016/j.trc.2020.02.026

Pennig, S., Quehl, J., & Rolny, V. (2012). Effects of aircraft cabin noise on passenger comfort. *Ergonomics*, 55(10), 1252–1265. https://doi.org/10.1080/00140139.2012.703698

Price, M., Venkatraman, V., Gibson, M., Lee, J., & Mutlu, B. (2016). Psychophysics of Trust in Vehicle Control Algorithms. *SAE Technical Papers*. https://doi.org/10.4271/2016-01-0144

Qatu, M. S. (2012). Recent research on vehicle noise and vibration. *International Journal of Vehicle Noise and Vibration*, *8*(4), 289–301. https://doi.org/10.1504/IJVNV.2012.051536

Radhakrishnan, V., Merat, N., Louw, T., Lenné, M. G., Romano, R., Paschalidis, E., Hajiseyedjavadi, F., Wei, C., & Boer, E. R. (2020). Measuring drivers' physiological response to different vehicle controllers in highly automated driving (HAD): Opportunities for establishing real-time values of driver discomfort. *Information (Switzerland)*, *11*(8), 1–14. https://doi.org/10.3390/INFO11080390

Ramm, S., Giacomin, J., Robertson, D., & Malizia, A. (2014). A first approach to understanding and measuring naturalness in driver-car interaction. *AutomotiveUI 2014 - 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, in Cooperation with ACM SIGCHI - Proceedings*, *c*. https://doi.org/10.1145/2667317.2667416

Rehder, E., Quehl, J., & Stiller, C. (2017). Driving Like a Human: Imitation Learning for Path Planning using Convolutional Neural Networks. *International Conference on Robotics and Automation Workshops*. http://ppniv17.irccyn.ec-nantes.fr/session1/Rehder/paper.pdf

Riendeau, J., Stinchcombe, A., Weaver, B., & Bédard, M. (2018). Personality factors are associated with simulated driving outcomes across the driving lifespan.

Transportation Research Part F: Traffic Psychology and Behaviour, *54*, 171–187. https://doi.org/10.1016/j.trf.2018.01.022

Rossner, P., & Bullinger, A. C. (2020). How Do You Want to be Driven? Investigation of Different Highly-Automated Driving Styles on a Highway Scenario. *Advances in Intelligent Systems and Computing*, *964*, 36–43. https://doi.org/10.1007/978-3-030-20503-4_4

SAE International. (2016). *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles*. SAE International. https://doi.org/https://doi.org/10.4271/J3016_201806

Siebert, F. W., Oehl, M., Höger, R., & Pfister, H. R. (2013). Discomfort in Automated Driving - The Disco-Scale. *Communications in Computer and Information Science*, *374*(PART II), 337–341. https://doi.org/10.1007/978-3-642-39476-8_69

Solernou, A., Romano, R., Souflas, I., Hajiseyedjavadi, F., & Paschalidis, E. (2020). Integration and training of a ROS autonomous driver for human-like driving style in a complex multi-component driving simulator. *DSC 2020 Europe*, 9–11.

Summala, H. (2007). Towards Understanding Motivational and Emotional Factors in Driver Behaviour: Comfort Through Satisficin. In *Modelling Driver Behaviour in Automotive Environments: Critical Issues in Driver Interactions with Intelligent Transport Systems* (pp. 189–207). https://doi.org/10.1007/978-1-84628-618-6

Taubman-Ben-Ari, O., Mikulincer, M., & Gillath, O. (2004). The multidimensional driving style inventory - Scale construct and validation. *Accident Analysis and Prevention*, *36*(3), 323–332. https://doi.org/10.1016/S0001-4575(03)00010-1

Ulleberg, P., & Rundmo, T. (2003). Personality, attitudes and risk perception as predictors of risky driving behaviour among young drivers. *Safety Science*, *41*(5), 427–443. https://doi.org/10.1016/S0925-7535(01)00077-7

Urmson, C., Anhalt, J., Bagnell, D., Baker, C., Bittner, R., Clark, M. N., Dolan, J., Duggins, D., Galatali, T., Geyer, C., Gittleman, M., Harbaugh, S., Hebert, M., Howard, T. M., Kolski, S., Kelly, A., Likhachev, M., McNaughton, M., Miller, N., … Ziglar, J. (2008). A Comparison of Automatic Nap-of-the-earth Guidance Strategies for Helicopters. *Journal of Field Robotics*, *25*(8), 425–466. https://doi.org/10.1002/rob

Wei, C., Romano, R., Merat, N., Wang, Y., Hu, C., Taghavifar, H., Hajiseyedjavadi, F., & Boer, E. R. (2019). Risk-based autonomous vehicle motion control with considering human driver's behaviour. *Transportation Research Part C: Emerging Technologies*, *107*(August), 1–14. https://doi.org/10.1016/j.trc.2019.08.003

Yusof, N. M., Karjanto, J., Terken, J., Delbressine, F., Hassan, M. Z., & Rauterberg, M. (2016). The exploration of autonomous vehicle driving styles: Preferred longitudinal, lateral, and vertical accelerations. *AutomotiveUI 2016 - 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, Proceedings*, 245–252. https://doi.org/10.1145/3003715.3005455

Zuckerman, M., & Neeb, M. (1980). Demographic influences in sensation seeking and expressions of sensation seeking in religion, smoking and driving habits. *Personality and Individual Differences*, *1*(3), 197–206. https://doi.org/https://doi.org/10.1016/0191-8869(80)90051-3

CHAPTER 3

User comfort and naturalness of automated driving: The effect of vehicle kinematics and proxemics on subjective response

Abstract

Higher-level Automated Vehicles (AVs, SAE Level 4+) need to provide a comfortable user experience to enhance public acceptance. AV driving styles, characterised by vehicle kinematics and proxemics, affect user comfort, with "human-like" driving styles expected to provide natural feelings to further improve user comfort. This study investigated how the kinematic and proxemic characteristics of an AV's driving style affect user comfort and naturalness of a ride. The similarities in automated and users' own manual driving style, and how these similarities affect evaluations, was also investigated. Using a motion-based driving simulator, participants experienced three Level 4 automated driving styles (Defensive, Aggressive, and Machine-Learning based), and a manual drive. Participants provided ratings (separately) for comfort and naturalness of each automated controller, as it negotiated twenty-four UK road sections, with varying geometric and roadside features. Linear mixed-effects models were used to examine the effect of kinematics and proxemics of the AV's driving style, on subjective evaluation of comfort and naturalness of the ride, and how similarities between users' own driving style and that of the AV affected riders' evaluation. Results showed that the AV controllers' lateral and rotational kinematics significantly influenced both comfort and naturalness, while longitudinal jerk only affected comfort. The Euclidean distance in a range of kinematics, characterising similarities between manual and automated driving styles, had varied effects on subjective evaluations. This research facilitates understanding how control

features of AVs affect user experience, which will contribute to designing more user-centred controllers, leading to better acceptance of higher-level AVs.

3.1. Introduction

The Society of Automotive Engineers (SAE) defines five levels for automated vehicles (AVs), ranging from Level 0 (no driving automation) to Level 5 (full driving automation, SAE, 2021). For SAE Level 4 and above, the automated system operates the vehicle without requiring user intervention, under certain (Level 4) or all (Level 5) driving conditions. For these SAE Level 4+ vehicles, users primarily act as passengers or riders, rather than drivers, even if seated in the driver's seat. However, due to imperfect controllers, for some road geometries and AV manoeuvres, the user experience can be unpleasant or uncomfortable, sometimes resulting in motion sickness (Carsten & Martens, 2018; Diels & Bos, 2015). Accordingly, the concept of user comfort has captured researchers' interest in recent years. Used broadly as a subjective concept, this term is associated with numerous positive experiences and definitions. A range of terms have been used to describe comfort, including: "*a subjective, pleasant state of relaxation given by confidence and an apparently safe vehicle operation*" (Hartwich et al., 2018). It is argued that ensuring user comfort is important for enhancing the public acceptance and uptake of AVs (Dichabeng et al., 2021; Nordhoff, Malmsten, et al., 2021).

Considering that users of Level 4+ AVs will lose active control of the vehicle, and experience a range of system-generated motions, understanding how an AV's driving style influences user comfort is a key factor for improving the user experience, as the AV negotiates a range of road geometries. We have previously described an AV's driving style as a feature that is influenced by the vehicle's kinematics, such as its acceleration and braking behaviour, and proxemics, which includes the distance kept to other road users, or roadside objects. A driving style also includes vehicle manoeuvres that are influenced by road surface and geometry, such as how it negotiates different road curvatures, or whether the ride is smooth or jerky (Peng et al., 2024, Chapter 4 in this thesis). Kinematics and proxemics of vehicle driving styles form the fundamental focus of research investigating the comfort and enjoyment, and ultimately the acceptance, of AVs (e.g., Kuderer et al., 2015; Lee et al., 2019).

One of the factors thought to affect the comfort of AVs is the “naturalness” of its driving style, which is the extent to which the vehicle’s handling of the driving task feels familiar and similar to a user’s own driving style and habits (Hartwich et al., 2018; Kamaraj et al., 2023; Peng et al., 2022, Chapter 2 in this thesis). Naturalness is also linked to terms such as human-like or personalised driving (Gu & Dolan, 2014; Li et al., 2022; Wei et al., 2019). The use of such human-like or personalised driving styles is intended to enhance the familiarity of the drive for users, helping them predict the AV’s upcoming manoeuvres (Elbanhawi et al., 2015), perhaps based on past experience. However, it is currently not clear if these concepts actually contribute to user comfort in AVs, with research showing mixed results (Basu et al., 2017; Hartwich et al., 2018; Peng et al., 2022, Chapter 2 in this thesis).

In order to create a more concrete link between the vehicle’s lateral and longitudinal movements during different driving scenarios, and users’ evaluation of the ride experience, it is useful to link subjective responses about the comfort and naturalness of manoeuvres, with the AV’s kinematic and proxemic characteristics. In terms of comfort, the International Organisation for Standardisation (ISO) has suggested several operational limits for the speed, acceleration and jerk of vehicles with Adaptive Cruise Control (ACC) functionalities (ISO 15622, 2018). However, such quantifications for lower-level AVs may not be relevant to higher-level AVs, due to the differences in user control between the two. With a focus on the effect of peak acceleration (0.4 – 2 m/s^2) and peak jerk (0.5 – 15 m/s^3) on discomfort, De Winkel et al. (2023) found that larger acceleration levels increased discomfort, while higher jerks with a shorter duration generated by sinusoidal pulses were more comfortable than jerks with a longer duration generated by triangular pulses. The authors also emphasised the role of the direction of motion, with forward motion reported as more comfortable than backward, and lateral motion as the least comfortable. However, since the focus of this study was on vehicle motions, participants were instructed to keep their eyes closed, which is obviously different from real driving environments.

The importance of considering proxemics for comfort is based on Summala (2007), who suggests that sufficient distance in space and time between the user's vehicle and other objects on the road constitutes a safety margin, within which users feel safe and comfortable. In the context of SAE Level 2 automated driving – which requires continuous monitoring by the driver - He et al. (2022) investigated users' perceived risk and trust during certain manoeuvres, such as when an adjacent vehicle merges or a lead vehicle brakes hard. The authors found that both spatial distance (e.g., minimum gap) and temporal distance (e.g., time to collision) significantly affect users' perceived risk and trust. However, the effect of these distances on comfort may differ from their impact on perceived risk and trust, due to differences in these concepts (Nordhoff, Stapel, et al., 2021; Paddeu et al., 2020; Peng et al., 2024, Chapter 4 in this thesis).

In terms of the link between vehicle kinematics, proxemics and naturalness of the driving experience, Kamaraj et al. (2023) explored whether participants' subjective evaluation of the similarity between manual and automated driving styles corresponds to objective similarities, characterised by Euclidean distance. The authors suggest that the differences in the speed profiles of the manual and automated driving styles served as an objective predictor of the subjectively evaluated similarity of manual-automated driving styles by participants. The study by Kamaraj et al. (2023) established a connection between vehicle kinematics and naturalness (termed as "similarity" in their study). However, it only considered longitudinal speed, leaving unanswered questions about whether other kinematics and/or proxemics play a role in users' subjective evaluations of naturalness.

3.1.1. Research gap

Although an AV's driving style is considered a critical factor in determining user comfort and naturalness, knowledge about how its kinematics and proxemics affect user experience and evaluations remains limited. Previous studies have primarily focused on vehicle acceleration and jerk. However, it is important to consider both kinematics and proxemics to comprehensively understand the effect of individual vehicle metrics on subjective evaluations. Furthermore, exploring whether these kinematics and proxemics play a different role in comfort versus naturalness could further enrich our understanding of the relationship between these two closely connected concepts.

3.1.2. The Current study

This research aims to investigate the effect of vehicle kinematics and proxemics, as two concepts characterising automated driving styles, on user comfort and naturalness, using data collected by the UK-funded HumanDrive project (TS/P012035/1). Participants evaluated two human-like and one machine-like AV driving style, in terms of their comfort and naturalness, in a moving-based high-fidelity driving simulator study (Peng et al., 2022, Chapter 2 in this thesis). We investigated the effect of a range of kinematics and proxemics of the AV, on subjective evaluations of its driving style. Moreover, we examined how user evaluation was affected by the objective similarities between the automated driving styles and participants' own manual driving, characterised by the Euclidean distance for a range of kinematic and proxemic features (Kamaraj et al., 2023).

The research objectives of the study were to:

1) Investigate the role of different vehicle kinematics and proxemics in shaping subjective evaluations of the AV ride, in terms of both comfort and naturalness.
2) Explore how similarities between an individual's manual driving style, and that of an automated vehicle affect their subjective response, in terms of comfort and naturalness.
3) Examine whether evaluations of comfort and naturalness are associated with the same vehicle kinematic and proxemic features.

3.2. Method

3.2.1. Participants

Twenty-four participants (12 female and 12 male); aged between 20 and 49 years (M = 35.7, SD = 7.1) were recruited for this study. We used the University of Leeds Driving Simulator database to recruit participants, who were required to hold a valid UK driving licence for at least 2 years and be in good health (e.g., not suffering from claustrophobia and severe motion sickness). All participants provided informed consent to attend the study and were compensated £30 for their time. The study was approved by the University of Leeds Ethics Committee (LTTRAN-086).

3.2.2. Apparatus

The experiment was conducted in the University of Leeds Driving Simulator (UoLDS), a high-fidelity, motion-based simulator. This includes a 2006 Jaguar S-type vehicle cab, housed within a spherical projection dome (4m diameter). Within the dome, eight visual channels render at 60 frames/s, at a resolution of 1920×1200 pixels. This provides a horizontal forward field of view of 270°. The simulator has an eight degree-of-freedom motion system, which provides acceleration within ±5.0 m/s^2 (Jamson et al., 2007).

3.2.3. Experimental design

This study used a 3 (AV driving styles: Defensive, Aggressive, and ML-based) × 24 (road sections) within-participant experimental design. Participants provided subjective evaluations of the three automated driving styles for each of the 24 road sections, which differed in terms of geometry, roadside environment, and speed limit. This resulted in 72 sets of kinematic and proxemic features in total, for evaluation. There were six automated drives in total, with three rated in terms of comfort, and the other three rated in terms of naturalness.

3.2.3.1. Road environment

The simulated road was approximately six miles long and replicated a real UK road, to reflect the real-world driving environment (Figure 3.1 and Figure 3.2). It contained diverse road widths and geometries, to enrich the driving styles, in terms of vehicle kinematics, such as acceleration/deceleration and curve negotiation, and proxemics, such as the distance of the vehicle from roadside furniture and objects.

As the road environment (e.g., rural versus village areas) and geometry (i.e., curve radii) were likely to influence subjective ratings of a driving style (Peng et al., 2022, Chapter 2 in this thesis), we further classified these road sections into four categories, according to the posted speed limit (high and low) and curvature of the road section (sharp and gentle) (Table 3.1). Road sections with a high-speed limit (60 mph) were primarily rural areas, where roadside furniture consisted mostly of vegetation. Road sections with a low-speed limit (30/40 mph) predominantly represented village and university areas, characterised by more buildings, pavements, and parked cars along the road. As a result, the kinematic and proxemic features of the drive were expected to vary.

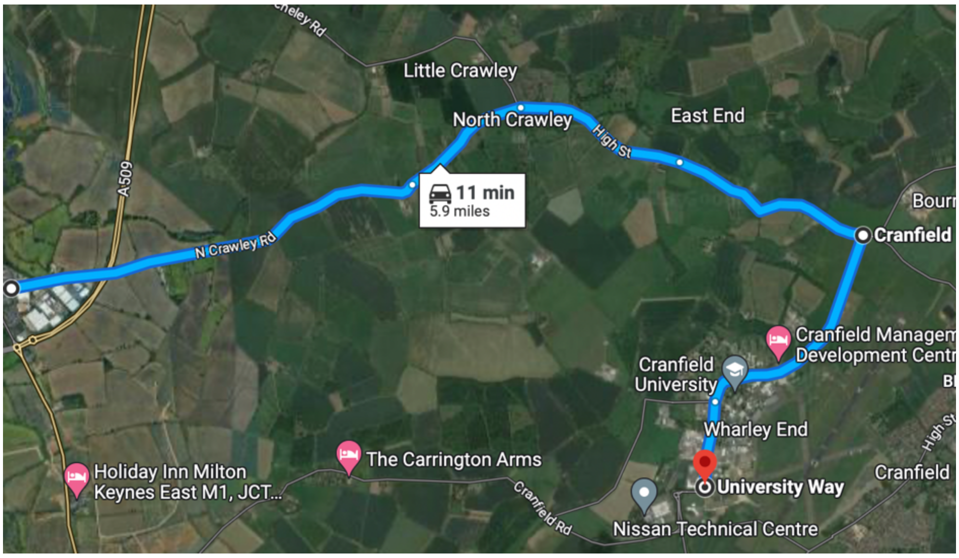


Figure 3.1. The stretch of a real UK road that was used to simulate the experimental driving route.

Figure 3.2. Examples of the simulated roads, showing road geometries such as different curves and on-road and roadside objects such as buildings, parked cars, and vegetation.

Table 3.1. Categorisation of road sections based on the posted speed limit and curve radius.

Speed limit	Curvature	Road context examples
Low	Sharp	Kerb, grass, parked cars, village
	Gentle	Kerb, grass, hedge, fence, village, bushes, pavement
High	Sharp	Kerb, grass, hedge, trees
	Gentle	Kerb, grass, hedge, bushes, fence

Note. The low speed limit was 30 or 40 mph, while the high speed limit was 60 mph. Sharp curves were with r <= 200, while gentle curves were with r > 200.

3.2.3.2. *The three driving styles*

Among the three driving styles, the machine-learning (ML)-based controller was able to imitate human driving behaviour, trained using driving data from 10 participants who drove freely on the same simulated road in a previous experiment (Solernou et al., 2020). The other two driving styles were recordings of representative drives from a different group of participants. Previous studies have found that an individual's sensation seeking propensities are associated with their driving styles, with higher sensation seekers generally driving faster (Louw et al., 2019; Zuckerman & Neeb, 1980). Therefore, ahead of the present study, a group of participants (N = 8) with varying sensation seeking propensities were recruited, and asked to manually drive through the same simulated environment. Following this manual drive, a cluster analysis was conducted to understand the relationship between driving behaviours and sensation seeking scores of these eight drivers. Data from two drivers (one high, one low sensation seeker) was then used as the representative human-like driving styles to create an Aggressive and Defensive controller, respectively. Further details regarding the development of these driving styles can be found in the work by Peng et al. (2022, Chapter 2 in this thesis).

3.2.4. Procedure

A two-day schedule was allocated for each participant to complete the experiment, to mitigate the potential influence of fatigue on results. Data collection lasted approximately 1.5 hours, for each day. For the first visit, upon arrival, participants were offered written information about the study, which also included a description of comfort and naturalness, and instructions about how to use the rating scales to evaluate each controller. A comfortable driving style was defined as "*a driving style that does not cause any feeling of uneasiness or discomfort*", while a natural driving style was defined as "*a driving style that is closest to your own driving*". Participants were asked to use an 11-point Likert scale to provide evaluations, ranging from -5 (Extremely Uncomfortable/ Unnatural) to +5 (Extremely Comfortable/ Natural). Participants then provided their written informed consent to take part in the experiment. After being introduced to the driving simulator and its controls, participants first completed two practice drives, including a practice manual drive and then a practice automated ride, in the presence of the experimenter, after which the experimenter exited the simulator dome. Participants then experienced the three automated driving styles in a counterbalanced order, evaluating each controller in terms of its comfort or naturalness. During their second visit, participants experienced the three automated driving styles again, evaluating them with respect to the other concept (Figure 3.3). For the evaluations, participants were cued via an auditory beep and a voice reminder saying “rate now” as the controller negotiated each road section (24 times in total), and also provided an overall rating of the controller, at the end of each drive. There was an additional manual driving task. For half of the participants, this task was completed before all automated drives, while for the other half, it was conducted after all automated drives. The order accounted for the potential influences of familiarity with the environment and exposure to automated driving on an individual’s manual driving. After all drives participants completed a set of questionnaires, which included questions on demographics and a range of personality traits, the latter are not reported in this study.

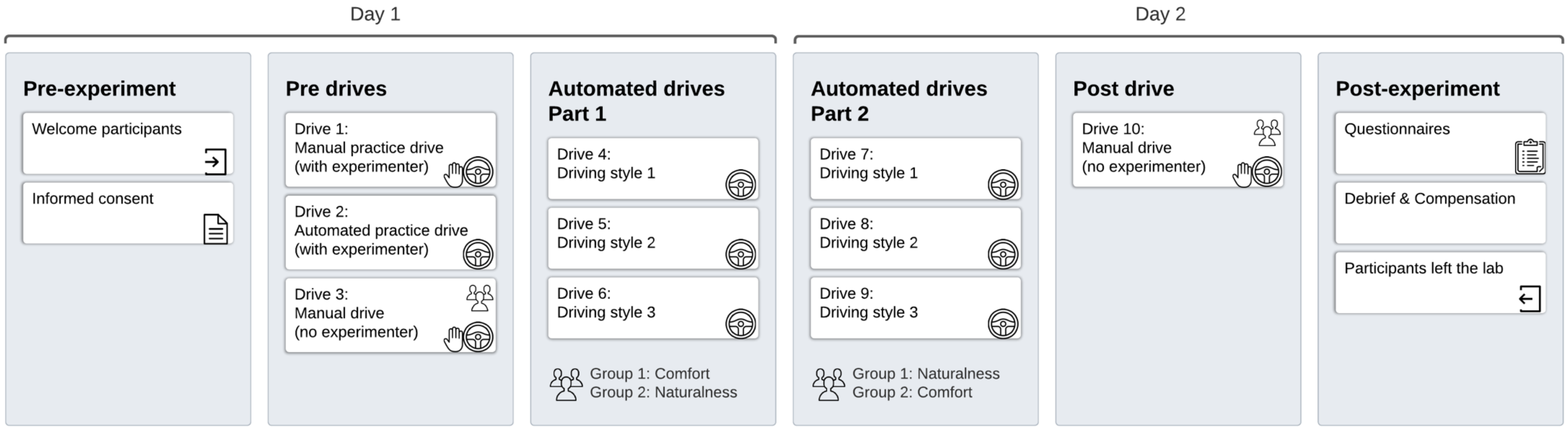


Figure 3.3. Experimental procedure. Half of the participants had Drive 3, and the other half had Drive 10 as the manual drive.

3.2.5. Data processing for vehicle kinematics and proxemics

The vehicle kinematics and proxemics of each AV controller and manual drive changed continuously in response to various road geometries and posted speed limits, while participants only provided evaluation for the AV controller once for each road section. Therefore, it is necessary to use indicators to characterise a driving style for each road section, in order to associate it with subjective evaluations.

The acceleration of the three automated driving styles and manual driving was firstly filtered to reduce noise. The filtering was necessitated by the discrepancy between the motion planner - particularly the longitudinal performance of the ML-based controller - and the capabilities of the driving simulator. This was, due to factors such as the relatively small training dataset and the usage of AI toolbox (see discussion in Peng et al., 2022, Chapter 2 in this thesis). For example, accelerations with very large magnitudes (e.g., -10 m/s^2) exceeded the capabilities of the simulator and could not be perceived by participants. Then, indicator calculations were based on the filtered data.

Regarding the indicator calculation, vehicle data for the road section with a roundabout was excluded, because the road geometry of a roundabout largely differed from the other road sections, resulting in kinematics and proxemics that were not comparable with the other road sections.

Participants' manual driving data were included in the analysis, with the exception of two missing recordings from two participants. Longitudinal and lateral acceleration was also filtered.

3.2.5.1. Acceleration data filtering

The longitudinal and lateral acceleration data was filtered to remove noise (Figure 3.4), using the *hampel* function in MATLAB 2019a. The filter calculates the median of a window containing the sample point and a specified number of surrounding points, as well as the standard deviation of the window. If the difference between the sample point and the median exceeds the specified number of standard deviations, the sample point is replaced with the median.

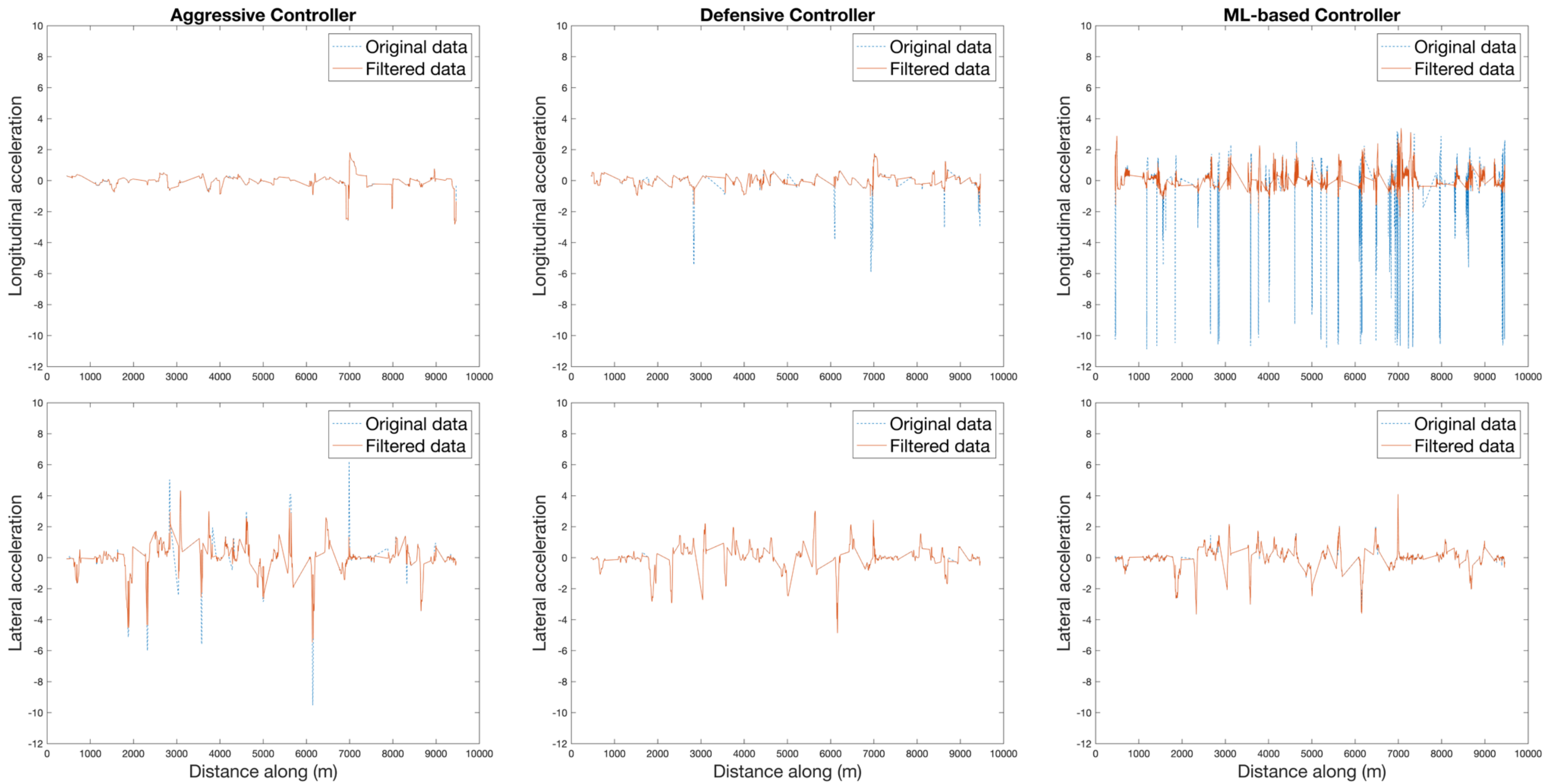


Figure 3.4. The original and filtered longitudinal and lateral acceleration values of the three controllers.

3.2.5.2. *Indicators for characterising driving styles*

Indicators of a driving style

Previous studies have used a range of vehicle metrics to classify driving styles. For example, Hartwich et al. (2018) used the cumulative absolute speed difference to identify similarities between automated driving and an individual's manual driving style. Murphey et al. (2009) used the standard deviation and the typical jerk during negotiation of a particular road type, to classify different manual driving styles, and Feng et al. (2017) suggest that a large negative jerk (i.e., a value that is smaller than the 99.9th percentile of the jerk distribution) can be used to identify aggressive drivers. Haghzare et al. (2021) used the average and maximum speed, the positive and negative peaks of acceleration, and the positive and negative peaks of jerk to characterise both manual and automated driving styles. Moreover, although rotational movements are regarded as important for ride comfort in the control engineering domain (e.g., Lee et al., 2014), the importance of rotational metrics has rarely been examined in human factors studies. Therefore, to add value, we used vehicle kinematics and proxemics for all three directions of the vehicle: longitudinal, lateral, and vertical/rotational, to characterise automated driving styles for each road section (Figure 3.5 and Table 3.2).

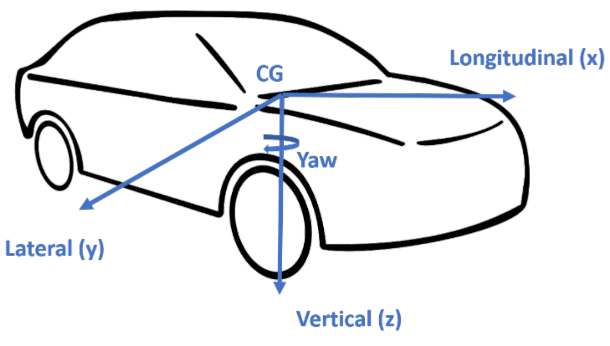


Figure 3.5. The coordinate system of a vehicle. CG is the centre of gravity.

Table 3.2. A summary of the vehicle kinematics and proxemics that are included in the present study.

Directions	Vehicle metrics
Longitudinal	Vehicle speed (m/s). Longitudinal acceleration (m/s²). Longitudinal jerk*: the rate of change of the longitudinal acceleration (m/s³). Calculated using $j_x = \ddot{u} - \dot{v}r - v\dot{r}$, where $\ddot{u}$ is the rate of change of longitudinal acceleration, $\dot{v}$ is lateral acceleration, r is yaw rate, v is lateral speed, and $\dot{r}$ is yaw acceleration(m/s³).**
Lateral	Lateral offset: vehicle position CG with regards to road centre (m) (negative values refer to the left of centre line). Lateral acceleration (m/s²). Lateral jerk*: the rate of change of the lateral acceleration (m/s³). Calculated using $j_y = \ddot{v} + \dot{u}r + u\dot{r}$, where $\ddot{v}$ is the rate of change of lateral acceleration, $\dot{u}$ is longitudinal acceleration, u is longitudinal speed, r is yaw rate, and $\dot{r}$ is yaw acceleration (m/s³).**
Vertical/ Rotational	Yaw: the rotation of the vehicle around the vertical axis (rad). It represents the angle between the vehicle and the road's forward direction. Yaw rate: the rotational speed of the vehicle about the vertical axis (rad/s). It determines how quickly the vehicle is turning. Yaw acceleration: the rate of change of velocity in the yaw axis (rad/s²).

Note. *Longitudinal and lateral jerk were calculated based on the Vehicle Dynamics Model (Abe, 2009), rather than directly using the derivative of acceleration, to avoid noise from discrete sampling. Details can be found in Appendix.

**For calculation of longitudinal jerk, the third term $v\dot{r}$ was omitted, as it is too small. For the calculation of the first term $\ddot{u}$, longitudinal acceleration was first linear-interpolated and then differentiated. Data pre-processing was conducted using MATLAB R2019a. For lateral jerk, the first term $\ddot{v}$ was omitted, as it is primarily affected by lateral tyre deformation, lateral disturbance, and lateral slip.

In this study, we adopted a method similar to that of Haghzare et al. (2021) to calculate indicators of a driving style. Specifically, we computed the maximum absolute value for each metric, rather than using average values. This approach was chosen because maximum values are more likely to be more noticeable to users and impact their ratings of the automated driving experience. Apart from speed, which is always positive, we focused on the absolute values of other metrics, disregarding their directional components. All values were standardised to account for the wide range of scales among these metrics.

The similarity between two driving styles

Based on Kamaraj et al. (2023), we used Euclidean distance to measure the "human-likeness" of automated controllers in relation to participants' own driving style. To be specific, assuming there are two driving styles negotiating a road, they can be represented as two time series, A and B, each consisting of a number of points. Each point includes a range of vehicle metrics. The similarity between driving style A and B can be calculated using the equation $d(A,B) = \sqrt{\sum_{i=1}^{n}(A_i - B_i)^2}$, where the distance between the i^{th} point of each series is computed. This equation was applied to each of the vehicle metrics listed in Table 3.2, to represent the similarity between two driving styles in terms of each metric. As the Euclidean distance method requires both time series to be of the same length, we conducted a resampling of the two series in each road section, to ensure two corresponding points from each series were always at the same location (i.e., spatial alignment).

3.2.6. Statistical models

Mixed-effects models were used for the statistical analysis in this study. A mixed-effects model is suitable for data with a hierarchical or nested structure and includes both fixed and random effects. Fixed effects represent our primary interest, anticipated to be constant and identical across all groups in a population. In contrast, random effects can vary across different groups and account for variations resulting from the clustered structure of the data, such as multiple responses from the same participant in repeated measures.

By combing fixed and random effects, mixed-effects models are suitable for analysing data in which observations within groups (e.g., evaluations for the same controller, or evaluations from the same participant) may be correlated. The accuracy of estimates of fixed effects is expected to improve by accounting for variability between groups (Gelman, 2005).

All models were fitted using the R package *lme4*. Statistical significance was set at 0.05.

3.3. Results

3.3.1. The effect of kinematics and proxemics of automated driving on comfort and naturalness

We first examined the impact of AV kinematics and proxemics, using indicators of driving styles (see 2.7.2), on comfort and naturalness. We used two linear mixed-effects models, with comfort and naturalness ratings as the dependent variable, respectively. For the fixed-effects part of independent variables, we considered eight variables, including maximum absolute values of speed, longitudinal acceleration, longitudinal jerk, lateral offset, lateral acceleration, yaw, yaw rate, and yaw acceleration in both models. Since our experiments involved repeated measurements over participants and AV controllers, it is important to capture the similarities between observations for the same participant and controller. We also expected similarities between observations for similar road environments (e.g., posted speed limit and road curvature). However, the inclusion of the two random effects (i.e., posted speed limit and road curvature) did not significantly improve the model fit, based on the Bayesian Information Criterion (BIC). Therefore, only participants and controllers were added to the models as random effects. Due to its high correlation with yaw acceleration ($r = 0.92$, $p < .01$), lateral jerk was not included as an independent variable. We examined potential multi-collinearities using the variance inflation factors (VIF) and found the VIFs for all predictors in each model were under five, indicating the absence of collinearities. The linear mixed-effects model assumes a normal distribution of residuals of the data; such an assumption was also verified by the examination of the Quantile-Quantile plot (QQ Plot).

3.3.1.1. Model results

For the fixed-effects analysis of the established models (Table 3.3), the maximum absolute values of longitudinal jerk were positively associated with comfort ratings ($p<.001$), while there was no significant association between this value and naturalness. For lateral metrics, both comfort and naturalness ratings were negatively associated with lateral acceleration ($p<.001$). Regarding the vertical/rotational direction, evaluations of both comfort and naturalness were negatively associated with yaw acceleration, but positively associated with yaw and yaw rate of the AV ($p<.001$). Overall, lateral acceleration appeared to be the most influential metric, as one unit increase in maximum lateral acceleration was associated with a 0.93 and 0.81 decrease in comfort and naturalness ratings, respectively.

For the random-effects (Table 3.3), the estimated variance of the random intercepts for participants and controllers suggests that there was considerable variability between participants in terms of their evaluations of comfort and naturalness for AV controllers, which are not explained by the predictor variables. Compared with the lower marginal R^2, the higher conditional R^2 values indicate that incorporating random effects into the models improved the overall fit and accounted for more of the variability in comfort and naturalness of the AV controllers.

Table 3.3. Results of linear mixed-effects models for comfort and naturalness ratings by AV kinematics and proxemics. ICC is the Intra-class Coefficient, reflecting how strongly the observations in the same group are similar to each other. Marginal R^2 indicates variance explained by fixed effects only, whereas conditional R^2 indicates variance explained by both fixed and random effects.

	Comfort			Naturalness		
Fixed effects						
	Estimate	SE	p	Estimate	SE	P
(Intercept)	2.10	0.68	0.06	2.00	0.54	0.04*
Speed	0.08	0.06	0.15	0.02	0.06	0.81
Longitudinal acceleration	-0.08	0.09	0.40	-0.08	0.10	0.41
Longitudinal jerk	0.34	0.09	0.00***	0.13	0.10	0.19
Lateral offset	-0.07	0.06	0.20	-0.11	0.06	0.08
Lateral acceleration	-0.93	0.09	0.00***	-0.81	0.10	0.00***
Yaw	0.19	0.06	0.00***	0.28	0.06	0.00***
Yaw rate	0.37	0.08	0.00***	0.40	0.09	0.00***
Yaw acceleration	-0.57	0.09	0.00***	-0.47	0.10	0.00***
Random effects						
	Variance (SD)	ICC		Variance (SD)	ICC	
Participant	1.43 (1.20)	0.18		0.86 (0.93)	0.11	
Controller	1.19 (1.09)	0.22		0.75 (0.86)	0.17	
Marginal/Conditional R^2	0.11 / 0.47			0.10 / 0.32		

Note: '***' $p < 0.001$, '**' $p < 0.01$, '*' $p < 0.05$. All vehicle metrics were calculated as absolute maximum values and were standardised. ICC values were calculated based on intercept-only models.

3.3.2. The effect of similarities in manual and automated driving on evaluation of comfort and naturalness

We investigated the effect of similarities between an individual's manual driving, and that of the different automated driving styles, using the Euclidean distance of a range of vehicle metrics, on the evaluation of comfort and naturalness of the AV controllers. A mixed-effects model was applied to comfort and naturalness ratings, respectively. For both models, independent variables included Euclidean distance in speed, longitudinal jerk, lateral offset, lateral acceleration, lateral jerk, and yaw, between manual and automated driving.

For both models, we included participants, AV controller type, road curvature, and the posted speed limit as random effects. The choice of random effects was supported by the lower BIC values, which indicate a better model fit, compared to models with fewer random effects.

Strong correlations were observed between the Euclidean distance of certain vehicle metrics, with all correlations being significant ($p < .001$) (Table 3.4). Therefore, longitudinal acceleration, yaw rate, and yaw acceleration were not included in the models, to avoid multi-collinearities, as verified with VIFs. Between longitudinal acceleration and longitudinal jerk, we excluded the former due to stronger correlations between comfort and naturalness with longitudinal jerk ($r = -0.29$, $r = -3.10$, respectively) than with longitudinal acceleration ($r = -0.26$, $r = -2.82$, respectively).

Table *3.4*. Correlations between Euclidean distance of certain vehicle metrics

	Long. Acc.	Long. jerk	Lateral jerk	Yaw rate	Yaw acc.
Long. acc.	1				
Long. jerk	0.93	1			
Lateral jerk	-	-	1		
Yaw rate	-	-	0.79	1	
Yaw acc.	0.52	0.55	0.95	0.70	1

Note. This table only shows strong correlations. All significant at $p < .001$

3.3.2.1. *Model results*

The fixed-effects analysis (Table 3.5) shows that Euclidean distance in speed and longitudinal jerk was negatively associated with both subjective evaluations ($p < .001$, $p < .01$, respectively). On the other hand, lateral jerk had a positive association ($p < .01$), and yaw showed a negative association with both evaluations ($p < .001$). The similarity in lateral jerk had the most significant impact on comfort, while naturalness was primarily influenced by speed, as indicated by the absolute estimate coefficients.

Regarding the random-effects part, the higher conditional R^2 values suggest that the inclusion of random effects in the two models improved the model fit and accounted for more variability in subjective evaluations of the AV driving styles.

Table 3.5. Model results for the effect of similarities in manual-automated driving on comfort and naturalness ratings. ICC is the Intra-class Coefficient, reflecting how strongly the observations in the same group are similar to each other. Marginal R^2 indicates variance explained by fixed effects only, whereas conditional R^2 indicates variance explained by both fixed and random effects.

	Comfort			Naturalness		
Fixed effects						
	Estimate	SE	Pr(>|t|)	Estimate	SE	Pr(>|t|)
(Intercept)	1.88	0.94	0.12	1.88	0.68	0.05*
Speed	-0.46	0.10	0.00***	-0.75	0.10	0.00***
Longitudinal jerk	-0.36	0.14	0.01*	-0.46	0.15	0.00**
Lateral offset	-0.14	0.09	0.12	-0.10	0.09	0.30
Lateral acceleration	0.12	0.11	0.27	0.20	0.12	0.08
Lateral jerk	0.56	0.12	0.00***	0.40	0.13	0.00**
Yaw	-0.46	0.10	0.00***	-0.37	0.10	0.00***
Random effects						
	Variance (SD)	ICC		Variance (SD)	ICC	
Participant	1.32 (1.15)	0.17		0.92 (0.96)	0.11	
Controller	1.61 (1.27)	0.22		0.62 (0.79)	0.16	
Curvature	0.49 (0.70)	0.07		0.29 (0.54)	0.05	
Speed Limit	0.09 (0.30)	0.01		0.13 (0.36)	0.01	
Marginal/Conditional R^2	0.04 / 0.46			0.10 / 0.34		

Note: '***' $p < 0.001$, '**' $p < 0.01$, '*' $p < 0.05$. All vehicle metrics are calculated as the Euclidean distance between manual and automated driving. ICC values were calculated based on intercept-only models.

3.4. Discussion

The present study investigated the relationship between subjective evaluations of three AV controllers, in terms of their perceived comfort and naturalness, and the AV's kinematic and proxemic features. We also examined how the similarities between an individual's manual driving style and the automated driving style experienced, affect participants' evaluation of AV controllers.

In terms of the effect of AV kinematics and proxemics on subjective evaluations, we found that most lateral and rotational kinematics have a role to play in influencing both comfort and naturalness. However, there was less of an effect from longitudinal kinematics on subjective evaluations, when compared to lateral kinematics. In particular, no effect of longitudinal acceleration was seen on subjective evaluations. This lack of an effect of longitudinal acceleration on evaluation of comfort is in contrast to previous studies (Bae et al., 2019; de Winkel et al., 2023). This may be explained by the geometry of the simulated road used in this study, with the curved road sections necessitating many lateral and rotational manoeuvres. On the other hand, there were no particular events that elicited strong changes in longitudinal kinematics, such as sudden brakes, which means most longitudinal kinematics may have consistently remained comfortable for users. Our findings highlight the importance of taking the road environment, including road geometries, into account when designing AV driving styles, which is in line with the findings of Hajiseyedjavadi et al. (2022). Despite the insignificance of most longitudinal metrics studied, we found that longitudinal jerk significantly affected comfort evaluation, which supports results from previous studies (Bellem et al., 2018; Martin & Litwhiler, 2008). Furthermore, the association between longitudinal jerk and comfort was found to be positive. This contrasts with the findings of Bellem et al. (2018), who suggested minimising jerk for acceleration and deceleration manoeuvres, but aligns with the results of de Winkel et al. (2023). The latter found a similarly "counterintuitive" positive relationship between jerk and comfort, and explained that a higher jerk usually has a shorter duration, which has a negligible effect on comfort. Taken together, these findings suggest that higher jerk can be comfortable when of shorter duration but can become uncomfortable when the duration exceeds a certain level. However, this conjecture requires further investigation to quantify the relationship between jerk, such as its amplitude and duration, and comfort evaluations.

In terms of the "human-likeness" of the automated driving styles (or objective similarities between manual and automated driving styles), and how these affected users' perceived comfort and naturalness of the AV controllers, we found that the similarity in vehicle speed improved users' perceived naturalness of the driving styles. This aligns with the results of Kamaraj et al. (2023), although we have extended this finding by confirming that similarity in speed was also associated with higher comfort ratings. In addition to speed, we discovered that similarities in longitudinal jerk and yaw positively influenced user evaluations of both comfort and naturalness, while the effect of similarity in lateral jerk on evaluations was negative. Previous research investigating the effects of natural driving styles on comfort has yielded mixed results, which might be explained that naturalness of these driving styles was characterised by different vehicle metrics (Basu et al., 2017; Hartwich et al., 2018; Peng et al., 2022; Yusof et al., 2016).

Moreover, we found that yaw, regardless of the driving direction, had a positive effect on both user comfort and naturalness. This effect might be attributed to users' preference for AV exhibiting human-like behaviour when negotiating curves. In manual driving, drivers tend to cut curves (Mulder et al., 2012; Wei et al., 2019). When drivers become passive passengers in AVs, they appear to maintain this preference for curve cutting. This conjecture is further supported by another finding: a greater similarity in yaw between AV and users' manual driving styles contributed to higher comfort and naturalness ratings.

3.4.1. Limitations

One limitation of our study is the driving scenario used in the experiment. While our replication of a real road provided participants with a variety of road geometries and roadside furniture, we did not include interactions with other road users (e.g., pedestrians and other cars). Consequently, we could only incorporate one proxemic-related metric (i.e., lateral offset) in our analyses, which did not yield any significant results. It is plausible that the scenarios employed in our study were not critical enough to elicit concerns regarding distance from roadside furniture, in comparison with scenarios involving interactions with other road users, such as merging vehicles on a highway (He et al., 2022). Moreover, scenarios that involve more interactions with other road users will bring more spatial or temporal proxemic-related metrics into analyses, such as (time) headway. Therefore, further investigation of scenarios and road environments, which encompass diverse interactions between the AV and different road users, is needed.

3.4.2. Implications for designs

In terms of implications for future AV designs, the fact that a large longitudinal jerk can be comfortable while it has no significant influence on perceived naturalness suggests that it could be used as a cue to communicate with users both inside and outside the vehicle. For example, Zgonnikov et al. (2023) designed a "nudge" manoeuvre (i.e., brief acceleration or deceleration) of an AV to interact with manually driven cars and they found that the deceleration nudge increased drivers' willingness to pass the AV. Regarding the design of human-like driving styles for AVs, we recommend that system designers consider users' perception of such human-likeness in the development of motion planner algorithms (e.g., Bae et al., 2022; Gu & Dolan, 2014), as objective similarities in different metrics can have varying and sometimes opposing effects on user comfort and perceived naturalness. These findings provide guidelines for designing more comfortable and acceptable driving styles for future automated vehicles.

3.5. References

Abe, M. (2009). *Vehicle handling dynamics theory and application* (First edition.). Butterworth-Heinemann.

Bae, I., Moon, J., Jhung, J., Suk, H., Kim, T., Park, H., Cha, J., Kim, J., Kim, D., & Kim, S. (2022). *Self-Driving like a Human driver instead of a Robocar: Personalized comfortable driving experience for autonomous vehicles* (arXiv:2001.03908). arXiv. https://doi.org/10.48550/arXiv.2001.03908

Bae, I., Moon, J., & Seo, J. (2019). Toward a comfortable driving experience for a self-driving shuttle bus. *Electronics (Switzerland)*, *8*(9), 1–13. https://doi.org/10.3390/electronics8090943

Basu, C., Yang, Q., Hungerman, D., Singhal, M., & Dragan, A. D. (2017). Do You Want Your Autonomous Car to Drive Like You? *ACM/IEEE International Conference on Human-Robot Interaction*, *Part F1271*, 417–425. https://doi.org/10.1145/2909824.3020250

Bellem, H., Thiel, B., Schrauf, M., & Krems, J. F. (2018). Comfort in automated driving: An analysis of preferences for different automated driving styles and their dependence on personality traits. *Transportation Research Part F: Traffic Psychology and Behaviour*, *55*, 90–100. https://doi.org/10.1016/j.trf.2018.02.036

Carsten, O., & Martens, M. H. (2018). How can humans understand their automated cars? HMI principles, problems and solutions. *Cognition, Technology and Work*, *21*(1), 3–20. https://doi.org/10.1007/s10111-018-0484-0

de Winkel, K., Irmak, T., Happee, R., & Shyrokau, B. (2023). Standards for passenger comfort in automated vehicles: Acceleration and jerk. *Applied Ergonomics*, *106*(103881). https://doi.org/10.1016/j.apergo.2022.103881

Dichabeng, P., Merat, N., & Markkula, G. (2021). Factors that influence the acceptance of future shared automated vehicles – A focus group study with

United Kingdom drivers. *Transportation Research Part F: Traffic Psychology and Behaviour*, *82*(December 2020), 121–140. https://doi.org/10.1016/j.trf.2021.08.009

Diels, C., & Bos, J. E. (2015). Self-driving carsickness. *Applied Ergonomics*, *53*, 374–382. https://doi.org/10.1016/j.apergo.2015.09.009

Elbanhawi, M., Simic, M., & Jazar, R. (2015). In the Passenger Seat: Investigating Ride Comfort Measures in Autonomous Cars. *IEEE Intelligent Transportation Systems Magazine*, *7*(3), 4–17. https://doi.org/10.1109/MITS.2015.2405571

Feng, F., Bao, S., Sayer, J. R., Flannagan, C., Manser, M., & Wunderlich, R. (2017). Can vehicle longitudinal jerk be used to identify aggressive drivers? An examination using naturalistic driving data. *Accident Analysis & Prevention*, *104*, 125–136. https://doi.org/10.1016/j.aap.2017.04.012

Gelman, A. (2005). Analysis of variance—Why it is more important than ever. *The Annals of Statistics*, *33*(1), 1–53. https://doi.org/10.1214/009053604000001048

Gu, T., & Dolan, J. M. (2014). Toward human-like motion planning in urban environments. *2014 IEEE Intelligent Vehicles Symposium Proceedings*, 350–355. https://doi.org/10.1109/IVS.2014.6856493

Haghzare, S., Campos, J. L., Bak, K., & Mihailidis, A. (2021). Older adults' acceptance of fully automated vehicles: Effects of exposure, driving style, age, and driving conditions. *Accident Analysis & Prevention*, *150*, 105919. https://doi.org/10.1016/j.aap.2020.105919

Hajiseyedjavadi, F., Boer, E. R., Romano, R., Paschalidis, E., Wei, C., Solernou, A., Forster, D., & Merat, N. (2022). Effect of environmental factors and individual differences on subjective evaluation of human-like and conventional automated vehicle controllers. *Transportation Research Part*

F: Traffic Psychology and Behaviour, *90*, 1–14. https://doi.org/10.1016/j.trf.2022.07.018

Hartwich, F., Beggiato, M., & Krems, J. F. (2018). Driving comfort, enjoyment and acceptance of automated driving–effects of drivers' age and driving style familiarity. *Ergonomics*, *61*(8), 1017–1032. https://doi.org/10.1080/00140139.2018.1441448

He, X., Stapel, J., Wang, M., & Happee, R. (2022). Modelling perceived risk and trust in driving automation reacting to merging and braking vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, *86*(January), 178–195. https://doi.org/10.1016/j.trf.2022.02.016

ISO 15622. (2018). *Intelligent transport systems—Adaptive cruise control systems—Performance requirements and test procedures*. https://www.iso.org/standard/71515.html

Jamson, A. H., Horrobin, A. J. ;, & Auckland, R. A. (2007). Whatever Happened to the LADS? Design and development of the new University of Leeds Driving Simulator. *DSC 2007 North America*.

Kamaraj, A. V., Lee, J., Domeyer, J. E., Liu, S.-Y., & Lee, J. D. (2023). Comparing Subjective Similarity of Automated Driving Styles to Objective Distance-Based Similarity. *Human Factors*, 00187208221142126. https://doi.org/10.1177/00187208221142126

Kuderer, M., Gulati, S., & Burgard, W. (2015). Learning driving styles for autonomous vehicles from demonstration. *Proceedings - IEEE International Conference on Robotics and Automation*, *2015-June*(June), 2641–2646. https://doi.org/10.1109/ICRA.2015.7139555

Lee, J., Choi, J., Yi, K., Shin, M., & Ko, B. (2014). Lane-keeping assistance control algorithm using differential braking to prevent unintended lane departures. *Control Engineering Practice*, *23*, 1–13. https://doi.org/10.1016/j.conengprac.2013.10.008

Lee, J., Liu, S. Y., Domeyer, J., & DinparastDjadid, A. (2019). Assessing Drivers' Trust of Automated Vehicle Driving Styles With a Two-Part Mixed Model of Intervention Tendency and Magnitude. *Human Factors*. https://doi.org/10.1177/0018720819880363

Li, P., Pei, X., Chen, Z., Zhou, X., & Xu, J. (2022). Human-like motion planning of autonomous vehicle based on probabilistic trajectory prediction. *Applied Soft Computing*, *118*, 108499. https://doi.org/10.1016/j.asoc.2022.108499

Louw, T., Hajiseyedjavadi, F. H., Jamson, H., Romano, R., Boer, E., & Merat, N. (2019). *The Relationship between Sensation Seeking and Speed Choice in Road Environments with Different Levels of Risk*. *April*, 29–35. https://doi.org/10.17077/drivingassessment.1671

Martin, D., & Litwhiler, D. (2008). An investigation of acceleration and jerk profiles of public transportation vehicles. *ASEE Annual Conference and Exposition, Conference Proceedings*, *1984*.

Mulder, M., Abbink, D. A., & Boer, E. R. (2012). Sharing Control With Haptics: Seamless Driver Support From Manual to Automatic Control. *Human Factors*, *54*(5), 786–798. https://doi.org/10.1177/0018720812443984

Murphey, Y. L., Milton, R., & Kiliaris, L. (2009). Driver's style classification using jerk analysis. *2009 IEEE Workshop on Computational Intelligence in Vehicles and Vehicular Systems, CIVVS 2009 - Proceedings*, 23–28. https://doi.org/10.1109/CIVVS.2009.4938719

Nordhoff, S., Malmsten, V., van Arem, B., Liu, P., & Happee, R. (2021). A structural equation modeling approach for the acceptance of driverless automated shuttles based on constructs from the Unified Theory of Acceptance and Use of Technology and the Diffusion of Innovation Theory. *Transportation Research Part F: Traffic Psychology and Behaviour*, *78*, 58–73. https://doi.org/10.1016/j.trf.2021.01.001

Nordhoff, S., Stapel, J., He, X., Gentner, A., & Happee, R. (2021). Perceived safety and trust in SAE Level 2 partially automated cars: Results from an online questionnaire. *PLoS ONE*, *16*(12 December), 1–21. https://doi.org/10.1371/journal.pone.0260953

Paddeu, D., Parkhurst, G., & Shergold, I. (2020). Passenger comfort and trust on first-time use of a shared autonomous shuttle vehicle. *Transportation Research Part C*, *115*(March), 102604. https://doi.org/10.1016/j.trc.2020.02.026

Peng, C., Horn, S., Madigan, R., Marberger, C., Lee, J., Krems, J., Beggiato, M., Romano, R., Wei, C., Wooldridge, E., Happee, R., Hagenzieker, M., & Merat, N. (2024). Conceptualising user comfort in automated driving: Findings from an expert group workshop. *Transportation Research Interdisciplinary Perspectives, 24*, 101070. https://doi.org/10.1016/j.trip.2024.101070

Peng, C., Merat, N., Romano, R., Hajiseyedjavadi, F., Paschalidis, E., Wei, C., Radhakrishnan, V., Solernou, A., Forster, D., & Boer, E. (2022). Drivers' Evaluation of Different Automated Driving Styles: Is It both Comfortable and Natural? *Human Factors*. https://doi.org/10.1177/00187208221113448

SAE. (2021). *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles*.

Solernou, A., Romano, R., Souflas, I., Hajiseyedjavadi, F., & Paschalidis, E. (2020). Integration and training of a ROS autonomous driver for human-like driving style in a complex multi-component driving simulator. *DSC 2020 Europe*, 9–11.

Summala, H. (2007). Towards Understanding Motivational and Emotional Factors in Driver Behaviour: Comfort Through Satisficin. In *Modelling Driver Behaviour in Automotive Environments: Critical Issues in Driver Interactions with Intelligent Transport Systems* (pp. 189–207). https://doi.org/10.1007/978-1-84628-618-6

Wei, C., Romano, R., Merat, N., Wang, Y., Hu, C., Taghavifar, H., Hajiseyedjavadi, F., & Boer, E. R. (2019). Risk-based autonomous vehicle motion control with considering human driver's behaviour. *Transportation Research Part C: Emerging Technologies*, *107*(August), 1–14. https://doi.org/10.1016/j.trc.2019.08.003

Yusof, N. M., Karjanto, J., Terken, J., Delbressine, F., Hassan, M. Z., & Rauterberg, M. (2016). The exploration of autonomous vehicle driving styles: Preferred longitudinal, lateral, and vertical accelerations. *AutomotiveUI 2016 - 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, Proceedings*, 245–252. https://doi.org/10.1145/3003715.3005455

Zgonnikov, A., Beckers, N., George, A., Abbink, D., & Jonker, C. (2023). *Subtle motion cues by automated vehicles can nudge human drivers' decisions: Empirical evidence and computational cognitive model*. https://doi.org/10.31234/osf.io/3cu8b

Zuckerman, M., & Neeb, M. (1980). Demographic influences in sensation seeking and expressions of sensation seeking in religion, smoking and driving habits. *Personality and Individual Differences*, *1*(3), 197–206. https://doi.org/10.1016/0191-8869(80)90051-3

CHAPTER 4

Conceptualising user comfort in automated driving: Findings from an expert group workshop

Abstract

The driving style of an automated vehicle (AV) needs to be comfortable to encourage the broad acceptance and use of this newly emerging transport mode. However, current research provides limited knowledge about what influences comfort, how this concept is described, and how it is measured. This knowledge is especially lacking when comfort is linked to the AV's driving styles. This paper presents results from an online workshop with nine experts, all with hands-on experience of AVs and a long track record of research in this context. Using online tools, experts were invited to introduce concepts they considered relevant to comfort/discomfort in currently available modes of transport which offer a ride (taxi/bus/train) to users and compare these to the concepts used to define comfort and discomfort in AVs. Results showed that a wide range of terms were used to describe user comfort and discomfort for both modes. Although all terms used for existing vehicles were found to apply to AVs, additional terms were proposed for determining comfort/discomfort of AVs. For example, to enhance comfort in AVs, designers should consider good communication channels, as well as ensuring that the AV's capabilities match users' expectations. Results also revealed that more terms were used, overall, to define discomfort, and that a comfortable ride in AVs is not just about mitigating discomfort. New concepts specific to AVs were also revealed when considering what increases their discomfort, such as whether riders' safety and privacy are affected, or if they feel in control. Experts' input from the workshop was used to enhance and expand a simple conceptual framework, explaining how AV driving styles, as well as other, non-driving-related factors, affect user comfort. It is hoped that this framework provides a more comprehensive list of the concepts affecting user comfort, also allowing more accurate measurement of the concept. As well as allowing for a more accurate comparison between empirical studies measuring comfort in AVs, this study will facilitate the design of more comfortable and acceptable automated driving for future vehicles.

Keywords: automated vehicles, user comfort, driving styles, expert workshop, conceptual framework.

4.1. Introduction

Comfort, as a positive user experience of automated driving, is essential for the broad acceptance of Automated Vehicles (AVs), (Dichabeng et al., 2021; Nordhoff, Malmsten, et al., 2021; Paddeu et al., 2020; Siebert et al., 2013). When being driven by a higher-level AV (SAE Level 4 and Level 5, SAE International, 2021), automated driving styles, such as the vehicle's kinematic behaviour, the distance it keeps with other road-based objects, and how it negotiates different road geometries, play an important role in user comfort (Beggiato et al., 2020; Bellem et al., 2016; Diels & Bos, 2015; Peng et al., 2022, Chapter 2 in this thesis). It is argued that a wide range of factors influence user comfort when being driven by AVs. For example, *perceived safety* and *trust* are thought to affect comfort (Diels et al., 2017; Hartwich et al., 2021; Nordhoff, Stapel, et al., 2021), with research showing that when users do not trust AVs, they will refrain from using automation, and not use the driving time for other (non-driving related) activities. Another concern is the prevalence of *motion sickness*. While manual driving does not necessarily result in motion sickness (Rolnick & Lubow, 1991), recent research suggests that as many as two-thirds of adults have suffered from car sickness (Diels & Bos, 2015) with around 10% of passengers of AVs predicted to suffer from this condition in the future (Sivak & Schoettle, 2015). It is assumed that such discomfort may also be associated with unexpected and abrupt manoeuvres of automated driving. Therefore, understanding what factors affect user comfort, especially regarding the AV's driving style, is critical. Without sufficient knowledge of user comfort in automated driving, such as how it is defined and measured, it is challenging for automated system designers to develop comfortable, enjoyable, and acceptable AVs. Thus, the main aim of the present explorative study, based on an expert workshop, was to enhance our understanding of factors that contribute to an individual's comfort, when being driven by an AV.

4.1.1. Comfort and discomfort in automated driving

Comfort is a highly complex concept, affected by physical factors such as the vehicle's motion, the visual context of the environment, the "driver's" posture, as well as the sound, climate and interior design of the vehicle cab (e.g., da Silva, 2002; Oborne, 1978). It is also influenced by psychological factors such as feelings of safety, pleasure, and peace of mind (Ahmadpour et al., 2016; Carsten & Martens, 2018; Summala, 2007). Research in the automotive, air, rail, and marine sector, and those related to general ergonomics of systems, have resulted in ample definitions of comfort. For example, Slater (1986) defines comfort as *"a pleasant state of physiological, psychological and physical harmony between a human being and its environment"*. De Looze et al. (2003) propose three main features, suggesting that comfort: a) is a subjective and personal construct; b) influenced by physical, physiological, and psychological factors; and c) comes from the interaction of the human with the environment. Comfort is derived from positive experiences, such as pleasure and trust, and the lack of negative experiences (discomfort), such as fatigue, anxiety, and fear. However, an overall comfortable experience is easily marred by a minor change in discomfort (Cohen-Lazry et al., 2022; Helander & Zhang, 1997).

Control in a highly or fully automated vehicle is shifted from the human driver to the automated system. In such situations, users will no longer have to monitor the road and can use the driving time for work or leisure activities. This means that users' experiences will be affected by how the automated system drives, i.e., its driving style. As the importance of comfort in AVs is gaining more interest, researchers have started to use a wide range of definitions for defining user comfort in this particular type of vehicle. For example, some studies emphasise the absence of discomfort (Bellem et al., 2016), where comfort is defined as "*a state which is achieved by the removal or absence of uneasiness and distress*" (p. 45). Other studies address both positive and negative aspects of comfort. For example, Carsten and Martens (2018) describe rider comfort as "*the subjective feeling of* *pleasantness of driving/riding in a vehicle in the absence of both physiological and psychological stress*". Others highlight the role of AV operations, such as "*a subjective, pleasant state of relaxation given by confidence and an apparently safe vehicle operation, which is achieved by the removal or absence of uneasiness and distress*" (Hartwich et al., 2018, p.1019). Similarly, Hartwich et al. (2018) describe discomfort as "*a subjective, unpleasant state of driving-related psychological tension or stress in moments of a restricted harmony between driver and environment, originating from unexpected, unpredictable or unclear actions of the automated system*" (p.1021).

Thus, there are currently various descriptions for user comfort in AVs, emphasising either the lack of discomfort, and/or the use of positive and pleasant concepts, while descriptions for discomfort are few, and are not exactly the opposite of that for comfort. When it comes to measurement of these states in automated driving, some studies have measured comfort directly (Hajiseyedjavadi et al., 2022), while others have solely measured discomfort (Radhakrishnan et al., 2020), by assuming that, for example, the physiological changes associated with this state are easier to detect and quantify (Siebert et al., 2013). These inconsistencies in the definition and measurement of comfort/discomfort for automated driving make cross-study comparisons, for example, about whether a particular AV driving style is comfortable, challenging.

4.1.2. A conceptual framework for comfort in automated driving

As outlined above, comfort in automated driving is an emerging research field which lacks definitions, methods, and models. Previously, conceptual models for comfort have been proposed based on cabin-based ergonomics. For example, in the aircraft cabin, factors such as peace of mind, physical well-being, and aesthetics (such as seat comfort) play a role in passenger comfort (Ahmadpour et al., 2014). Gaining similar knowledge for AVs will support the design of comfortable vehicle interiors, such as information about seat position. However, new insights and models will also be needed to design comfortable driving styles, managed by the AV's motion control strategies. Therefore, to assist with a better understanding of how AV driving styles, in particular, affect user comfort, we first created a simple conceptual framework to help facilitate the discussions of our expert group workshop (Figure 4.1). This conceptual framework was then further developed by incorporating the experts' feedback, which forms the bulk of the manuscript. The next section provides more detail about each of the concepts chosen for the original framework.

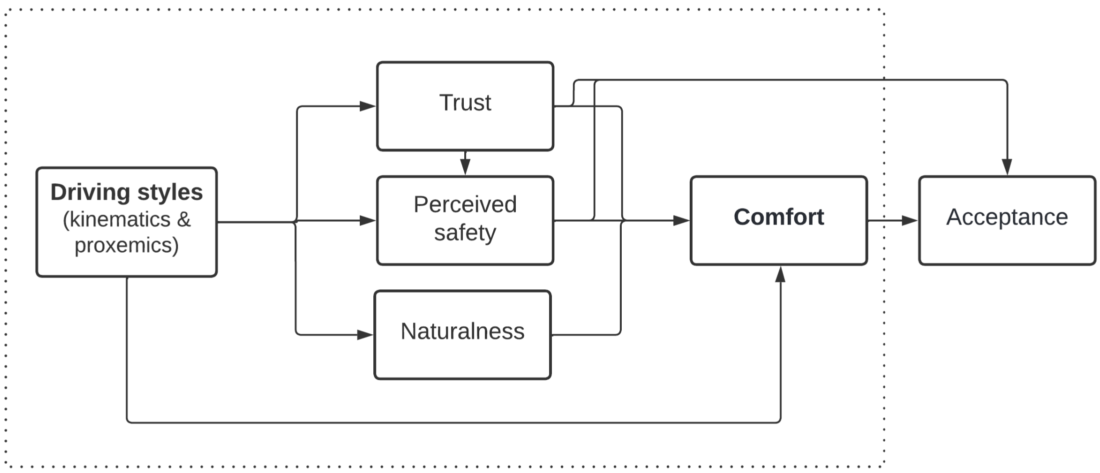


Figure 4.1. The original conceptual framework for comfort in automated driving. This literature-based framework focused on incorporating psychological concepts to understand influences on comfort. The concepts and terms included in the dashed box are discussed in the present study.

<u>The link between driving styles and comfort</u>

The original framework focused especially on how automated driving styles affect user comfort. Adapted from a description of manual driving styles (Elander et al., 1993), automated driving styles are related to vehicle kinematics (e.g., acceleration and braking behaviour), and vehicle proxemics (e.g., distance kept to other on-road or roadside objects). Driving style is also about how the vehicle manoeuvre is influenced by road surface and geometry, such as how it negotiates different road curvatures, or whether the ride is smooth or jerky. A number of studies have investigated the link between changes in these aspects of driving style, and user comfort in AVs (Dettmann et al., 2021; Elbanhawi et al., 2015; Hajiseyedjavadi et al., 2022; Hartwich et al., 2018; Peng et al., 2022; Summala, 2007). For example, Bellem et al. (2018) propose a range of kinematics to assist with user comfort during different manoeuvres of highly automated vehicles, such as minimising acceleration and jerk – i.e. the rate at which the acceleration changes with respect to time. Peng et al. (2022, Chapter 2 in this thesis) measured user comfort for two human-like and one machine-like driving style, and found that the replay of real human participants' driving (categorised as a "defensive" driving style - driving at lower speeds), was evaluated as more comfortable than the other two.

High levels of automation increase the importance of driving style for user comfort. SAE level 4 and 5 AVs (SAE International, 2021) can operate autonomously, without any input or action by users. This can detach the on-board users from the surrounding environment, taking them "out of the loop" (Merat et al., 2019). This reduces their overall situation awareness, especially if they are engaged in other, non-driving related, activities (NDRAs). In these situations, any unexpected or unpredictable manoeuvres of the AV (e.g., a sudden brake) may not only interrupt the user's engagement in the NDRA, but also cause concern, discomfort, or even motion sickness (Beggiato et al., 2020; Carsten & Martens, 2018; Hartwich et al., 2018; Kuiper et al., 2020). Elbanhawi et al. (2015) argue that a comfortable AV ride demands natural and familiar manoeuvres (see also Peng et al., 2022, Chapter 2 in this thesis), smooth control, safe operations, and the mitigation of motion sickness, in addition to the traditional (physical) factors that enhance comfort (e.g., temperature, noise, and seat design; De Looze et al., 2003; Silva, 2002). Therefore, for our original framework, we focused particularly on understanding what *psychological aspects* affect comfort in AVs, to help enhance users' psychological experience (i.e., how they feel about different driving styles).

Perceived safety, trust, and naturalness

Perceived safety, trust, and naturalness (sometimes referred to as familiarity), have also been linked to comfort in automated driving (Elbanhawi et al., 2015; Paddeu et al., 2020), and each concept is also considered to be influenced by a vehicle's driving style (Hajiseyedjavadi et al., 2022; He et al., 2022; Lee et al., 2019; Oliveira et al., 2019; Summala, 2007). Some of these concepts, together with comfort, are frequently used interchangeably. For example, He et al. (2022) describe perceived safety as "*feeling relaxed, safe and comfortable*" (p.179). Although a number of studies have described trust in automation, perhaps the most cited is one provided by Lee and See (2004) as: "*the attitude that an agent will help achieve an individual's goal in a situation characterised by uncertainty and vulnerability*" (p.51). Finally, Peng et al. (2022, Chapter 2 in this thesis) describe natural driving as "*a driving style that is closest to your own*" (p.6), while Hajiseyedjavadi et al. (2022) use a combined description of feeling "*safe/natural/comfortable*" to evaluate an overall pleasant experience with automated driving. Overall, similar (positive) affects are used to describe these concepts and also comfort, when discussing the effect of automated driving style on user experience. Hartwich et al. (2018) suggest that feeling safe, relaxed and certain can all lead to a positive experience of automated driving, which will ultimately enhance acceptance of these new forms of mobility (see also acceptance models reported by Madigan et al., 2016; Motamedi et al., 2020; Nordhoff, Stapel, et al., 2021). Therefore, the original conceptual framework included these mostly investigated concepts (i.e., perceived safety, trust, and naturalness), in order to clarify the relationship between these, and establish if and how each contributes to comfort, based on different automated driving styles.

4.1.3. The current study

Based on the above literature review, and the resulting conceptual framework, the aim of the current study was to address the gaps in knowledge about the definitions and measurements used for comfort. To help address this gap, we conducted an online expert workshop with individuals who had a long tracking record of working with different types of AVs. Our objective was to improve the current understanding of what contributes to user comfort/discomfort in automated driving, with a particular focus on the role of driving styles. We believe this knowledge can ease cross-study comparisons for future empirical studies in this area. It can also help AV designers have a better understanding of user comfort, creating more comfortable, pleasant, and acceptable vehicles for a wide-ranging user group.

In particular, the main objectives of the present study were to:

1) Conceptualise comfort/discomfort in automated driving, by identifying the descriptions and terms used for both comfort and discomfort, as well as highlighting any differences and similarities between the terms used for these two states.

2) Elaborate our original conceptual framework of AV driving comfort, clarifying the relationship between a number of commonly used concepts, and comfort, especially for AV driving styles.

We expected a partial overlap between comfort when being driven by currently available human-driven vehicles (e.g., taxis, buses, and trains), and being driven by AV-controlled computer systems, because for both modes, the human is a passenger not controlling the vehicle. To assess this partial overlap, we discussed comfort in, and between, these transport modes.

4.2. Method

In this section, we provide a brief introduction of the method used in the workshop. More details can be found in Appendix A, including the rationale for the method used, how the discussion was facilitated, and the method used for data analysis.

4.2.1. Experts and the group workshop

Due to the Covid-19 pandemic, we conducted an online workshop with nine internationally-recognised experts in this field, which took place on the 27th July, 2021. These nine attendees (RM, CM, JL, JK, MB, RR, CW, EW, and NM), and two more experts (MH and RH), were invited to comment on the manuscript, and are all co-authors of the manuscript, due to their verbal and written contributions [1]. We were keen to include experts with some hands-on experience with higher-level AVs, because these vehicles are currently unavailable on the market (Madigan et al., 2017), and research shows that actual experience with new technologies is essential for understanding their limitations and capabilities (e.g., Hancock et al., 2020; Kyriakidis et al., 2019; Tabone et al., 2021). The group workshop loosely followed a focus group format, where experts discussed a range of proposed topics via the online meeting platform Microsoft Teams (https://www.microsoft.com/en-gb/microsoft-teams/online-meetings). In order to stimulate discussions, experts were encouraged to brainstorm a range of proposed topics, as well as write notes, grouping similar items, using the online collaborative whiteboard tool: Miro (https://miro.com). These notes were visible on the whiteboard, allowing the facilitators and experts to further discuss the

---

[1] The initials of the experts - RM, CM, JL, JK, MB, RR, CW, EW, NM, MH, and RH - represent Ruth Madigan, Claus Marberger, John D. Lee, Josef Krems, Matthias Beggiato, Richard Romano, Chongfeng Wei, Ellie Wooldridge, Natasha Merat, Riender Happee, and Marjan Hagenzieker, respectively.

evolving themes. The whole workshop was recorded via Microsoft Teams, and lasted two hours.

4.2.2. Procedure

Figure 4.2 shows the procedure used in the workshop. The workshop discussions were divided into four separate sessions, in which different, but connected, topics were covered:

Session 1: This session focused on a discussion of the terms used to describe comfortable and uncomfortable experiences when driven by currently available vehicles as a passenger, such as a taxi, bus, or train. This was done for two reasons: first, it helped experts familiarise themselves with the topic by talking about currently available transport modes. Second, we wished to understand if there were any similarities and differences in the perceived comfort/discomfort of "being driven" by a taxi/bus/train, compared to that of a Level 4 AV, because, in both cases, the user does not control the vehicle, and is also able to engage in NDRAs (Hecht et al., 2019).

Session 2: This session involved a discussion of any differences between being driven by a taxi/bus/train versus an AV, in terms of the experienced comfort/discomfort. This session was expected to connect with, and facilitate, the discussions in Session 3.

Session 3: This session involved a discussion of terms used to describe comfortable and uncomfortable experiences of being driven by AVs. Discussions in this session were based on the previous two sessions. After reflecting on the unique characteristics of AVs in Session 2, it was expected that experts would add or remove terms about comfortable/uncomfortable experiences of being driven by AVs, based on existing terms for a taxi/bus/train from session 1.

Session 4: This session focused on discussing the original conceptual framework for user comfort in automated driving (Figure 4.1), with an emphasis on how comfort is affected by different driving styles. After discussions in the preceding sessions, experts were expected to give constructive feedback on the original framework, in terms of complementing and revising relevant aspects and concepts, rather than clarifying concrete terms. Here, we explicitly instructed experts to take driving styles into consideration, compared to the preceding sessions, in which the term "being driven" was used to implicitly remind experts of the driving scenario. However, we still encouraged discussions of broad but relevant concepts, in addition to driving styles.

4.2.3. Data analysis

Figure 4.4 shows the approaches that we used to analyse the data, following the online workshop. Written notes from the experts were categorised, and verbal discussions were summarised. Experts were given an opportunity to suggest amendments to the categorisation of notes, the summarisation of their discussions, and the refined framework.

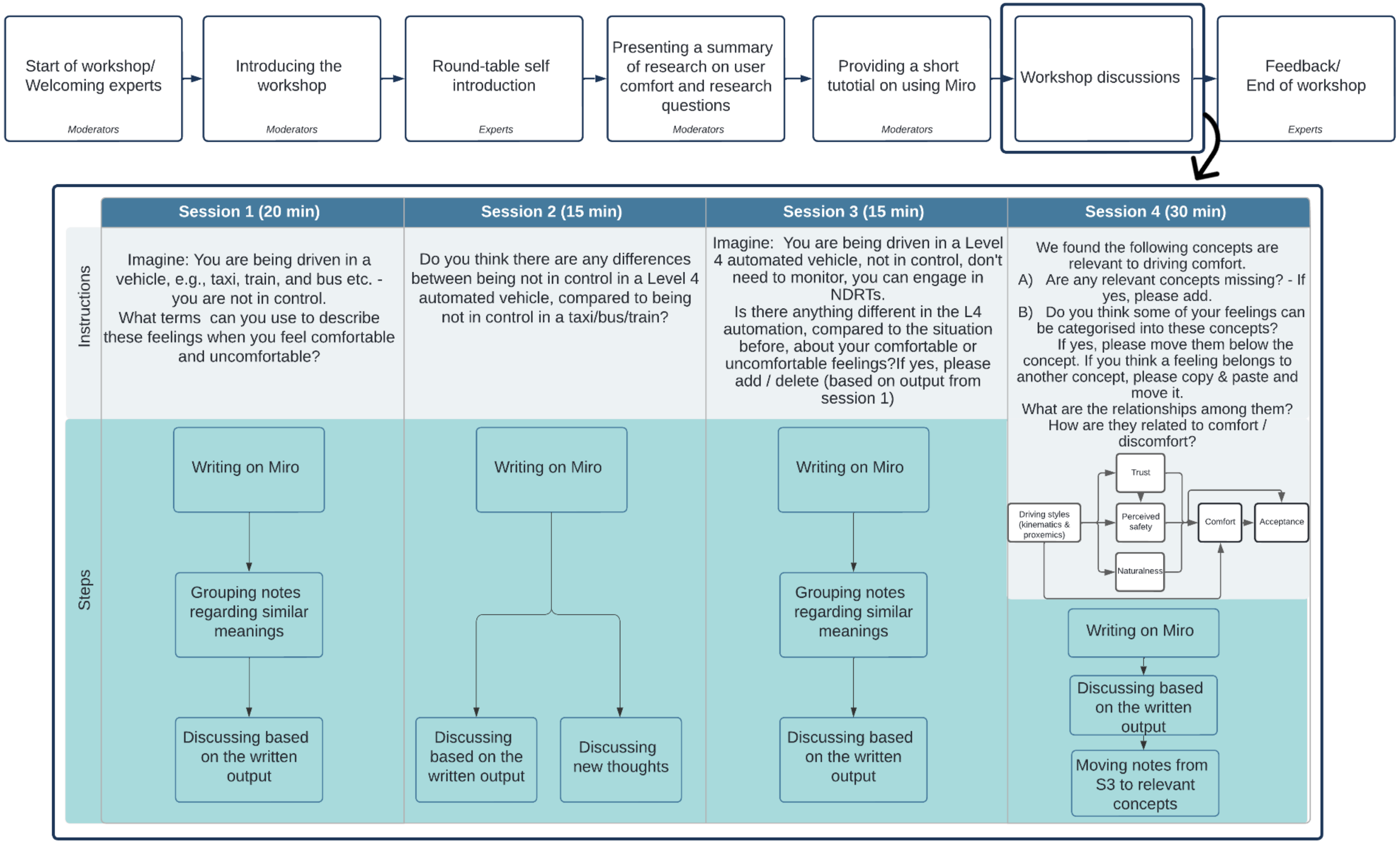


Figure 4.2. Full procedure (top) and the four main sessions in the workshop. All introductions and the tutorial before the four sessions took around 15 mins, followed by around 5 mins for feedback and reflection. A 10-min break was included between Session 3 and 4.

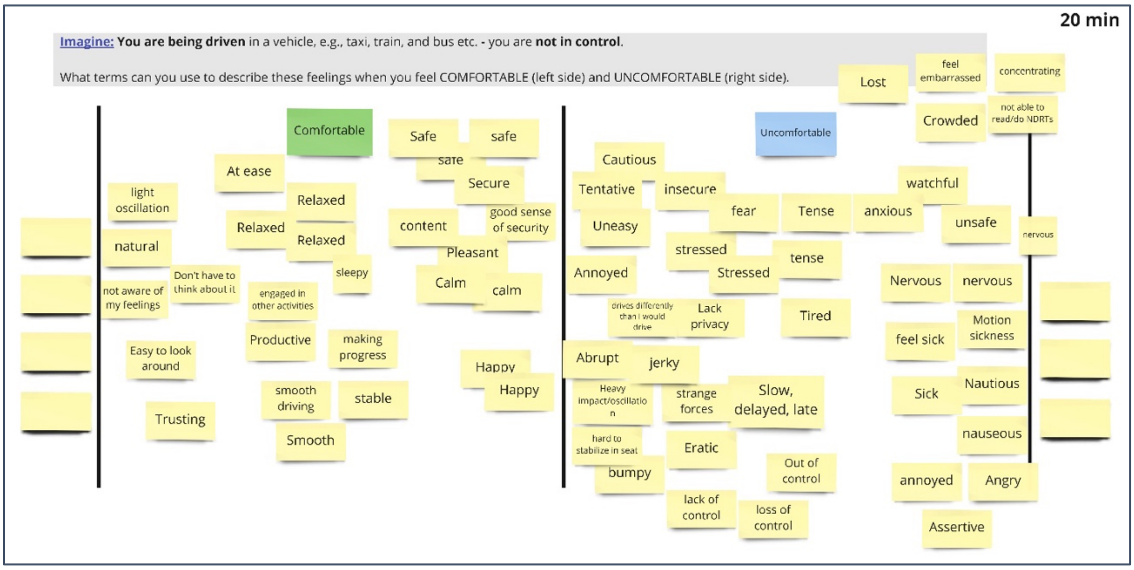


Figure 4.3. The Miro whiteboard used for Session 1, in which experts posted notes to describe comfortable (left) and uncomfortable (right) experiences of being driven by a taxi/bus/train in the designated areas. The text in the shaded area on the top is the written instructions about the discussed topic, and the empty yellow sticky notes were "a pile of notes" for easy use, prepared by the moderators in advance of the workshop. The yellow sticky notes with texts were posted by experts during the writing session.

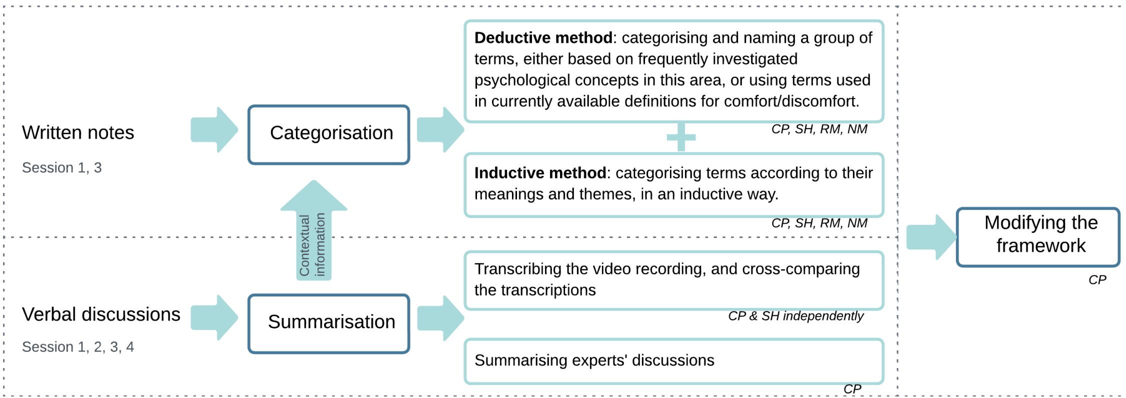


Figure 4.4. Procedures used for the data analysis. Initials represent people who were responsible for different steps of the analysis.

4.3. Results and Discussion

Results are presented in order, based on the timeline of the four workshop sessions, outlined above. We first present the terms used by experts to describe comfort and discomfort when being driven by currently available transport modes (e.g., taxi/bus/train), in Session 1. Then, differences between these transport modes and AVs in terms of comfort/discomfort are summarised (Session 2), followed by additional notes associated with the comfortable and uncomfortable aspects of being driven by AVs (Session 3). Finally, a refined conceptual framework is outlined, by incorporating the input of this expert workshop into the original model. In each section, we discuss and summarise the key findings, to interpret their theoretical and practical implications.

4.3.1. Session 1: Comfort and discomfort of being driven by a taxi/bus/train

In this section, we present a categorisation of the terms used by the experts to describe comfort/discomfort when driven by currently available transport modes (Figure 4.5). The terms were first provided and roughly grouped by experts during the workshop, after which a categorisation of these terms into new groups was done independently, and then as a team, by CP, SH, RM, and NM, after the workshop[2]. We also provide a summary of experts' comments on emerging patterns for these terms.

[2] CP, SH, RM, and NM represents Chen Peng, Stefanie Horn, Ruth Madigan, and Natasha Merat, respectively.

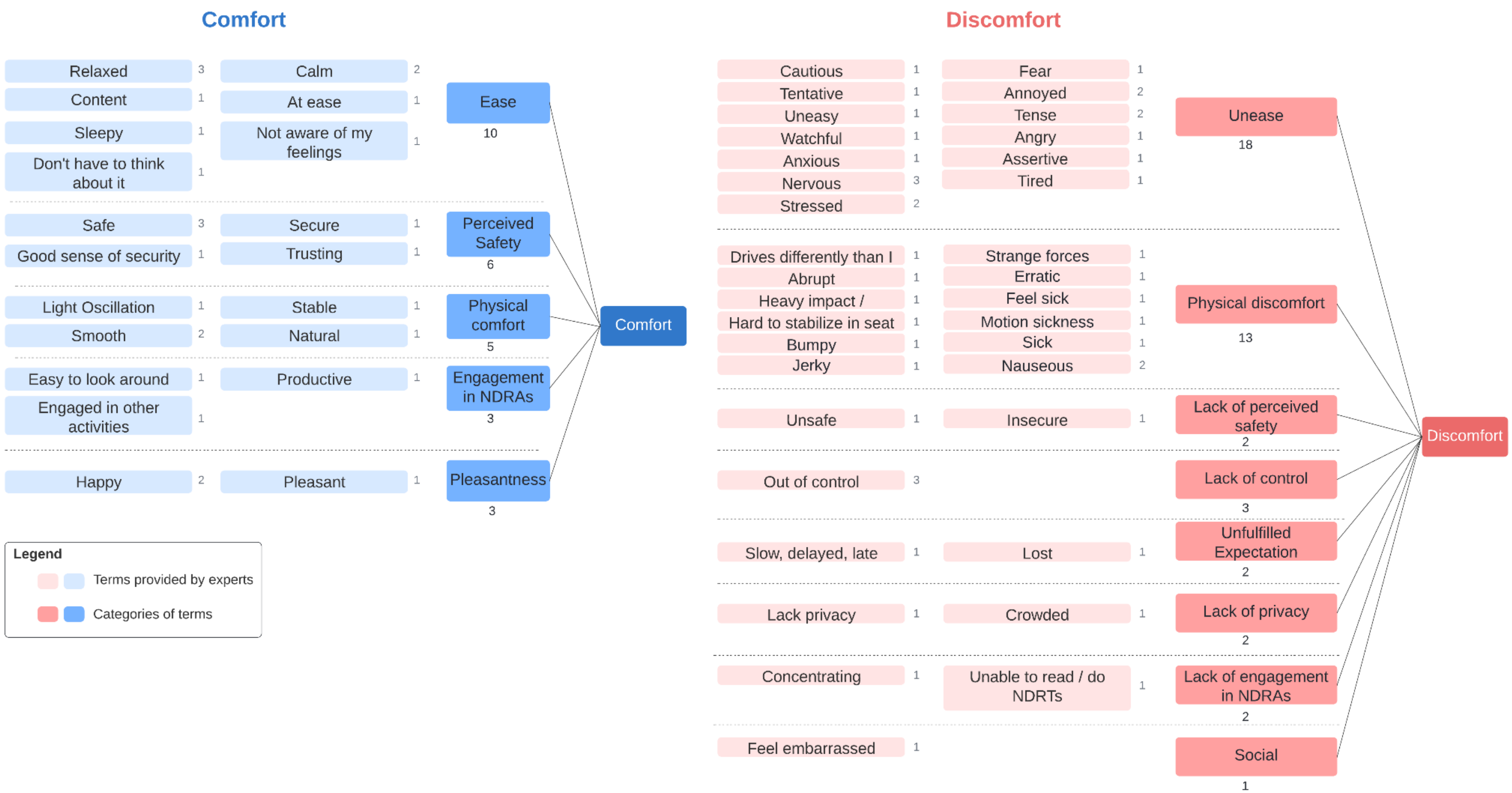


Figure 4.5. Categorisation of the terms describing comfort and discomfort when driven by a taxi/bus/train. Numbers next to each box represent the number of times each term was mentioned by experts, and numbers below each category represent the number of terms in the category. Experts were instructed to write as many notes as they could and avoid repetitions, but they sometimes could not avoid repetition when writing in parallel, so a larger number of a term was not interpreted as more important.

4.3.1.1. Categorisations of terms provided by experts in Session 1

Regarding comfort, we categorised the terms used to describe a comfortable experience when being driven by a taxi/bus/train into five groups (Figure 4.5). A single term was then used to define each category of terms with similar definitions. These five categories were 1) *ease*, 2) *perceived safety*, 3) *physical comfort*, 4) *engagement in NDRAs, and* 5) *pleasantness.* As mentioned in the Method section (section 4.2.3, and Appendix A), when the content shared similarities with keywords from previously used definitions, we chose these same terms or concepts, with new terms used for new, previously absent, groups of terms. Further details are provided in Table 4.1.

Regarding discomfort, the terms used to describe an uncomfortable experience of being driven by a taxi/bus/train were grouped into eight categories: 1) *unease*, 2) *physical discomfort*, 3) *lack of perceived safety*, 4) *lack of control*, 5) *unfulfilled expectation*, 6) *lack of privacy*, 7) *lack of engagement in NDRAs*, and 8) *social* (Figure 4.5). Some terms are antonyms of the terms used for comfort, such as *unease*, *physical discomfort*, *lack of perceived safety*, and *lack of engagement in NDRAs*, while explanations for other (new) terms are provided below (Table 4.2).

Table 4.1. The categories used for comfort.

Category	**Inclusion of terms**	**Rationale for category name**
Ease	This category included terms such as calm, content, and relaxed, mostly describing a feeling of being at ease.	This term has been frequently used in previous definitions of comfort (e.g., Carsten & Martens, 2018).
Perceived safety	This category consisted of a group of terms describing feeling safe, secure, and trust.	This term is considered to contribute to comfort (Elbanhawi et al., 2015), and also used previously (e.g., Hartwich et al., 2018).
Physical comfort	This category included terms describing physical vehicle movements (e.g., smooth and stable), and natural driving styles.	This theme was derived from "physical harmony" between the user and the vehicle, used in previous studies (e.g., Slater, 1985).
Engagement in NDRAs	This category comprised terms about people's willingness to do non-driving-related activities.	The theme has been considered as a key attractive feature of highly automated driving (Merat et al., 2012) and broadly investigated in this area.
Pleasantness	This category consisted of terms describing feelings around happiness and positive affect.	This term was chosen because of its presence in previous studies (e.g., Summala, 2007)

Table 4.2. The categories used for discomfort.

Category	Inclusion of terms	Rationale for category name
Unease	This category contained the most terms used for discomfort, which were all about people's negative affective feelings (e.g., anxious, nervous, and annoyed).	Thematic summary of terms. The opposite of ease.
Physical discomfort	This category included terms describing uncomfortable vehicle movements (e.g., jerky, abrupt, and erratic) as well as motion sickness.	Thematic summary of terms. The opposite of physical comfort.
Lack of perceived safety	This category included two terms describing unsafe and insecure feelings.	Thematic summary of terms. The opposite of perceived safety.
Lack of control	The category comprised of terms about the user's loss of active control over the vehicle.	This name was chosen because being a passenger without control over the vehicle is seen as one factor resulting in discomfort and motion sickness (Rolnick & Lubow, 1991).
Unfulfilled expectation	This category included terms which describe unexpected operations (e.g., slow) or consequences of an uncomfortable ride (e.g., was lost).	Thematic summary of included terms.
Lack of privacy	This category included two terms describing users' privacy concerns, for example, because of the presence of unknown co-passengers. The term crowded was grouped into this category as we interpreted that being in	Thematic summary of included terms.

	a crowded vehicle reduces personal space and increases privacy concerns.	
Lack of engagement in NDRAs	This category contained terms describing the user's inability to concentrate on NDRAs.	The opposite of engagement in NDRAs.
Social	This category only included one term describing how the social context and other people's judgements affect user comfort.	Thematic summary of the included term.

4.3.1.2. *Experts' discussions on emerging patterns from the written notes in Session 1*

After writing and roughly grouping the notes, experts selected and discussed the pattern of results that were of interest to them, rather than going through all of the possible terms and categories. In particular, the experts highlighted the differences between comfort and discomfort, with regards to affective and physical aspects, as summarised and presented below.

Two experts highlighted that affective feelings of comfort (e.g., calm, relaxed, pleasant) are less intense than that of discomfort (e.g., anxious, stressed, tense). When feeling comfortable, people may be unaware of the feeling, or unconscious of what is going on in the vehicle, whereas being uncomfortable is very "tangible and extreme". Another expert added that if expectations about a comfortable experience cannot be fulfilled, all aspects that cause discomfort become conscious, which may also cause them to feel insecure and uncomfortable. On the other hand, this expert also added that: "*If we expect uncomfortable situations of a taxi journey, but we are lucky that things turn out nicely and the taxi driver is skilled at everything, we are very much aware of the comfortable aspects*".

With respect to the physical aspects of comfort/discomfort, four experts pointed out that terms related to the vehicle's movement were used more often when describing discomfort than comfort, and one of them emphasised the role of vibrations. This expert explained that in the vehicle and control domain, the concept of ride comfort is not about comfort itself, but refers to the lack of oscillations or vibrations in the vertical direction of the vehicle. For example, both high- and low-frequency vibrations, as well as noise are uncomfortable for vehicle users. This expert argued that this is because "*vibrations that are far away from the natural frequency of the humans make the user sick*", while another expert added that low-frequency vibrations are typically associated with carsickness. Therefore, it seems that the physical vehicle movement manifests more uncomfortable than comfortable feelings.

To summarise, both categorisation of the terms and experts' discussions about the patterns arising from these terms indicate that when being driven by currently available transport modes, the feelings and terms associated with comfort are different from the lack of discomfort. For example, more (and more concrete) terms were used to describe discomfort than comfort, whereas comfort demands more (and more positive) psychological and emotions than discomfort. This difference in the number of descriptions for comfort/discomfort might also be explained by the fact that humans have a wider vocabulary for expressing negative, than positive, emotions (Schrauf & Sanchez, 2004). This is also because negative experiences are associated with more elaborate and detailed cognitive interpretations compared with positive experiences (the psychological theory of *affect-as-information*; Schwarz, 1990). In terms of the intensity of these two states, the *Circumplex Model of Affect* (Russell, 1980) is used to represent affective concepts in two dimensions: *valence* (ranging from displeasure to pleasure) and *arousal* (ranging from sleep to arousal). Our results suggest that the affect-related terms for comfort are lower in arousal, but higher in valence, compared to discomfort. This implies that solely eliminating discomfort (e.g., lowering the arousal) does not necessarily lead to comfort, because comfort is also associated with pleasantness and enjoyment. This finding also has implications for measuring these two states, because physiological responses (e.g., heart rate, electrodermal activity) are more suitable for identifying the high arousal associated with discomfort (Beggiato et al., 2019; Radhakrishnan et al., 2020), and less likely to detect the lower levels of arousal linked to comfort.

4.3.2. Sessions 2 and 3: Differences between being driven by a taxi/bus/train versus an AV

In Session 2, when considering the differences in comfort/discomfort of being driven by currently available transport modes compared to an AV, experts focused on brainstorming and discussing the different terms, rather than writing notes. Four main topics were highlighted as being relevant to AVs, compared to current transport modes. These were: i) the duration of using AVs, ii) user expectations about AV driving styles, iii) privacy concerns, and iv) the presence of a human operator.

In terms of the duration of using AVs, an expert suggested that, at the early stages of AV deployment, there will either be no boundaries within what users believe the AV should and should not do, or no understanding of how the AV should behave, compared to that of a human taxi driver. Two experts also pointed out that, in the initial stages, the experience of comfort with AVs will be influenced by its novelty. Also, who will take responsibility of controlling the AVs is unclear for users, compared with a taxi, where the driver is responsible. However, it was also argued that these experiences and beliefs will likely change with the passage of time, and repeated use of AVs.

Regarding driving styles, four individuals agreed that AV driving styles should meet *users' expectations*, in order to ensure user comfort, which is thought to be different for expectations about how taxis/buses/trains should be driven. Although how users' expectations will develop over time remains unclear, experts suggested a number of factors, with regards to the AV's driving style, which might help with meeting expectations. First, an expert advised that at the very least, the automated drive should be smooth. Furthermore, the use of "human-like" and personalised driving styles (i.e., similar to the users' own driving behaviours) was also suggested, to meet users' anticipated trajectories and behaviour for automated driving. However, what should be personalised, and how, remained unclear. One expert mentioned a study on Level 2 vehicles which found that participants preferred not to change lanes all the time. However, there was a debate on whether or not users of personalised Level 4 AVs would like the AV to drive like a "good citizen" (e.g., staying in one lane or not speeding). For example, an individual commented that: "*I would be unhappy with a car that is too cautious. I do not want to totally waste time on my trip. But maybe it would change if I feel less stress about getting to the destination*". There is a question here, therefore, regarding safety versus efficiency offered by these new forms of transport. Further work is required to understand what driving styles users want from a Level 4 AV.

An expert highlighted a couple of examples regarding the privacy issues that influence user comfort in AVs, compared to taxis/buses/trains. This included issues around invasion of privacy, for example because their conversation may be heard by a remote operator, or unfamiliar co-passengers, which may or may not be different to being heard by a taxi driver. There was also concern about the use of user information by data owners, which can infringe user privacy, for example regarding route choice and location, and causing discomfort.

Three experts discussed how the presence of a driver in AVs might also affect user comfort. One expert suggested that sharing a taxi with an unfamiliar man might be uncomfortable for a woman; but that the presence of a driver might mitigate such discomfort. In comparison, when driven by an AV, where no driver is present, users might be uncomfortable with other unknown passengers, rather than being uncomfortable with the AV. On the other hand, it was noted that humans tend to trust other human beings more, even though algorithms may be much better for controlling the vehicle. This expert speculated that the sense of "self-preservation" of humans might play a role in this human-algorithm preference; in that human drivers do not typically intend to cause a crash, while this is perhaps more of a worry for the algorithms that control AVs. This led to the conclusion that such concerns cannot be solely mitigated by vehicle behaviour, its control or motion, and is more related to features such as the role of AVs as social agents.

To summarise, experts used knowledge about currently available transport modes to suggest how different aspects of driving style for future AVs can be used to improve user comfort. This information can be used by system designers and manufacturers of future AVs to create more comfortable driving, increasing the acceptance and uptake of these vehicles. However, there is currently little understanding of whether/how AV driving style should be personalised (e.g., Butakov & Ioannou, 2015), or human-like (e.g., Basu et al., 2017; Wei et al., 2019). An understanding of the value of these changes for different user groups is also limited (e.g., Feierle et al., 2020). Current technological and infrastructure-based limitations mean that AV capabilities are not matching user expectations, which can, in turn, lead to a more uncomfortable/unsatisfactory ride. This corresponds with work conducted by Nordhoff et al. (2019), who found that users' impressions of automated shuttles were idealised and unrealistic, resulting in disappointment, after experiencing a ride in a very slowly-operated automated shuttle prototype. Therefore, until the technology that enables these vehicles is improved, educating users on AV capabilities will play a key role in calibrating user expectations about AV driving styles.

Finally, experts' concerns about privacy are in agreement with other studies which found that users were worried and uncomfortable about access to their privacy, such as tracking their location and destination, or image capturing, and issues around how this data is protected from abuse by others (Bloom et al., 2017; Nordhoff et al., 2019). The importance of considering other factors not related to driving style in this context can be supported by the theory of constructed emotion, which suggests that the way that feelings and emotions are constructed is highly context-bound (Barrett, 2017). In our case, whether or not a particular driving style is experienced as comfortable may depend on, for example, whether or not the user is concerned about their privacy. However, this issue is unlikely to be solved via driving styles. Future studies should investigate ways to cope with these concerns, via, for example, personalised data-sharing settings.

As highlighted above, some additional terms were identified in Session 3, that were specific to feeling comfortable/uncomfortable when driven by AVs. Similar to the results of Session 1, we present the categorisations of these terms, combining the previously suggested terms with those which were newly added (Figure 4.6). We also provide a summary of the experts' discussions about the observed patterns and the commonalities between these additional terms.

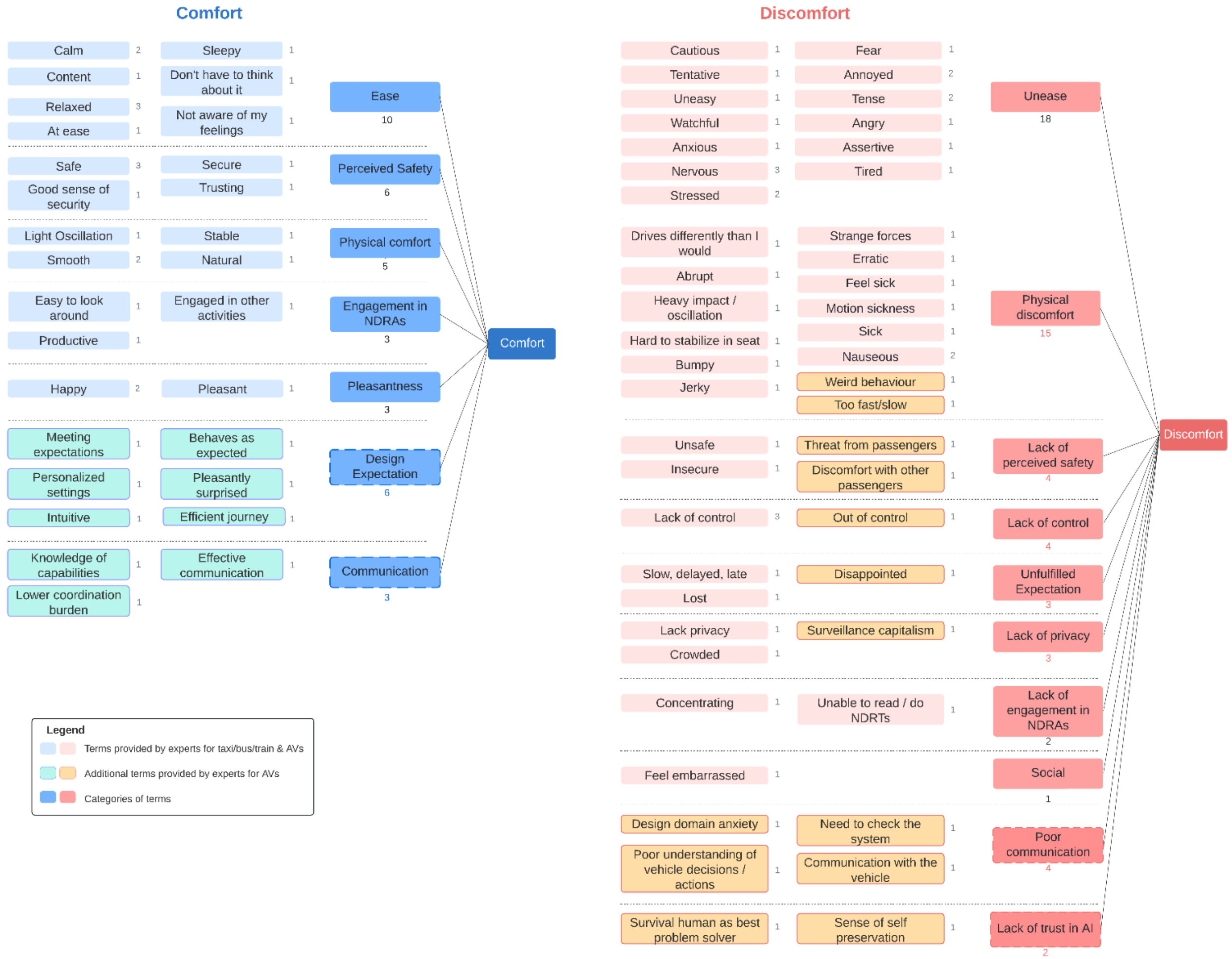


Figure 4.6. Categorisations of terms describing comfort and discomfort of being driven by AVs. Numbers next to each box represent the number of times each term was mentioned by experts, and numbers below each category represent the number of terms in the category.

4.3.2.1. Categorisations of additional terms provided by experts in Session 3

In addition to the five categories of user comfort already defined above (i.e., *ease*, *perceived safety*, *physical comfort*, *engagement in NDRAs*, and *pleasantness*; see also section 4.3.1.1), we identified two more categories for the terms describing a comfortable experience of being driven by an AV: *Design expectation*, and *communication* (Figure 4.6 and Table 4.3).

Table 4.3. The additional categories used for comfort in automated driving

Category	Inclusion of terms	Rationale for category names
Design expectation	This category included terms describing users' high expectations about AVs, and these expectations relate to design aspects of AVs, such as personalisation, being intuitive, and being "pleasantly surprised".	Thematic summary of terms.
Communication	This category included terms describing effective communication between the user and the AV, such as sufficient communication of AV capabilities with users	Thematic summary of terms.

With regards to terms describing an uncomfortable AV ride, several new terms were used that could be added to the existing categories, namely, *physical discomfort*, *lack of perceived safety*, *lack of control*, *unfulfilled expectation*, and *lack of privacy* (see also Figure 4.6). For example, we added the term "*threat from passengers*" to the category "*lack of perceived safety*", because the user may feel unsafe when sharing an AV with strangers, in the absence of a driver (see also section 4.3.1.1). In addition to these categories, we grouped a number of newly added terms into two more categories: *Poor communication*, and *lack of trust in AI* (Table 4.4).

Table 4.4. The additional categories used for discomfort in automated driving.

Categories	Inclusion of terms	Rationales for category names
Poor communication	This category included terms characterising users' poor understanding of the AV capabilities and manoeuvres, and linked to discomfort.	Thematic summary of terms. The opposite to *communication* for comfort.
Lack of trust in AI	This category included two terms describing the reduced trust of users in the automated system, compared to a human driver	Thematic summary of terms.

4.3.2.2. Experts' discussions on emerging patterns from terms for comfort/discomfort of being driven by AVs in Session 3

In Session 3, two experts commented that the *communication* with the AV is an important factor for user comfort, with the lack of communication leading to discomfort. One expert suggested that communication will become more important for users, especially when something unexpected happens. This is because it makes the user uncomfortable, especially if there is no explanation from the AV. However, explicit communication might be unnecessary if the vehicle acts as expected. Another expert added that *interaction* will be needed to improve human-AV communication, such as providing information about what the system is doing, its planned manoeuvres, or a message at the end of the Operational Design Domain (ODD). Moreover, the information provided by the AV system should not be disturbing, and, as an expert suggested, "*I would like to have a choice to select how much information I want to get*". Another type of interaction mentioned was the user's ability to change the settings of the system in certain circumstances. For example: "*for lane changing, if I am not in a hurry, it is totally ok that the AV drives defensively and stays in the same lane, but if I have to reach the destination in a certain time, I may change it to drive more aggressively*".

To summarise, when automated driving was considered (in both Session 2 and 3), further new terms and categories were added, but the number of terms and themes for discomfort was again higher than those provided for comfort. This pattern is in line with findings for currently available vehicles (section 4.3.1), and those of other studies, on ergonomics and product design (Helander & Zhang, 1997; Vink & Hallbeck, 2012). Thus, we suggest that the relationship between comfort and discomfort is not limited within a particular transport mode or a specific product, but applies to a broader area. Moreover, the discussions from Session 2 and 3 suggest that the factors which affect user comfort in currently available transport modes are clearly different to what is expected from automated driving. This suggests that actual experience with future transport modes is needed to further enhance our understanding of how their comfort can be improved, especially with respect to driving style.

4.3.3. Session 4: The refined conceptual framework of user comfort in automated driving

In this section, we present the refined conceptual framework (Figure 4.7), by integrating the outputs from this expert workshop, also following feedback from our experts (Session 4). Experts re-emphasised some concepts that were discussed, but also suggested changes to the original framework. Using this conceptual framework, we explain how driving styles, as well as non-driving-related factors, influence user comfort of AVs. As suggested by the experts, we divided user comfort in automated driving into two layers: The physical layer and the psychological layer, both of which can influence each other in an iterative manner.

Physical factors

Regarding the physical layer, apart from driving styles, one expert emphasised that traditional aspects of the physical environment, such as stabilising the head and body, avoiding high G-force, reducing high levels of vibration/temperature/noise, and considerations about seating comfort, should be thought out for AVs, just as they are for traditional vehicles (see also section 4.3.1). This expert also suggested that although some of these aspects may not actually hurt the user, they will cause strong physical discomfort, and may also affect users' trust and perceived safety. Therefore, we highlighted *physical comfort* as a component of the model, which is directly influenced by AV driving styles.

Psychological factors

Regarding the psychological layer, *psychological comfort* was highlighted in the model, because becoming psychologically comfortable is linked to several positive affective feelings (e.g., happy, content, at ease) (see also section 4.3.1).

A number of factors were considered to contribute to this state of feeling comfortable. In addition to *trust*, *perceived safety,* and *naturalness,* proposed in the original model, the concepts *privacy, engagement in NDRAs, situation awareness,* and *expectation,* were added to the psychological layer. Here, we provide explanations for why and how these concepts fit the framework.

- Regarding *privacy,* although it may be considered somewhat irrelevant to driving styles, it is still an important factor that will ensure user comfort of AVs (as outlined in section 3.2).
- In terms of *engagement in NDRAs,* this can also be influenced by driving styles, when, for example, hard braking patterns impede users' ability to engage in reading. A more comfortable ride encourages engagement in NDRAs, which can, in turn, lead to a content passenger, reducing boredom and increasing enjoyment/productivity. Conversely, experts commented that looking away from the road and engaging in NDRAs may make some users feel sick.

- *Situation awareness* was added to the framework and linked to comfort, as suggested by experts in Session 4. This can be influenced by the AV's driving style (e.g., by providing the user with particular driving kinematic cues to keep them aware of the surrounding environment). Conversely, by allowing users to engage in other tasks, and not paying attention to the driving task, the AV can actually reduce situation awareness.
- With regards to the addition of *expectation* to the model, users are thought to hold a large number of high expectations about AV capabilities and driving styles (e.g., linked to personalisation), and whether or not these expectations can be realised and fulfilled leads to either pleasantness, or disappointment (see also section 3.2). Moreover, we added links between *expectation* and *trust*, *perceived safety*, as well as *naturalness*. For example, by having sufficient communication and interactions with AVs to calibrate users' expectations, their trust and perceived safety of the system might be enhanced. In terms of its link to naturalness, if the AV could drive as expected, users may feel the driving styles are intuitive and natural. One expert also pointed out that *expectation* is heavily featured in the Unified Theory of Acceptance and Use of Technology Model (UTAUT) and the Technology Acceptance Model (TAM), which also supports the importance of taking this concept into consideration.

Factors across the two layers

Experts suggested that the influence of *environmental and traffic* conditions on comfort of AVs is broad and applies to both physical and psychological layers in the framework. This is because the behaviour of the automated vehicle is not independent of the surrounding infrastructural and road geometry, and is likely to be influenced by the behaviour of other road users sharing the same space.

Across the two layers, physical *driving styles* can influence *psychological comfort* directly, not solely because of an enjoyable driving style, but also because being driven by an AV is in a social context, as suggested by experts (see also section 3.1). Other road users will look at the AV, and the way they think about the user can influence the user's wellbeing. For example, an expert explained that the AV user would be embarrassed to be stuck waiting for road obstacles due to the AV's limitations, if all other manually driven cars can pass the obstacle. Another example included the use of ACC: "*I do not use my ACC very often because I have to override it – speed up or change lane. When it strictly follows the speed limit, everyone around me is like going faster than me.*"

Interaction is embedded in the framework on both layers, rather than being an independent concept. As re-emphasised by an expert, users will demand different types of interaction to communicate with the AVs. For example, on the physical level, users may be willing to set up a slower AV driving style for better physical comfort (e.g., avoiding motion sickness). From a psychological perspective, users might expect to have various information about the system to feel secure.

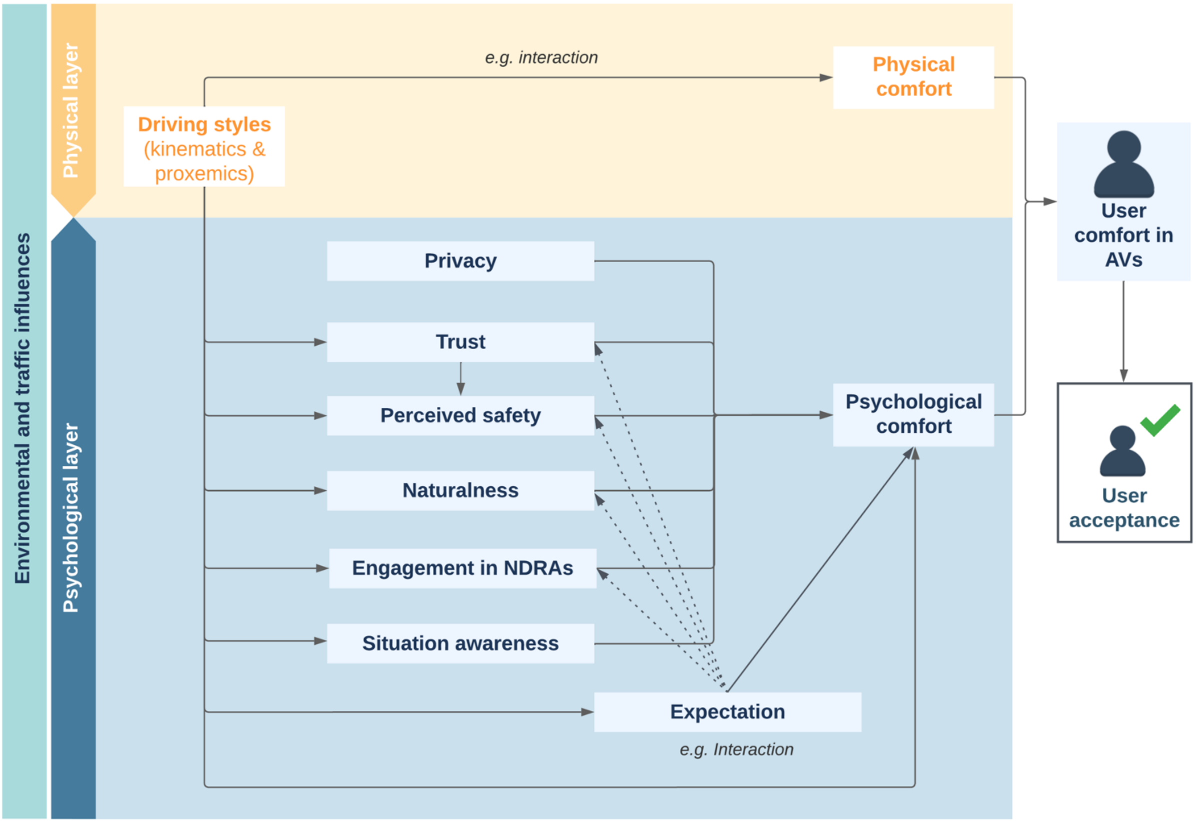


Figure 4.7. The refined conceptual framework of user comfort in automated driving. Arrows represent the direction of the factors, either based on current literature (Section 1.2) or experts' considerations (Section 3.3). Dashed lines are used to ensure relationships are visible when lines intersect with each other.

4.4. General Discussion

In the present study, we used an online workshop to gather experts' insights on user comfort/discomfort when driven by automated vehicles (AVs). Based on the output from the workshop, we refined a conceptual framework of user comfort in automated driving, focusing on the effect of driving styles, but also taking into account the effect of factors not immediately related to driving style. To help discussions, we compared the concepts used for defining comfort and discomfort in current modes of transport where the user is "driven", with that used for AVs.

Our results identified seven aspects of user comfort (Defined as: *ease*, *perceived safety*, *physical comfort*, *engagement in NDRAs*, *pleasantness*, *design expectation*, and *communication*) and ten related to discomfort in automated driving (Defined as: *unease*, *physical discomfort*, *lack of perceived safety*, *lack of control*, *unfulfilled expectation*, *lack of privacy*, *lack of engagement in NDRAs*, *social, poor communication*, and *lack of trust in AI*). For both of these states, more terms were used for AVs, when compared to current modes of transport. When it comes to definitions and measurements of comfort, we recommend that future studies consider a wider range of concepts when assessing comfort and discomfort to help support the research, design and evaluation of these states in AVs. This also calls for new measures, including suitable questionnaires that can be validated in terms of their ability to discriminate a wide range of aspects of comfort and discomfort.

Apart from the content of the workshop, we found that the format of the online setup worked well in this study. By guiding experts to brainstorm, write, and discuss a series of devised topics, we gained clear and novel insights on user comfort/discomfort, such as how these can be described, and the relationship between these two states, to support future studies in this context.

In terms of follow-on work, we suggest a number of possibilities. First, the conceptual framework was developed based on the current literature, and discussions between a group of selected experts, but this needs further examination and validation, based on empirical studies. Second, our results illustrate that comfort is not the opposite of discomfort; since many more terms were used to define the latter. Therefore, further investigations will help identify the best methods for measuring user comfort in automated driving, focusing on how to quantify the relationship between the two states and the underlying aspects. Moreover, it will be valuable to consider the opinions of other, non-experts, for example, members of the general population, and users with mobility challenges (e.g., the elderly and physically impaired people) who are expected to benefit most from such AVs (Milakis et al., 2017; Reimer, 2014). Comparing these findings with our results from experts can provide a more comprehensive understanding of user comfort. Finally, understanding how interactions between the concepts proposed in the model affect comfort/discomfort would be valuable. For example, it would be useful to understand how changes in comfort/discomfort affect users' attention to the ride, and how this then influences their subsequent comfort/discomfort. For example, it can be argued that a higher level of jerk may cause users to disengage from NDRAs and observe the AV's behaviour. This may then lead to a higher level of attention to the ride, enhancing discomfort, which may not be the case if riders continue to be distracted by the NDRA.

In terms of study limitations, the conceptual framework is currently limited by how different factors influence comfort at different timeframes. For example, the impact of driving styles on the ability to engage in NDRAs can be immediate, whereas understanding the influence of trust on comfort may need a longer timeframe, following a period of user interaction and experience with the AV (Hoff & Bashir, 2015). Therefore, further work is required on how these factors influence user comfort over time, with repeated use of AVs. Moreover, to encourage discussions in this workshop, we did not limit debate on how the *type* of automated vehicle might affect comfort. We therefore found that experts mentioned both privately-owned, and shared automated vehicles during the workshop. However, it can be argued that due to some fundamental differences between these two categories of AV, such as the presence of co-passengers or an on-board safety driver, and the pre-planned route of AVs (Wang et al., 2020). Future work should consider how comfort might differ between these two AV categories. Finally, in terms of the variety of experts, while we included individuals from a wide range of areas working on automated vehicles, not all relevant domains were represented. Therefore, future research may benefit by including a wider range of experts, such as policy makers and individuals from standardisation bodies working on implementing AVs.

To conclude, using an expert group workshop, this study discovered a range of aspects of user comfort and discomfort in automated driving. We hope our findings improve the understanding, definitions, and measurements of user comfort in automated driving, and help system designers and manufacturers to design and develop more comfortable, pleasant, and acceptable automated vehicles.

4.5. References

Agbali, M., Trillo, C., Fernando, T., Oyedele, L., Ibrahim, I. A., & Olatunji, V. O. (2019). Towards a Refined Conceptual Framework Model for a Smart and Sustainable City Assessment. *2019 IEEE International Smart Cities Conference (ISC2)*, 658–664. https://doi.org/10.1109/ISC246665.2019.9071697

Ahmadpour, N., Lindgaard, G., Robert, J. M., & Pownall, B. (2014). The thematic structure of passenger comfort experience and its relationship to the context features in the aircraft cabin. In *Ergonomics* (Vol. 57, Issue 6, pp. 801–815). Taylor & Francis. https://doi.org/10.1080/00140139.2014.899632

Ahmadpour, N., Robert, J. M., & Lindgaard, G. (2016). Aircraft passenger comfort experience: Underlying factors and differentiation from discomfort. *Applied Ergonomics*, *52*, 301–308. https://doi.org/10.1016/j.apergo.2015.07.029

Aiken, M., Vanjani, M., & Paolillo, J. (1996). A comparison of two electronic idea generation techniques. *Information & Management*, *30*(2), 91–99. https://doi.org/10.1016/0378-7206(95)00048-8

Basu, C., Yang, Q., Hungerman, D., Singhal, M., & Dragan, A. D. (2017). Do You Want Your Autonomous Car to Drive Like You? *ACM/IEEE International Conference on Human-Robot Interaction*, *Part F1271*, 417–425. https://doi.org/10.1145/2909824.3020250

Beggiato, M., Hartwich, F., & Krems, J. (2019). Physiological correlates of discomfort in automated driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, *66*, 445–458. https://doi.org/10.1016/j.trf.2019.09.018

Beggiato, M., Hartwich, F., Roßner, P., Dettmann, A., Enhuber, S., Pech, T., Gesmann-nuissl, D., Mößner, K., Bullinger, A. C., & Krems, J. (2020). *KomfoPilot—Comfortable Automated Driving*.

Bellem, H., Schönenberg, T., Krems, J. F., & Schrauf, M. (2016). Objective metrics of comfort: Developing a driving style for highly automated vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour, 41*, 45–54. https://doi.org/10.1016/j.trf.2016.05.005

Bellem, H., Thiel, B., Schrauf, M., & Krems, J. F. (2018). Comfort in automated driving: An analysis of preferences for different automated driving styles and their dependence on personality traits. *Transportation Research Part F: Traffic Psychology and Behaviour*, *55*, 90–100. https://doi.org/10.1016/j.trf.2018.02.036

Berg, B. L., & Lune, H. (2017). *Qualitative research methods for the social sciences* (Ninth edition). Pearson.

Bussolon, S., Russi, B., & Del Missier, F. (2006). Online card sorting: As good as the paper version. *ACM International Conference Proceeding Series*, *250*, 113–114. https://doi.org/10.1145/1274892.1274912

Butakov, V., & Ioannou, P. (2015). Driving Autopilot with Personalization Feature for Improved Safety and Comfort. *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, *2015-Octob*, 387–393. https://doi.org/10.1109/ITSC.2015.72

Caretta, M. A., & Vacchelli, E. (2015). Re-Thinking the Boundaries of the Focus Group: A Reflexive Analysis on the Use and Legitimacy of Group Methodologies in Qualitative Research. *Sociological Research Online*, *20*(4), 58–70. https://doi.org/10.5153/sro.3812

Carsten, O., & Martens, M. H. (2018). How can humans understand their automated cars? HMI principles, problems and solutions. *Cognition, Technology and Work*, *21*(1), 3–20. https://doi.org/10.1007/s10111-018-0484-0

Clayphan, A., Kay, J., & Weinberger, A. (2014). ScriptStorm: Scripting to enhance tabletop brainstorming. *Personal and Ubiquitous Computing*, *18*(6), 1433–1453. https://doi.org/10.1007/s00779-013-0746-z

Coenen, M., Stamm, T. A., Stucki, G., & Cieza, A. (2012). Individual interviews and focus groups in patients with rheumatoid arthritis: A comparison of two qualitative methods. *Quality of Life Research*, *21*(2), 359–370. https://doi.org/10.1007/s11136-011-9943-2

Cohen-Lazry, G., Degani, A., Oron-Gilad, T., & Hancock, P. A. (2022). Discomfort: An assessment and a model. *Theoretical Issues in Ergonomics Science*, 1–24. https://doi.org/10.1080/1463922X.2022.2103201

da Silva, M. C. G. (2002). Measurements of comfort in vehicles. *Measurement Science and Technology*, *13*(6). https://doi.org/10.1088/0957-0233/13/6/201

De Looze, M. P., Kuijt-Evers, L. F. M., & Van Dieën, J. (2003). Sitting comfort and discomfort and the relationships with objective measures. *Ergonomics*, *46*(10), 985–997. https://doi.org/10.1080/0014013031000121977

Dettmann, A., Hartwich, F., Roßner, P., Beggiato, M., Felbel, K., Krems, J., & Bullinger, A. C. (2021). Comfort or Not? Automated Driving Style and User Characteristics Causing Human Discomfort in Automated Driving. *International Journal of Human-Computer Interaction*, *37*(4), 331–339. https://doi.org/10.1080/10447318.2020.1860518

Dichabeng, P., Merat, N., & Markkula, G. (2021). Factors that influence the acceptance of future shared automated vehicles – A focus group study with United Kingdom drivers. *Transportation Research Part F: Traffic Psychology and Behaviour*, *82*(December 2020), 121–140. https://doi.org/10.1016/j.trf.2021.08.009

Diels, C., & Bos, J. E. (2015). Self-driving carsickness. *Applied Ergonomics*, *53*, 374–382. https://doi.org/10.1016/j.apergo.2015.09.009

Diels, C., Erol, T., Kukova, M., Wasser, J., Cieslak, M., Miglani, A., Mansfield, N., Hodder, S., & Bos, J. (2017). Designing for Comfort in Shared and Automated Vehicles (SAV): A Conceptual Framework. *Loughborough University Institutional Repository, June*, 1–8.

Duboz, A., Mourtzouchou, A., Grosso, M., Kolarova, V., Cordera, R., Nägele, S., Alonso Raposo, M., Krause, J., Garus, A., Eisenmann, C., dell'Olio, L., Alonso, B., & Ciuffo, B. (2022). Exploring the acceptance of connected and automated vehicles: Focus group discussions with experts and non-experts in transport. *Transportation Research Part F: Traffic Psychology and Behaviour*, *89*, 200–221. https://doi.org/10.1016/j.trf.2022.06.013

Elander, J., West, R., & French, D. (1993). Behavioral Correlates of Individual Differences in Road-Traffic Crash Risk: An Examination of Methods and Findings. *Psychological Bulletin*, *113*(2), 279–294. https://doi.org/10.1037/0033-2909.113.2.279

Elbanhawi, M., Simic, M., & Jazar, R. (2015). In the Passenger Seat: Investigating Ride Comfort Measures in Autonomous Cars. *IEEE Intelligent Transportation Systems Magazine*, *7*(3), 4–17. https://doi.org/10.1109/MITS.2015.2405571

Elliott, P. M., Anastasakis, A., Asimaki, A., Basso, C., Bauce, B., Brooke, M. A., Calkins, H., Corrado, D., Duru, F., Green, K. J., Judge, D. P., Kelsell, D., Lambiase, P. D., McKenna, W. J., Pilichou, K., Protonotarios, A., Saffitz, J. E., Syrris, P., Tandri, H., … van Tintelen, J. P. (2019). Definition and treatment of arrhythmogenic cardiomyopathy: An updated expert panel report. *European Journal of Heart Failure*, *21*(8), 955–964. https://doi.org/10.1002/ejhf.1534

Feierle, A., Danner, S., Steininger, S., & Bengler, K. (2020). Information needs and visual attention during urban, highly automated driving-An investigation of potential influencing factors. *Information (Switzerland)*, *11*(2), 1–17. https://doi.org/10.3390/info11020062

Hagger, M. S., Luszczynska, A., de Wit, J., Benyamini, Y., Burkert, S., Chamberland, P.-E., Chater, A., Dombrowski, S. U., van Dongen, A., French, D. P., Gauchet, A., Hankonen, N., Karekla, M., Kinney, A. Y., Kwasnicka, D., Hing Lo, S., López-Roig, S., Meslot, C., Marques, M. M., … Gollwitzer, P. M. (2016).

Implementation intention and planning interventions in Health Psychology: Recommendations from the Synergy Expert Group for research and practice. *Psychology & Health*, *31*(7), 814–839. https://doi.org/10.1080/08870446.2016.1146719

Hajiseyedjavadi, F., Boer, E. R., Romano, R., Paschalidis, E., Wei, C., Solernou, A., Forster, D., & Merat, N. (2022). Effect of environmental factors and individual differences on subjective evaluation of human-like and conventional automated vehicle controllers. *Transportation Research Part F: Traffic Psychology and Behaviour*, *90*, 1–14. https://doi.org/10.1016/j.trf.2022.07.018

Hancock, P. A., Kajaks, T., Caird, J. K., Chignell, M. H., Mizobuchi, S., Burns, P. C., Feng, J., Fernie, G. R., Lavallière, M., Noy, I. Y., Redelmeier, D. A., & Vrkljan, B. H. (2020). Challenges to Human Drivers in Increasingly Automated Vehicles. *Human Factors*, *62*(2), 310–328. https://doi.org/10.1177/0018720819900402

Hartwich, F., Beggiato, M., & Krems, J. F. (2018). Driving comfort, enjoyment and acceptance of automated driving–effects of drivers' age and driving style familiarity. *Ergonomics*, *61*(8), 1017–1032. https://doi.org/10.1080/00140139.2018.1441448

Hartwich, F., Hollander, C., Johannmeyer, D., & Krems, J. F. (2021). Improving Passenger Experience and Trust in Automated Vehicles Through User-Adaptive HMIs: "The More the Better" Does Not Apply to Everyone. *Frontiers in Human Dynamics*, *3*(June). https://doi.org/10.3389/fhumd.2021.669030

He, X., Stapel, J., Wang, M., & Happee, R. (2022). Modelling perceived risk and trust in driving automation reacting to merging and braking vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, *86*(January), 178–195. https://doi.org/10.1016/j.trf.2022.02.016

Hecht, T., Darlagiannis, E., & Bengler, K. (2019). Non-driving Related Activities in Automated Driving – An Online Survey Investigating User Needs. *International Conference on Human Systems Engineering and Design: Future Trends and Applications*, *1026*, 182–188.

Helander, M. G., & Zhang, L. (1997). *Field studies of comfort and discomfort in sitting*. *0139*(1997). https://doi.org/10.1080/001401397187739

Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human Factors*, *57*(3), 407–434. https://doi.org/10.1177/0018720814547570

Hsieh, H.-F., & Shannon, S. E. (2005). Three Approaches to Qualitative Content Analysis. *Qualitative Health Research*, *15*(9), 1277–1288. https://doi.org/10.1177/1049732305276687

Iliffe, S., De Lepeleire, J., van Hout, H., Kenny, G., Lewis, A., Vernooij-Dassen, M., & The Diadem Group. (2005). Understanding obstacles to the recognition of and response to dementia in different European countries: A modified focus group approach using multinational, multi-disciplinary expert groups. *Aging & Mental Health*, *9*(1), 1–6. https://doi.org/10.1080/13607860412331323791

Kuiper, O. X., Bos, J. E., Schmidt, E. A., Diels, C., & Wolter, S. (2020). Knowing What's Coming: Unpredictable Motion Causes More Motion Sickness. *Human Factors*, *62*(8), 1339–1348. https://doi.org/10.1177/0018720819876139

Kyriakidis, M., de Winter, J. C. F., Stanton, N., Bellet, T., van Arem, B., Brookhuis, K., Martens, M. H., Bengler, K., Andersson, J., Merat, N., Reed, N., Flament, M., Hagenzieker, M., & Happee, R. (2019). A human factors perspective on automated driving. *Theoretical Issues in Ergonomics Science*, *20*(3), 223–249. https://doi.org/10.1080/1463922X.2017.1293187

Lee, J. D., Liu, S. Y., Domeyer, J., & DinparastDjadid, A. (2019). Assessing Drivers' Trust of Automated Vehicle Driving Styles With a Two-Part Mixed Model of Intervention Tendency and Magnitude. *Human Factors*. https://doi.org/10.1177/0018720819880363

Lockton, D., Harrison, D., & Stanton, N. A. (2016). Models of the user: Designers' perspectives on influencing sustainable behaviour. *Annual Review of Policy Design*, *4*(1), Article 1.

Madigan, R., Louw, T., Dziennus, M., Graindorge, T., Ortega, E., Graindorge, M., & Merat, N. (2016). Acceptance of Automated Road Transport Systems (ARTS): An Adaptation of the UTAUT Model. *Transportation Research Procedia*, *14*(0), 2217–2226. https://doi.org/10.1016/j.trpro.2016.05.237

Madigan, R., Louw, T., Wilbrink, M., Schieben, A., & Merat, N. (2017). What influences the decision to use automated public transport? Using UTAUT to understand public acceptance of automated road transport systems. *Transportation Research Part F: Traffic Psychology and Behaviour*, *50*, 55–64. https://doi.org/10.1016/j.trf.2017.07.007

Merat, N., Jamson, A. H., Lai, F. C. H., & Carsten, O. (2012). Highly Automated Driving, Secondary Task Performance, and Driver State. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *54*(5), 762–771. https://doi.org/10.1177/0018720812442087

Merat, N., Seppelt, B., Louw, T., Engström, J., Lee, J. D., Johansson, E., Green, C. A., Katazaki, S., Monk, C., Itoh, M., McGehee, D., Sunda, T., Unoura, K., Victor, T., Schieben, A., & Keinath, A. (2019). The "Out-of-the-Loop" concept in automated driving: Proposed definition, measures and implications. *Cognition, Technology and Work*, *21*(1), 87–98. https://doi.org/10.1007/s10111-018-0525-8

Michinov, N., & Jeanson, S. (2021). Creativity in Scientific Research: Multidisciplinarity Fosters Depth of Ideas Among Scientists in Electronic "Brainwriting" Groups. *Human Factors*, 00187208211048301. https://doi.org/10.1177/00187208211048301

Milakis, D., van Arem, B., & van Wee, B. (2017). Policy and society related implications of automated driving: A review of literature and directions for future research. *Journal of Intelligent Transportation Systems*, *21*(4), 324–348. https://doi.org/10.1080/15472450.2017.1291351

Morgan, D. (1998). *The Focus Group Guidebook*. https://doi.org/10.4135/9781483328164

Motamedi, S., Wang, P., Zhang, T., & Chan, C. Y. (2020). Acceptance of Full Driving Automation: Personally Owned and Shared-Use Concepts. *Human Factors*, *62*(2), 288–309. https://doi.org/10.1177/0018720819870658

Nordhoff, S., de Winter, J., Payre, W., van Arem, B., & Happee, R. (2019). What impressions do users have after a ride in an automated shuttle? An interview study. *Transportation Research Part F: Traffic Psychology and Behaviour*, *63*(May), 252–269. https://doi.org/10.1016/j.trf.2019.04.009

Nordhoff, S., Malmsten, V., van Arem, B., Liu, P., & Happee, R. (2021). A structural equation modeling approach for the acceptance of driverless automated shuttles based on constructs from the Unified Theory of Acceptance and Use of Technology and the Diffusion of Innovation Theory. *Transportation Research Part F: Traffic Psychology and Behaviour*, *78*, 58–73. https://doi.org/10.1016/j.trf.2021.01.001

Nordhoff, S., Stapel, J., He, X., Gentner, A., & Happee, R. (2021). Perceived safety and trust in SAE Level 2 partially automated cars: Results from an online questionnaire. *PLoS ONE*, *16*(12 December), 1–21. https://doi.org/10.1371/journal.pone.0260953

Oborne, D. J. (1978). Passenger comfort—An overview. *Applied Ergonomics*, *9*(3), 131–136. https://doi.org/10.1016/0003-6870(78)90002-9

Oliveira, L., Proctor, K., Burns, C. G., & Birrell, S. (2019). Driving style: How should an automated vehicle behave? *Information (Switzerland)*, *10*(6), 1–20. https://doi.org/10.3390/INFO10060219

Ørngreen, R., & Levinsen, K. (2017). *Workshops as a Research Methodology*. *15*(1), 12.

Paddeu, D., Parkhurst, G., & Shergold, I. (2020). Passenger comfort and trust on first-time use of a shared autonomous shuttle vehicle. *Transportation Research Part C*, *115*(March), 102604. https://doi.org/10.1016/j.trc.2020.02.026

Peng, C., Merat, N., Romano, R., Hajiseyedjavadi, F., Paschalidis, E., Wei, C., Radhakrishnan, V., Solernou, A., Forster, D., & Boer, E. (2022). Drivers' Evaluation of Different Automated Driving Styles: Is It both Comfortable and Natural? *Human Factors*. https://doi.org/10.1177/00187208221113448

Pettit, T. J., Fiksel, J., & Croxton, K. L. (2010). Ensuring Supply Chain Resilience: Development of a Conceptual Framework. *Journal of Business Logistics*, *31*(1), 1–21. https://doi.org/10.1002/j.2158-1592.2010.tb00125.x

Radhakrishnan, V., Merat, N., Louw, T., Lenné, M. G., Romano, R., Paschalidis, E., Hajiseyedjavadi, F., Wei, C., & Boer, E. R. (2020). Measuring drivers' physiological response to different vehicle controllers in highly automated driving (HAD): Opportunities for establishing real-time values of driver discomfort. *Information (Switzerland)*, *11*(8), 1–14. https://doi.org/10.3390/INFO11080390

Reimer, B. (2014). Driver Assistance Systems and the Transition to Automated Vehicles: A Path to Increase Older Adult Safety and Mobility? *Public Policy & Aging Report*, *24*(1), 27–31. https://doi.org/10.1093/ppar/prt006

Rolnick, A., & Lubow, R. E. (1991). Why is the driver rarely motion sick? The role of controllability in motion sickness. *Ergonomics*, *34*(7), 867–879. https://doi.org/10.1080/00140139108964831

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, *39*(6), 1161–1178. https://doi.org/10.1037/h0077714

SAE International. (2021). *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles*.

Schrauf, R. W., & Sanchez, J. (2004). The preponderance of negative emotion words in the emotion lexicon: A cross-generational and cross-linguistic study. *Journal of Multilingual and Multicultural Development*, *25*(2–3), 266–284. https://doi.org/10.1080/01434630408666532

Schwarz, N. (1990). Feelings as information: Informational and motivational functions of affective states. In E. T. Higgins & R. M. Sorrentino (Eds.), *Handbook of motivation and cognition: Foundations of social behavior* (pp. 527–561). The Guilford Press.

Siebert, F. W., Oehl, M., Höger, R., & Pfister, H. R. (2013). Discomfort in Automated Driving—The Disco-Scale. *Communications in Computer and Information Science*, *374*(PART II), 337–341. https://doi.org/10.1007/978-3-642-39476-8_69

Sivak, M., & Schoettle, B. (2015). *Motion sickness in self-driving vehicles* (Issue April). https://deepblue.lib.umich.edu/handle/2027.42/111747

Slater, K. (1985). *Human Comfort* (Vol. 2). Charles C Thomas Pub Ltd. https://doi.org/10.2307/2071632

Stewart, D. W., & Shamdasani, P. N. (2014). *Focus Groups: Theory and Practice*. SAGE Publications.

Summala, H. (2007). Towards Understanding Motivational and Emotional Factors in Driver Behaviour: Comfort Through Satisficin. In *Modelling Driver Behaviour in Automotive Environments: Critical Issues in Driver Interactions with Intelligent Transport Systems* (pp. 189–207). https://doi.org/10.1007/978-1-84628-618-6

Tabone, W., de Winter, J., Ackermann, C., Bärgman, J., Baumann, M., Deb, S., Emmenegger, C., Habibovic, A., Hagenzieker, M., Hancock, P. A., Happee, R., Krems, J., Lee, J. D., Martens, M., Merat, N., Norman, D., Sheridan, T. B., & Stanton, N. A. (2021). Vulnerable road users and the coming wave of automated vehicles: Expert perspectives. *Transportation Research*

Interdisciplinary Perspectives, *9*(October 2020), 100293. https://doi.org/10.1016/j.trip.2020.100293

VanGundy, A. B. (1984). BRAIN WRITING FOR NEW PRODUCT IDEAS: AN ALTERNATIVE TO BRAINSTORMING. *Journal of Consumer Marketing*, *1*(2), 67–74. https://doi.org/10.1108/eb008097

Vink, P., & Hallbeck, S. (2012). Editorial: Comfort and discomfort studies demonstrate the need for a new model. *Applied Ergonomics*, *43*(2), 271–276. https://doi.org/10.1016/j.apergo.2011.06.001

Wang, S., Jiang, Z., Noland, R. B., & Mondschein, A. S. (2020). Attitudes towards privately-owned and shared autonomous vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, *72*, 297–306. https://doi.org/10.1016/j.trf.2020.05.014

Wei, C., Romano, R., Merat, N., Wang, Y., Hu, C., Taghavifar, H., Hajiseyedjavadi, F., & Boer, E. R. (2019). Risk-based autonomous vehicle motion control with considering human driver's behaviour. *Transportation Research Part C: Emerging Technologies*, *107*(August), 1–14. https://doi.org/10.1016/j.trc.2019.08.003

Wilson, C. (2006). Brainstorming pitfalls and best practices. *Interactions*, *13*, 50–63. https://doi.org/10.1145/1151314.11513

CHAPTER 5

Discussions and conclusions

5.1. Summary

User comfort is an important factor in shaping the public acceptance of automated vehicles (AVs). However, existing literature has left unsolved questions as to understanding the complexities of this concept, particularly in terms of its conceptualisation and measurements. It also remains unclear what factors affect comfort in automated driving, from the perspective of the AVs' driving styles. The three papers included in this thesis all revolve around the theme of understanding and improving user comfort in higher-level automated driving, employing either quantitative or qualitative methods.

To address the identified research gaps, this thesis provides empirical evidence on how different driving styles may shape users' evaluations of comfort, and sheds light on the relationship between a range of vehicle metrics and subjective evaluations. The thesis also develops a conceptual framework of user comfort in automated driving, by exploring its intricate definitions and potentially influential factors. Based on the findings, several implications could be made for system designers and future research. These implications aim to assist the development of more comfortable and acceptable AVs. They are also expected to guide clearer definitions and more accurate measurements of the concept of user comfort, thereby facilitating better cross-research comparability in this field. This chapter discusses how the main research questions have been addressed, outlines theoretical, methodological, and practical contributions, and discusses research limitations and recommendations for future research.

5.2. Overview of principal findings

This section revisits the three research questions introduced in Chapter 1, providing an overview of key findings.

- ***RQ 1:** How comfortable and natural do users perceive and evaluate human-like and non-human-like automated driving styles, considering the influences of users' sensation seeking propensities and environmental factors?*

The study in Chapter 2 showed a preference for human-like automated driving styles in terms of comfort and naturalness. This empirical evidence supports the hypothesis that users would like the AV to drive like a human, rather than a machine, in higher-level automated driving (Elbanhawi et al., 2015; Gu & Dolan, 2014). This preference was associated with both the comfortable and natural experiences of users. This work contributes to existing research, particularly on naturalness (or familiarity), as previous research did not establish a clear relationship between naturalness and comfort in terms of driving styles. For example, Yusof et al. (2016) found most participants, including both defensive and assertive drivers, indicated familiarity with and preference for a defensive automated driving style. Hartwich et al. (2018) found the automated replication of users' manual driving only enhanced younger users' experiences rather than older users. In comparison, the study in Chapter 2 provided a clear definition of naturalness for participants and explicitly measured if they felt familiar/natural with the automated driving styles, in addition to the measurement of comfort. With this approach, this study contributes to the understanding that a natural driving style is not necessarily evaluated as comfortable by users. While both are positive experiences, comfort and naturalness can be interpreted and evaluated differently by users. This also highlights that comfort and naturalness should not be used interchangeably. In previous studies, other concepts, like trust, were found to be associated with driving styles in a different way. For example, Price et al. (2016) suggested that a more rigid, machine-like style was evaluated to be more trustful in lower-level automated driving. Oliveira et al. (2019) found no difference in trust between human-like and machine-like behaviours of an AV crossing road junctions. It is uncertain whether our findings, which focus on comfort and naturalness, can be directly compared to other studies, which focus on different concepts, given many variations in factors like levels of automated driving, scenarios, and evaluated concepts. Therefore, understanding the relationships between these different concepts is important, which is one of the motivations for the study in Chapter 4.

While both Defensive and Aggressive human-like driving styles were evaluated as more natural than the machine-like controller, the Defensive driving style was considered the most comfortable one. The preference for defensive driving styles aligns with previous findings (Basu et al., 2017; Rossner & Bullinger, 2020; Yusof et al., 2016). Such preference might be because users, as passive passengers, like AVs to drive cautiously and carefully. This might stem from a desire for safety, which might be prioritised and surpass their manual driving styles. The preference for defensive driving could also be because participants, as novice AV users, are more cautious in novel and unfamiliar situations. However, this conjecture needs further exploration through repeated and long-term exposure to AVs, to understand if user preferences change over time with more experience with AVs.

Apart from the effect of driving styles, the study in Chapter 2 also found that environmental factors affected subjective evaluations. It suggested that both comfort and naturalness evaluations declined, particularly in rural areas with tighter curves and higher posted speed limits. This finding is in line with Hajiseyedjavadi et al. (2022), who found that human-like AV controllers, either faster or slower, were rated as unpleasant for roads with sharp curves. On top of this finding, our study showed that the slower and more cautious Defensive human-like driving style was preferred on these challenging road sections.

Moreover, in less risky road sections with milder curves and lower speed limits, differences in subjective evaluations of AVs' driving styles became less prominent. These observations highlight the importance of considering road geometries and the environment when designing AVs' driving styles. Specific road environments demand more careful manoeuvres from AVs to ensure optimal user experiences. Moreover, when comparing preferences for driving styles across various studies, differences in road environments should be considered. For example, the insignificant differences between trust evaluations for different driving styles reported by Oliveira et al. (2019) might be attributed to the low-risk environment in their study. The low speed of the automated shuttle operating in a warehouse possibly was not challenging enough for participants to exhibit strong preferences.

Regarding individual personality traits, the study in Chapter 2 found that individuals with high sensation seeking tendencies, which potentially involve a preference for novel and intense experiences, evaluated the Aggressive driving style as natural. In other words, they agreed that the faster and more aggressive driving style was similar to their manual driving style. However, this did not translate to increased comfort when being driven by AVs. Instead, they found the slower and more defensive driving style to be more comfortable. Again, this might be associated with the users' role change from active drivers to passive passengers in AVs. The context of this study might have influenced their perceptions. Participants were not instructed to consider urgent travel needs, like being late for an important meeting. In this case, a defensive driving style might have satisfied travel requirements for all participants, regardless of their sensation seeking tendencies. This finding particularly contributes to existing understandings by distinguishing and specifying the two concepts when evaluating preferences for automated driving styles of different user groups.

The study in Chapter 4 expanded on these results and provided more qualitative insights gained from a focus-group-type expert workshop. It highlights that users' expectations from AVs, which evolve with time, are likely to affect their comfort with driving styles. This finding can be relevant to some manufacturers, who may need to reconsider their excessive marketing strategies which overstate capabilities of AVs (Abraham et al., 2017). Overstated advertisements could cause unrealistic expectations for potential users, resulting in disappointment and discomfort once users have the chance to experience AVs (Nordhoff et al., 2019; van Dijk et al., 2003). In addition, Chapter 4 highlighted the importance of non-driving related factors, such as privacy concerns, which could prevent users from feeling comfortable in a well-designed automated ride. This chapter also pointed out the potential benefits of smooth and human-like driving styles, while the extent to which a driving style should be personalised needs further investigation.

The subjective exploration left questions about particular vehicle metrics that contribute to comfortable and natural feelings when users are driven by AV controllers. In Chapter 2, the main focus was on comparing subjective evaluations, with visual inspection into speed and lateral offset. However, the relationship between a more comprehensive set of vehicle metrics and subjective ratings needed more quantified examinations. This question motivated the study presented in Chapter 3.

- ***RQ 2:*** *How do vehicle metrics (i.e., kinematics and proxemics) influence subjective evaluations of automated rides in terms of comfort and naturalness, considering the interplay between an individual's manual driving style and the automated vehicle's driving style?*

This RQ was addressed in Chapter 3, by modelling the effect of various vehicle metrics on subjectively rated comfort and naturalness. This analysis accounted for different driving styles, road features, and individual characteristics by treating these factors as random effects. The study showed a significant influence of lateral and rotational kinematics on both comfort and naturalness evaluations, whereas longitudinal kinematics had a less prominent effect. This might be attributed to the curvy road simulated in this study. While resembling many real road environments in the UK, these roads required frequent lateral adjustments, such as steering, by the AV controllers. The lack of changes in the longitudinal direction (e.g., decelerating due to a cut-in vehicle) might explain why longitudinal kinematics were less important in subjective evaluations. The study in Chapter 3 found that speed and lateral offset were not significantly associated with comfort or naturalness. This contrasts with the speculation based on visual inspection in Chapter 2, which suggested speed was more important than lateral offset in affecting subjective evaluations. This discrepancy might also be because the results in Chapter 3 accounted for variations in road environments and individual characteristics and thus were more accurate. Notably, an exception among these insignificant longitudinal kinematic factors was longitudinal jerk, which positively affected comfort assessments. This is contrary to the general idea of minimising jerk for comfort (Bae et al., 2019; Eriksson & Svensson, 2015) but aligns with a recent study suggesting jerk can be comfortable if of short duration (de Winkel et al., 2023). However, this also brings out a new question about the acceptable duration of such jerk before it becomes uncomfortable.

Moreover, the study in Chapter 3 examined the association between the "human-likeness" of AV's driving styles and user evaluations of comfort and naturalness. Here, human-likeness refers to how close the AV's driving is compared to human driving. Objective similarities between automated and manual driving styles were characterised by calculating Euclidean distances (i.e., the distance between two points) in several vehicle kinematic factors. Objective similarities in specific vehicle metrics, such as speed, longitudinal jerk, lateral offset, and yaw, were found to enhance perceived naturalness and comfort for users. This result extends the finding by Kamaraj et al. (2023), which identified a similar association between the Euclidean distance in speed profiles of two driving styles and users' perceived naturalness. The study in Chapter 3 went beyond just speed, including a broader range of vehicle metrics to assess objective similarities and their link with comfort. In Chapter 3, while most similarities contributed positively, the similarity in lateral jerk was associated with decreased comfort and naturalness, suggesting that not all aspects of mimicking users' manual driving styles are beneficial for user experiences. These findings indicated that aligning certain vehicle metrics, such as speed, with users' manual driving styles can enhance the naturalness and comfort of an automated driving style. However, how the AV's lateral jerk should be set up to ensure user comfort remains unclear.

- ***RQ3:*** *How can a conceptual framework be developed to comprehensively explain the influence of an automated vehicle's driving style on user comfort, by identifying and contrasting terms describing comfort and discomfort, and clarifying the relationships among various related concepts?*

The studies presented in Chapters 2 and 3 highlighted that comfort and naturalness in automated driving were evaluated differently and associated with different vehicle metrics. However, existing literature often uses some of these terms, including comfort and naturalness, interchangeably. Moreover, descriptions of comfort in automated driving are of great variety, indicating a lack of consensus. This is accompanied by the inadequacy of existing conceptual models of comfort, which are insufficient to depict relevant factors and their interrelationships, specifically in automated driving. Taken together, this prompted the development of the qualitative study in Chapter 4, which aimed to clearly define comfort and discomfort, particularly in automated driving. Another aim was to explain how AVs' driving styles affect user comfort, integrating other closely related concepts.

In this study, a wide range of terms were used by experts to describe comfort and discomfort. From these terms, seven aspects were identified as leading to a more comfortable experience in automated driving: *ease*, *perceived safety*, *physical comfort*, *engagement in NDRAs*, *pleasantness*, *design expectation*, and *communication*. Ten aspects were identified as leading to uncomfortable experiences in AVs, including *unease*, *physical discomfort*, *lack of perceived safety*, *lack of control*, *unfulfilled expectation*, *lack of privacy*, *lack of engagement in NDRAs*, *social*, *poor communication*, and *lack of trust in AI*. These aspects expanded upon those for currently available transport modes, such as taxis, buses, and trains, where users do not have control. As more aspects were identified for AVs than existing transport modes, it indicates that improving user comfort and/or mitigating discomfort in AVs is more challenging than in current transport modes. This might be attributed to the novelty of AVs, which leads to more expectations and concerns, as AVs represent an emerging transport mode still under development and testing. Also, the integration of advanced technologies in AVs, such as various sensors, computer algorithms, and AI systems, may introduce additional discomfort. Such discomfort is towards new technologies (e.g., cybersecurity), beyond typical concerns users might have about current transport modes. Therefore, understanding user comfort in AVs requires comprehensive considerations from both transport and technological perspectives.

The relationship between comfort and discomfort has been a long-debated topic in previous research. In Chapter 4, these identified aspects of comfort and discomfort are not always the opposite of each other. For example, the aspect of *pleasantness* for comfort does not have a corresponding one for discomfort, and similarly, the aspect of *lack of privacy* for discomfort has no corresponding one for comfort. This observation suggests that comfort and discomfort are not merely two ends of a spectrum, but rather two states influenced by different factors. While this is in line with Helander & Zhang (1997) in the context of seating comfort, it is in contrast with Ahmadpour et al. (2016), who suggested comfort and discomfort are opposite to each other in the context of aircraft cabins. It might be expected that the experience of riding in an AV is closer to the experience in an aircraft than solely sitting on a chair. However, the comfort-discomfort relationship established in this study inclines toward that based on seating comfort. This might be attributed to the expertise of the participants in our study, who identified more potentially relevant factors with their knowledge and foresight. In comparison, Ahmadpour et al. (2016) relied on ordinary passengers' recall of their recent experiences, which might have overlooked certain factors. This finding suggests the need to consider a range of factors when evaluating the comfort and discomfort in automated driving. For example, the identified aspects of comfort/discomfort can be translated into a checklist for a thorough assessment in AVs, similar to that used to evaluate seating comfort (Helander & Zhang, 1997; Zhang et al., 1996). Moreover, the finding indicates that simply inverting findings based on the measurement of discomfort may not necessarily apply to comfort in automated driving.

The conceptual framework presented in Chapter 4 encompasses various concepts/factors related to comfort based on existing literature and discussion in the expert workshop. The framework divides factors that affect comfort in AVs into physical and psychological layers to provide a more comprehensive overview. The psychological part involves a range of concepts/factors, including trust, perceived safety, naturalness, engagement in NDRAs, situation awareness, expectations, and privacy. While certain factors like trust and perceived safety have been widely investigated in this field, other factors, such as expectations and privacy concerns, have not received as much attention. The concept of situation awareness is usually more associated with lower levels of automated driving (Level 3 and below), where user engagement in the driving process is necessary. However, for higher levels of automated driving, where users are not in control, the optimal degree of situation awareness for ensuring user comfort remains unclear. For example, higher situation awareness might involve awareness of the planned manoeuvres and surroundings, whereas lower situation awareness could be the complete immersion in NDRAs, like watching a film. While the starting point for developing this framework was from the driving style's perspective, it also highlights the importance of non-driving related factors (e.g., privacy concerns) in user comfort. Moreover, the framework points out the importance of social contexts and the ambient environment. In summary, this conceptual framework provides a thorough list of concepts/factors that are potentially related to user comfort, and suggests potential relationships among them. This would encourage more explorations into these concepts, particularly those less examined and their connections. It also calls for empirical research to validate and refine this model by, for example, adding missing concepts to this model, examining the effect of expectations on other concepts, and evaluating the intricate interrelationships among them.

5.3. Contributions

This section highlights the contributions made in this thesis, from theoretical, methodological, and practical perspectives.

5.3.1. Theoretical contributions

For the concept of user comfort in automated driving, the study in Chapter 4 identified a range of aspects underpinning comfort, as well as several aspects of discomfort. These aspects include physical movements, psychological feelings, and social context, particularly in automated driving. To the author's knowledge, this is the first study to systematically propose a detailed range of factors affecting both comfort and discomfort in highly automated driving, at the time of writing this thesis. At the time this study was conducted in 2021, the automated driving company Waymo had just begun offering ride-hailing services to the public in certain areas in the U.S. As access to highly automated driving increases, understanding user comfort needs and accurately measuring comfort in AVs becomes increasingly important. With a comprehensive list of these aspects, characterising comfort and discomfort becomes more concrete. By measuring these aspects, the study offers a method to approximate the comfort and discomfort experienced by users in AVs. In terms of the relationship between comfort and discomfort, the study also suggested that comfort and discomfort are likely to be affected by different factors in automated driving. This finding challenges a common approach of measuring easier-to-detect discomfort and inversely applying the results to comfort in automated driving (e.g., de Winkel et al., 2023). These findings in Chapter 4 are expected to prompt new definitions and methods of measuring comfort and discomfort in this field of automated driving.

Regarding the relationship between comfort and naturalness, the work in Chapter 2 indicates that a natural driving style is *not* necessarily perceived as comfortable by users, particularly for high sensation seekers. Moreover, investigations into vehicle metrics in Chapter 3 suggested that evaluations of comfort and naturalness were not always associated with the same vehicle metrics. This thesis provides more knowledge to the hypothesis by Elbanhawi et al. (2015), who suggested that feeling natural contributes to comfort. Taking these subjective and objective perspectives together, the two concepts should be defined and measured separately in future studies to clarify the relationship between driving styles and intricate subjective perceptions of these driving styles. This thesis extends the findings by Hajiseyedjavadi et al. (2022), who combined measures of comfort and naturalness to represent generally positive and pleasant experiences, as a way to examine user preferences for different automated driving styles. Moreover, by separating measurements of the two concepts, this thesis contributes to further exploration of the mixed results in previous studies regarding the preference for driving styles by certain user groups. For example, the familiar driving style was only preferred by younger, not older, users (Hartwich et al., 2018).

The conceptual framework presented in Chapter 4 highlights several concepts/factors associated with user comfort in automated driving. Some of these concepts are closely related, such as trust and perceived safety, and are often used interchangeably with comfort. Other factors such as expectations, interaction, and situation awareness have not been adequately explored in terms of their relationship with user comfort in highly automated driving. The framework suggests potential relationships among them and how these factors are associated with comfort, which could encourage further research to provide empirical evidence examining their relationships. This in turn would enhance our understanding of these intricate concepts. This framework provides a comprehensive view of user comfort in automated driving, by considering the specific context of highly automated driving, such as driving styles, traffic influences, and privacy considerations. In comparison, existing conceptual frameworks for comfort in the literature have limitations. For example, the model proposed by Ahmadpour et al. (2016) focuses on passenger comfort in the aircraft cabin. While it includes a wide range of factors, its applicability to highly automated driving is limited due to differences in these two transport modes and operating environments. Other models that consider the context of automated driving, such as those proposed by Cohen-Lazry et al. (2022), Diels et al. (2017), and Elbanhawi et al. (2015), fail to adequately consider all relevant factors and/or their relationships. Beyond an AV's driving styles, the framework also contributes to the consideration of Human-Artificial Intelligence (AI) interaction in the context of automated driving. With the rapid growth of AI and the potential replacement of drivers with AI systems in higher-level AVs, factors like trust in AI, privacy concerns, and communications between the automated system and users are likely to affect user comfort. These factors likely support the application of Explainable AI in automated driving. This ensures the decisions, predictions, and actions made by the AI system are transparent, understandable, and interpretable by users (Atakishiyev et al., 2021). For example, providing such communications to inform users of upcoming manoeuvres may enhance their comfort.

A new definition for user comfort in automated driving can be proposed based on the study in Chapter 4:

> *In automated driving, user comfort is a state involving subjective feelings of ease and pleasantness, and the mere elimination of discomfort is not enough to ensure user comfort in automated vehicles (AVs). Comfort in AVs has both physical and psychological dimensions, which affect each other. Physical comfort is influenced by factors such as the AV's interior environment (e.g., temperature, seat design) and its interaction with the external environment (e.g., G-force, vehicle stability). Psychological comfort is associated with factors such as situation awareness, trust, perceived safety, and perceived naturalness of driving styles. User comfort is a dynamic concept, evolving in response to users' expectations, their communication with automated vehicles, and the varying environmental and traffic conditions. When in a comfortable state, users are more likely to engage in non-driving-related activities in AVs.*

Previous studies (e.g., Bellem et al., 2016; Carsten & Martens et al., 2018; Hartwich et al., 2018; Wasser et al., 2017) provide definitions with significant variations (see also discussions in Chapter 1.3.1). First, these definitions often use terms like uneasiness and stress interchangeably, despite differences in the intensity of feelings they characterise. Second, physical, physiological, and psychological factors that affect comfort are often mentioned briefly and in combination, lacking specification. Third, previous definitions are mostly vague about how user comfort originates from interactions with AVs. In comparison, the new definition proposed in this thesis provides a comprehensive description of user comfort, including detailed subjective feelings and a range of physical and psychological factors, considering the context of automated driving in particular. It highlights the dynamic nature of comfort and its association with individual and environmental features. Moreover, it suggests a relationship between comfort and discomfort, a relationship that has been in debate for a long time. By providing this detailed definition, it is hoped to enhance the development of accurate measurement for user comfort and facilitate cross-study comparisons.

5.3.2. Methodological contributions

Studies in Chapters 2 and 3 applied statistical approaches from various perspectives to understand both subjective evaluations and their relationships with objective metrics in automated driving. This combination is particularly useful in the design of human-like or personalised driving styles for AVs. In this domain, a repeated measures design is commonly used, involving multiple evaluations from the same participant in a single ride. Such experimental design potentially results in correlations between responses. The implementation of more naturalistic driving scenarios may also introduce imbalances in study designs. In this case, traditional approaches, such as the linear regression model based on ordinary least squares (OLS), are constrained by several assumptions, specific data structures, missing data, and complex experimental designs, which can undermine the reliability of results. Thus, the Generalised Estimating Equation (GEE) model was used to compare subjective evaluations, considering the effects of environment and personality traits. The GEE model addressed correlated data, as evaluations of each controller were provided by the same participant and provided population-averaged estimates (i.e., how comfortable and natural the different driving styles were generally perceived) (Liang & Zeger, 1986). On the other hand, the Mixed Effect Model (MEM) was selected for its capability to handle both fixed and random effects (Bates et al., 2014). MEM was used to investigate the effect of driving style characteristics on subjective evaluations, and how individuals' own driving styles affect their evaluations of AVs' driving styles. MEM accounted for repeated measures from the same participant for each automated ride, by treating these variabilities as random effects. This thesis combined both the population-average insights based on GEE and the individual-level findings based on MEM, to provide a more comprehensive understanding.

This thesis integrated views from both users and experts to broaden the understanding of comfort in higher-level automated driving. The simulator study in Chapters 2 and 3 focused on users with different risk-taking personality traits and gathered practical insights into their perception and evaluations of automated driving styles. However, such a short-term experimental exposure to automated driving was considered inadequate to understand more real-world factors and influences. Thus, the expert workshop was designed to further explore the specialised knowledge of experts. Considering that higher-level AVs are not widely available to the public yet, the knowledge and foresight from experts, derived from their hands-on experiences with advanced AV prototypes were crucial. The expert workshop employed a mixture of focus group, brainstorming, note-writing, and card-sorting techniques to stimulate in-depth discussions effectively in a relatively short duration. Future studies in this area could adopt a similar approach by combining experimental studies and qualitative queries, as well as combining user and expert perspectives. This could provide more comprehensive insights for understanding user experiences that rely on actual, and long-term, usage of technologies. This is particularly valuable for technologies that are still in development or in the early adoption stage.

In exploring methodologies for measuring user experiences in automated driving, the candidate compared two methodologies (Peng, Hajiseyedjavadi, et al., 2022, not included in the thesis). The two methodologies were employed in two separate studies which were both conducted as part of the UK-funded HumanDrive project. The first methodology, used by Hajiseyedjavadi et al. (2022), required participants to press one of the two buttons on a handset to indicate if they felt comfortable/safe/natural along the automated ride. Note that this evaluation combined three concepts. The second methodology, used in Chapters 2 and 3, involved participants speaking ratings out at certain points along the automated ride. They used an 11-point Likert scale to evaluate either comfort or naturalness. The candidate collaborated with Hajiseyedjavadi, with the help of the principal investigator of the HumanDrive project (Prof Natasha Merat), to review data from the two separate studies for this comparison. Both methodologies allow real-time evaluations in automated driving, which is necessary for capturing the effect of vehicle motion and varying road conditions. The comparison suggested that the Likert scale, with its multiple response options, is useful for identifying subtle differences in user perceptions. On the other hand, the binary button-pressing technique was found to be useful in its simplicity and the freedom it allows users to rate their experiences as often as desired. It is challenging to compare studies with different experimental designs and experiments; however, summarising the experience from systematic practice and providing suggestions for methodology selection is hoped to help future studies, especially in this under-explored area. This comparison provided insights for research in selecting the most suitable methodology for measuring subjective user experiences in automated driving.

5.3.3. Practical contributions and design implications

This thesis highlights the importance of designing adaptive AV driving styles to cater to different groups of users' preferences and various road environments. The study in Chapter 2 suggested that a generally defensive human-like driving style could be a suitable default setting. As discussed in Chapter 4, users may wish to adjust the driving style in specific situations, such as being late for an appointment and encountering traffic jams. While how much input users can put into higher-level automated driving is not clear, such adjustment can contribute to consistent user comfort along the trip. The study in Chapter 3 provided further suggestions regarding vehicle metrics. For example, lateral and rotational metrics play a key role in comfort and naturalness and should be carefully configured. Taking users' manual driving style into account, a human-like or personalised automated driving style could be designed to match certain vehicle metrics in their manual driving, such as speed, longitudinal jerk, and yaw, to ensure the AV ride is natural and comfortable.

Higher-level AVs do not require user intervention, but it does not mean users do not want to know what the AV is doing. The work in Chapter 4 suggested that providing effective and intuitive communications with the AV is likely to improve user comfort, especially in the early deployment phase. The communication content could make the decision-making of the AV transparent to users, by providing information about, for example, the planned manoeuvres. This can also enhance the predictability of the AV's behaviour and further improve user comfort. This thesis points out the potential of using vehicle kinematics to convey certain information without negatively affecting users' comfortable experience. As found in Chapter 3 and perhaps counterintuitively, a larger longitudinal jerk can be more comfortable, and thus has the potential to be adapted to communicate a vehicle's intention both internally and externally. This approach aligns with the concept of "dynamic HMI (dHMI)" (Bengler et al., 2020). The concept of dHMI aims to inform internal users without disrupting their riding experiences or engagement in NDRAs, as well as inform the AV's intention to external road users. However, existing research employing dHMIs in AVs focuses on how other road users, like drivers in manually driven vehicles, feel about and how they react to AVs (Li et al., 2023; Zgonnikov et al., 2023). These studies often overlook whether users inside the AV feel comfortable when the vehicle performs specific movements as dHMIs. This thesis points out the need for further investigation into onboard users' comfort.

Work in Chapter 4 suggested that a higher level of user comfort in an AV does not solely result from well-designed driving styles; it is also associated with the social context of the ride. For example, users do not wish to feel embarrassed in the AV when using AVs in a public environment. Thus, designers are encouraged to take social context considerations into AV development. For example, in terms of driving styles, social norms can be considered, by ensuring AVs adhere to traffic rules and maintain a respectful distance from other road users. Implementing pro-social behaviours in AVs, where the vehicle acts in a way that benefits others (Larsson et al., 2021; Sahin et al., 2021), might address the comfort concerns in social contexts, particularly in mixed traffic. Beyond driving style implementations, education can be utilised to facilitate the public acceptability of AV usage. Here, acceptability refers to the prospective attitude of users about AVs without actual experience or exposure to them (Merat et al., 2017; Schade & Schlag, 2003). Thus, public acceptability implies that individuals would accept others using AVs even if they are not necessarily AV users. This could contribute to the social environment where users are less likely to feel embarrassed and hesitant to take AV rides.

5.4. Reflections on research limitations

This thesis contributes to the current knowledge of user comfort, with a particular focus on driving styles in automated driving. However, it is important to acknowledge certain limitations for future studies to address.

While the findings from this thesis provide valuable insights, the generalisation might be constrained by the scenarios employed and driving styles compared in Chapters 2 and 3. First, the free-driving scenarios represent less complicated contexts than the varied and often more challenging real-world scenarios, where multiple interactions with other objects, such as car-following, merging, and intersection negotiation, are frequent. Real-world scenarios, especially in mixed traffic with both human-driven vehicles and AVs of different levels operating on the same road, introduce more uncertainties. These scenarios require distinct driving styles that could subsequently affect onboard users' comfort. Second, it is crucial to consider more complicated scenarios because users tend to judge the AV according to its performance in challenging situations. This judgement could further affect their experiences, such as trust and comfort (Peng et al., 2023). Third, a more enriched scenario will also result in a more comprehensive set of vehicle metrics (e.g., time to collision with regards to pedestrians) to investigate its impact on comfort. Fourth, the driving styles in this thesis might not cover the full range of capabilities expected in future AVs. For example, more dynamic driving styles that adapt to varying road conditions might be evaluated differently compared to the more consistent ones. Finally, variations in traffic rules and driving cultures across different countries could also limit the generalisation of these findings to global contexts.

The expert workshop in Chapter 4 provided qualitative insights into user comfort. However, this approach lacked diverse perspectives from a broader range of general users, such as older adults and individuals with mobility challenges. These groups might have specific needs. For example, in terms of physical comfort, older users might be more sensitive and vulnerable to environmental factors, such as G-forces and noises (Anderson & Gagn, 2011; Piirtola & Era, 2006). In terms of psychological comfort, these users are likely to have different expectations about automated driving (e.g., accessibility), which will further affect their experiences if these expectations are not met. Considering the potential benefit of driving automation for enhancing mobility in these user groups, incorporating their insights and needs in future research will be essential.

5.5. Recommendations for future research

This section suggests potential directions for future research based on the findings of this thesis.

First, the studies reported in this thesis primarily focus on short-term user experiences with AVs. However, when it comes to the long-term usage of AVs in the future, a new question emerges: Will users demand increased comfort over time, or will they adapt to the technology and tolerate more discomfort? Future research could investigate how user behaviours, attitudes, and feelings towards AVs evolve over time and through more interactions with AVs. This adaptation to AVs, including its driving styles, might play a role in various concepts beyond comfort, such as trust and acceptance.

Second, future studies should address the generalisability of users' comfort needs to populations with different backgrounds. One focus should be directed towards more vulnerable populations who are likely to benefit more from automated driving, such as the elderly, people with mobility issues, children, and young parents with toddlers. This emphasises the need for inclusive designs that consider not only driving styles but also the interior and exterior vehicle features (e.g., accessible entrances). Moreover, understanding how user expectations vary across cultures and nations is important to enhance the broad acceptance of automated driving. In addition, the term "user" can be used to describe more than passengers in future AVs. Remote operators who are not physically present in the vehicle and safety drivers who are responsible for certain safety-critical events will also be "users" of AVs in a broad sense. In the meanwhile, the variety in the types of AVs, such as private cars, shared taxis, and shuttles, can also make a difference in these users' experiences. The comfort requirements of users in these AVs, in a broader sense, still need further investigation.

Third, this thesis examined the relationship between a range of vehicle metrics and subjectively evaluated comfort, which also left unanswered questions. Further investigations are needed to quantify the subtle influences of various metrics, which can occasionally be contradictory to each other, on user comfort. More advanced modelling methods might be useful to capture the interplay between these vehicle metrics and various user experiences across multiple scenarios. Moreover, for each of impactful metric, investigating the comfort thresholds in different contexts would provide more practical guidelines for system designers and manufacturers.

Finally, understanding what “being in a social context” means for AV users is another key area for future research. A potential direction is exploring the impact of integrating AVs into urban traffic and public transport systems. This can include various types of AVs, such as taxis and buses, which might be different from private cars due to the nature of sharing space with other passengers and no responsibility to control the vehicle. Users may have other specific comfort needs in these AVs. Research could also investigate how the social image of AV usage affects user comfort, for example, whether AVs are considered safe for other road users, and if using AVs is considered a sustainable way of travelling.

5.6. References

Abraham, H., Seppelt, B., Mehler, B., & Reimer, B. (2017). What's in a Name: Vehicle Technology Branding & Consumer Expectations for Automation. *Proceedings of the 9th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 226–234. https://doi.org/10.1145/3122986.3123018

Ahmadpour, N., Robert, J. M., & Lindgaard, G. (2016). Aircraft passenger comfort experience: Underlying factors and differentiation from discomfort. *Applied Ergonomics*, *52*, 301–308. https://doi.org/10.1016/j.apergo.2015.07.029

Anderson, G. P., & Gagn, é J.-P. (2011). Older Adults Expend More Listening Effort Than Young Adults Recognizing Speech in Noise. *Journal of Speech, Language, and Hearing Research*, *54*(3), 944–958. https://doi.org/10.1044/1092-4388(2010/10-0069)

Atakishiyev, S., Salameh, M., Yao, H., & Goebel, R. (2021, December 21). *Explainable Artificial Intelligence for Autonomous Driving: A Comprehensive Overview and Field Guide for Future Research Directions*. arXiv.Org. https://arxiv.org/abs/2112.11561v3

Bae, I., Moon, J., & Seo, J. (2019). Toward a comfortable driving experience for a self-driving shuttle bus. *Electronics (Switzerland)*, *8*(9), 1–13. https://doi.org/10.3390/electronics8090943

Basu, C., Yang, Q., Hungerman, D., Singhal, M., & Dragan, A. D. (2017). Do You Want Your Autonomous Car to Drive Like You? *ACM/IEEE International Conference on Human-Robot Interaction, Part F1271*, 417–425. https://doi.org/10.1145/2909824.3020250

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2014). *Fitting Linear Mixed-Effects Models using lme4* (arXiv:1406.5823). arXiv. https://doi.org/10.48550/arXiv.1406.5823

Wasser, J., Diels, C., Baxendale, A., & Tovey, M. (2017). Driverless pods: From technology demonstrators to desirable mobility solutions. In N. Stanton (Ed.), *Advances in Human Aspects of Transportation. AHFE 2017. Advances in Intelligent Systems and Computing* (Vol. 597, pp. 538–550). Springer, Cham. https://doi.org/10.1007/978-3-319-60441-1_53

Bengler, K., Rettenmaier, M., Fritz, N., & Feierle, A. (2020). From HMI to HMIs: Towards an HMI framework for automated driving. *Information (Switzerland)*, *11*(2). https://doi.org/10.3390/info11020061

Carsten, O., & Martens, M. H. (2018). How can humans understand their automated cars? HMI principles, problems and solutions. *Cognition, Technology and Work*, *21*(1), 3–20. https://doi.org/10.1007/s10111-018-0484-0

Cohen-Lazry, G., Degani, A., Oron-Gilad, T., & Hancock, P. A. (2022). Discomfort: An assessment and a model. *Theoretical Issues in Ergonomics Science*, 1–24. https://doi.org/10.1080/1463922X.2022.2103201

de Winkel, K., Irmak, T., Happee, R., & Shyrokau, B. (2023). Standards for passenger comfort in automated vehicles: Acceleration and jerk. *Applied Ergonomics*, *106*(103881). https://doi.org/10.1016/j.apergo.2022.103881

Diels, C., Erol, T., Kukova, M., Wasser, J., Cieslak, M., Miglani, A., Mansfield, N., Hodder, S., & Bos, J. (2017). Designing for Comfort in Shared and Automated Vehicles (SAV): A Conceptual Framework. *Loughborough University Institutional Repository*, *June*, 1–8.

Elbanhawi, M., Simic, M., & Jazar, R. (2015). In the Passenger Seat: Investigating Ride Comfort Measures in Autonomous Cars. *IEEE Intelligent Transportation Systems Magazine*, 7(3), 4–17. https://doi.org/10.1109/MITS.2015.2405571

Eriksson, J., & Svensson, L. (2015). Tuning for Ride Quality in Autonomous Vehicle Application to Linear Quadratic Path Planning Algorithm. In *Master Thesis, Uppsala Universitet*. http://www.teknat.uu.se/student

Gu, T., & Dolan, J. M. (2014). Toward human-like motion planning in urban environments. *2014 IEEE Intelligent Vehicles Symposium Proceedings*, 350–355. https://doi.org/10.1109/IVS.2014.6856493

Hajiseyedjavadi, F., Boer, E. R., Romano, R., Paschalidis, E., Wei, C., Solernou, A., Forster, D., & Merat, N. (2022). Effect of environmental factors and individual differences on subjective evaluation of human-like and conventional automated vehicle controllers. *Transportation Research Part F: Traffic Psychology and Behaviour*, *90*, 1–14. https://doi.org/10.1016/j.trf.2022.07.018

Hartwich, F., Beggiato, M., & Krems, J. F. (2018). Driving comfort, enjoyment and acceptance of automated driving–effects of drivers' age and driving style familiarity. *Ergonomics*, *61*(8), 1017–1032. https://doi.org/10.1080/00140139.2018.1441448

Helander, M. G., & Zhang, L. (1997). *Field studies of comfort and discomfort in sitting*. *0139*(1997). https://doi.org/10.1080/001401397187739

Kamaraj, A. V., Lee, J., Domeyer, J. E., Liu, S.-Y., & Lee, J. D. (2023). Comparing Subjective Similarity of Automated Driving Styles to Objective Distance-Based Similarity. *Human Factors*, 00187208221142126. https://doi.org/10.1177/00187208221142126

Larsson, J., Keskin, M. F., Peng, B., Kulcsár, B., & Wymeersch, H. (2021). Pro-social control of connected automated vehicles in mixed-autonomy multi-lane highway traffic. *Communications in Transportation Research*, *1*, 100019. https://doi.org/10.1016/j.commtr.2021.100019

Li, Y., Lee, Y. M., Yang, Y., Tian, K., Daly, M., Horrobin, A., Solernou, A., & Merat, N. (2023). Do Drivers have Preconceived Ideas about an Automated Vehicle's Driving Behaviour? *Proceedings of the 15th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 291–299. https://doi.org/10.1145/3580585.3607155

Liang, K. Y., & Zeger, S. L. (1986). Longitudinal data analysis using generalized linear models. *Biometrika*, *73*(1), 13–22. https://doi.org/10.1093/biomet/73.1.13

Merat, N., Madigan, R., & Nordhoff, S. (2017). Human Factors, User Requirements, and User Acceptance of Ride-Sharing in Automated Vehicles. *International Transport Forum*, *10*(February), 1–30.

Nordhoff, S., de Winter, J., Payre, W., van Arem, B., & Happee, R. (2019). What impressions do users have after a ride in an automated shuttle? An interview study. *Transportation Research Part F: Traffic Psychology and Behaviour*, *63*(May), 252–269. https://doi.org/10.1016/j.trf.2019.04.009

Oliveira, L., Proctor, K., Burns, C. G., & Birrell, S. (2019). Driving style: How should an automated vehicle behave? *Information (Switzerland)*, *10*(6), 1–20. https://doi.org/10.3390/INFO10060219

Peng, C., Hajiseyedjavadi, F., & Merat, N. (2022). A comparison of two methodologies for subjective evaluation of comfort in automated vehicles. *12th International Conference on Methods and Techniques in Behavioral Research and 6th Seminar on Behavioral Methods*, *May*, 192–199. https://doi.org/10.6084/m9.figshare.20066849.v1

Peng, C., Öztürk, İ., Nordhoff, S., Madigan, R., Hoogendoorn-Lanser, S., Hagenzieker, M., & Merat, N. (2023). *Exploring user comfort in automated driving: A qualitative study with younger and older users using the Wizard-Of-Oz method*. 15th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI ’23 Adjunct), ngolstadt, Germany. https://doi.org/10.1145/3581961.3609853

Piirtola, M., & Era, P. (2006). Force Platform Measurements as Predictors of Falls among Older People – A Review. *Gerontology*, *52*(1), 1–16. https://doi.org/10.1159/000089820

Price, M., Venkatraman, V., Gibson, M., Lee, J., & Mutlu, B. (2016). Psychophysics of Trust in Vehicle Control Algorithms. *SAE Technical Papers*. https://doi.org/10.4271/2016-01-0144

Rossner, P., & Bullinger, A. C. (2020). How Do You Want to be Driven? Investigation of Different Highly-Automated Driving Styles on a Highway Scenario. *Advances in Intelligent Systems and Computing*, *964*, 36–43. https://doi.org/10.1007/978-3-030-20503-4_4

Sahin, H., Mueller, H., Sadeghian, S., Dey, D., Löcken, A., Matviienko, A., Colley, M., Habibovic, A., & Wintersberger, P. (2021). Workshop on Prosocial Behavior in Future Mixed Traffic. *13th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 167–170. https://doi.org/10.1145/3473682.3477438

Schade, J., & Schlag, B. (2003). Acceptability of Transport Pricing Strategies: An Introduction. In J. Schade & B. Schlag (Eds.), *Acceptability of Transport Pricing Strategies* (pp. 1–9). Emerald Group Publishing Limited. https://doi.org/10.1108/9781786359506-001

van Dijk, W. W., Zeelenberg, M., & van der Pligt, J. (2003). Blessed are those who expect nothing: Lowering expectations as a way of avoiding disappointment. *Journal of Economic Psychology*, *24*(4), 505–516. https://doi.org/10.1016/S0167-4870(02)00211-8

Wasser, J., Diels, C., Baxendale, A., & Tovey, M. (2017). Driverless pods: From technology demonstrators to desirable mobility solutions. In N. Stanton (Ed.), *Advances in Human Aspects of Transportation. AHFE 2017. Advances in Intelligent Systems and Computing* (Vol. 597, pp. 538–550). Springer, Cham. https://doi.org/10.1007/978-3-319-60441-1_53

Yusof, N. M., Karjanto, J., Terken, J., Delbressine, F., Hassan, M. Z., & Rauterberg, M. (2016). The exploration of autonomous vehicle driving styles: Preferred longitudinal, lateral, and vertical accelerations. *AutomotiveUI 2016 - 8th International Conference on Automotive User Interfaces and Interactive*

Vehicular Applications, Proceedings, 245–252. https://doi.org/10.1145/3003715.3005455

Zgonnikov, A., Beckers, N., George, A., Abbink, D., & Jonker, C. (2023). *Subtle motion cues by automated vehicles can nudge human drivers' decisions: Empirical evidence and computational cognitive model*. https://doi.org/10.31234/osf.io/3cu8b

Zhang, L., Helander, M. G., & Drury, C. G. (1996). Identifying Factors of Comfort and Discomfort in Sitting. *Human Factors*, *38*(3), 377–389. https://doi.org/10.1518/001872096778701962

APPENDIX TO CHAPTER 2

Appendix 1 - Cluster analysis for categorising driving behaviour

From a previous study of the project, driving behaviours were collected from a sharp curve (radius < 150m), a zone with parked cars (length = 162.68m), and the entire drive. The variables used as behavioural indicators for clustering were: root mean square of speed, standard deviation of longitudinal acceleration, and standard deviation of yaw rate. The k-means clustering analysis was conducted.

Appendix 2 - Configuration of the GEE model

The working correlation matrix was specified as *exchangeable*, which characterises the correlation structure of multiple observations within a participant as the same. As the comfort and naturalness were rated using an ordinal Eleven-point Likert scale, the distribution of the dependent variable was specified as a *multinomial* distribution. A link function is used to characterise the relationship between the mean of the response (i.e., subjective ratings) and the linear predictor (i.e., controllers). The *ordered logit regression* was specified as the link function.

However, in some Village road segments, including the Straight road sections, the 200-300 Radius sections, and the 150-200 Radius sections, the statistical model did not provide valid results, because the participants' responses to the three controllers in these sections showed very similar patterns, which resulted in collinearity. For example, in the Curve Radius 150-200 section, most responses clustered between 2 to 5 for all three driving styles. Therefore, we treated the data as continuous in these road sections, to allow statistical comparisons. The distribution was specified as normal in the GEE.

Appendix 3 - Vehicle kinematics inspection for the two village road sections with unexpected assessments

Inspection of the vehicle-based metrics for these two particular road sections (Figure 6.1) showed that the Aggressive controller's speed was markedly higher than that of the two other controllers in the 300-800 Radius section, and higher than the designated speed limit of 30 mph. A sudden fluctuation of speed for the Turner controller was also seen in the 200-300 Radius section, although it was within the speed limit of 40 mph. Further inspection of the simulated scene did not show the presence of any unusually placed road furniture, such as parked cars. A possible explanation here is that the Turner controller did not look far enough ahead to smooth out the speed changes, and was also inadequately sensitive to roadside furniture. Regardless, these results show that the effect of these kinematic changes were clearly felt by our users, which can possibly explain their evaluation of the controllers for these two sections.

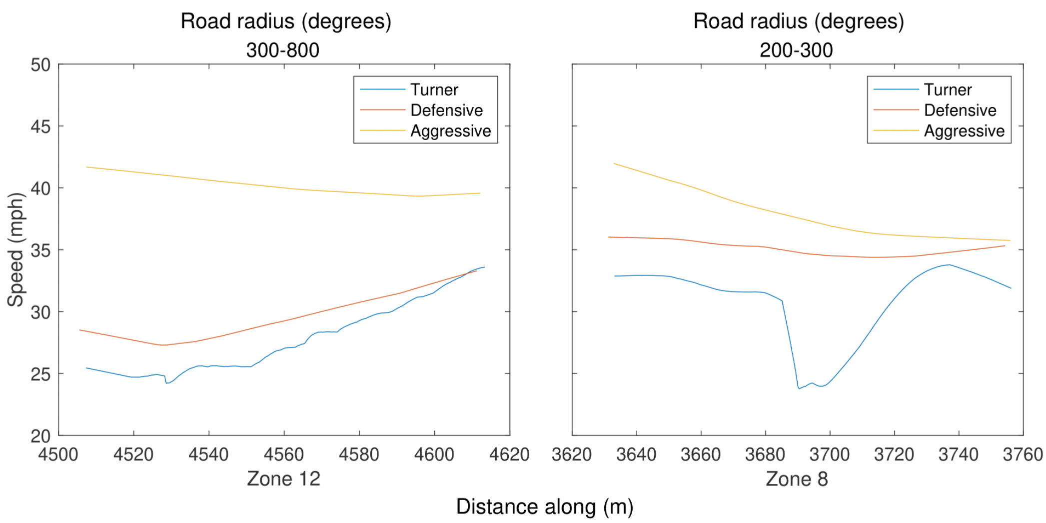


Figure 6.1. Vehicle speed of three controllers in the two village road curves

APPENDIX TO CHAPTER 3

According to Abe (2009), the equations of vehicle motion, based on fixed coordinates on the vehicle, are illustrated below.

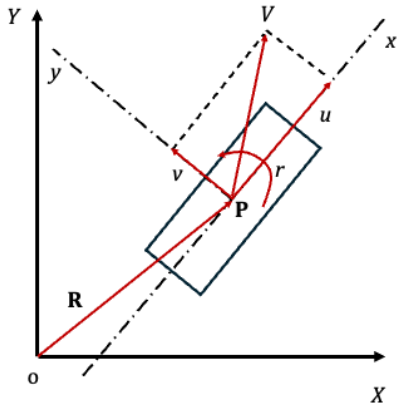


Figure 7.1. Coordinate axes for vehicle plane motion. Redrawn from Abe (2009).

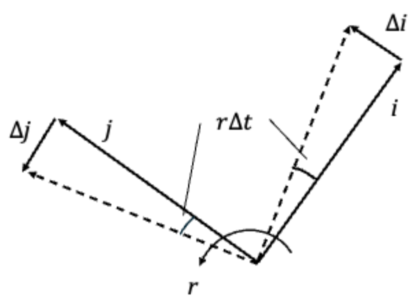


Figure 7.2. Time derivative of unit vectors. Redrawn from Abe (2009).

$X - Y$ represent the fixed plane coordinates on the ground, while $x - y$ represent the fixed coordinates on the vehicle, with x in the longitudinal direction and y in the lateral direction. P represents the vehicle's centre of gravity. $\boldsymbol{R}$ is the position vector of point P relative to the $X - Y$ coordinate system.

The velocity vector $\dot{\boldsymbol{R}}$ can be written as

APPENDIX TO CHAPTER 3

$$\dot{\boldsymbol{R}} = u\boldsymbol{i} + v\boldsymbol{j} \qquad \text{Equation 1}$$

Here, $\boldsymbol{i}$ and $\boldsymbol{j}$ denote the unit vectors in x and y directions, respectively. u and v refer to the velocity components of point P in the x and y directions, respectively.

Acceleration vector is calculated by differentiating equation 1:

$$\ddot{\boldsymbol{R}} = \dot{u}\boldsymbol{i} + u\dot{\boldsymbol{i}} + \dot{v}\boldsymbol{j} + v\dot{\boldsymbol{j}} \qquad \text{Equation 2}$$

The $x - y$ coordinate system is fixed to the vehicle, while the vehicle has a yaw angular velocity of r around the vertical axis passing through point P, referred to as the yaw rate.

The changes in i and j with time Δt are represented as:

$$\Delta\boldsymbol{i} = r\Delta t\boldsymbol{j} \qquad \text{Equation 3}$$

$$\Delta\boldsymbol{j} = -r\Delta t\boldsymbol{i} \qquad \text{Equation 4}$$

Thus,

$$\dot{\boldsymbol{i}} = \lim_{\Delta t \to 0} \frac{\Delta \mathbf{i}}{\Delta t} = r\boldsymbol{j} \qquad \text{Equation 5}$$

$$\dot{\boldsymbol{j}} = \lim_{\Delta t \to 0} \frac{\Delta \boldsymbol{j}}{\Delta t} = -r\boldsymbol{i} \qquad \text{Equation 6}$$

Then, the acceleration vector

$$\ddot{\boldsymbol{R}} = (\dot{u} - vr)\boldsymbol{i} + (\dot{v} + ur)\boldsymbol{j} \qquad \text{Equation 7}$$

APPENDIX TO CHAPTER 3

Here, longitudinal acceleration a_x and lateral acceleration a_y are:

$$a_x = \dot{u} - vr \qquad \text{Equation 8}$$

$$a_y = \dot{v} + ur \qquad \text{Equation 9}$$

By differentiating Equation 8, longitudinal jerk is calculated as:

$$j_x = \ddot{u} - \dot{v}r - v\dot{r}$$

Here, $\ddot{u}$ is the rate of change of longitudinal acceleration, $\dot{v}$ is lateral acceleration, r is yaw rate, v is lateral speed, and $\dot{r}$ is yaw acceleration.

By differentiating Equation 9, lateral jerk is:

$$j_y = \ddot{v} + \dot{u}r + u\dot{r}$$

Here, $\ddot{v}$ is the rate of change of lateral acceleration, $\dot{u}$ is longitudinal acceleration, u is longitudinal speed, r is yaw rate, and $\dot{r}$ is yaw acceleration. The item $\ddot{v}$ can be omitted, as it is primarily affected by lateral tyre deformation, lateral disturbance, and lateral slip.

APPENDIX TO CHAPTER 4

Appendix A

Method

Experts

Due to the COVID-19 pandemic, and related travel restrictions, we conducted an online workshop with nine internationally recognised experts in this field, chosen due to their long-term research experience with AVs, and balanced between industry and academia, as well as background expertise (engineering, psychology, human factors, and industrial design). These attendees, and two more experts (Prof Marjan Hagenzieker and Prof Riender Happee), who were invited to comment on the manuscript, are all co-authors of the manuscript, due to their verbal and written contributions to the work. We were keen to include experts with some hands-on experience with higher-level AVs, because these vehicles are currently unavailable on the market (Madigan et al., 2017), yet research shows that actual experience with new technology is effective for highlighting their limitations and capabilities (e.g., Hancock et al., 2020; Kyriakidis et al., 2019; Tabone et al., 2021). Moreover, because comfort/discomfort is the actual experience that results from interaction with AVs, we considered experts' direct experience with AVs as crucial and valuable. Experts were invited via emails, in which the date, estimated duration, the main topic of the workshop, and the expected output (i.e., an academic paper with attendees as co-authors) was briefly stated. Eleven out of thirteen experts accepted the invitation, and nine of them attended the workshop.

Techniques used for the workshop

A group workshop, loosely following a focus group format was considered more useful than individual interviews for this research. Focus groups are considered useful for investigating complex topics, allowing in-depth discussions between the participants, and gathering diverse information from a small group of people (Caretta & Vacchelli, 2015; Morgan, 1998; Ørngreen & Levinsen, 2017; Stewart & Shamdasani, 2014). By fostering discussions and interactions between the experts, a wide range of aspects related to this topic could be explored and uncovered, and it was favoured over individual interviews which only collect opinions from individuals, without interactions between interviewees, and thus produce less comprehensive information than group work (Coenen et al., 2012).

Apart from the group discussion via the online meeting platform Microsoft Teams (https://www.microsoft.com/en-gb/microsoft-teams/online-meetings), in order to stimulate discussions, experts were encouraged to brainstorm a range of proposed topics, as well as write notes and group similar notes, by using the online collaborative whiteboard tool; Miro (https://miro.com) (see examples of approaches of facilitating group discussion: Hagger et al., 2016; Iliffe et al., 2005). This combination of brainstorming and writing is sometimes called "brain-writing" (VanGundy, 1984). Writing notes in a shared workspace helps both the individual and the group to brainstorm ideas, while also providing an overview of all notes, with existing notes providing inspiration for new ideas (Aiken et al., 1996; Lockton et al., 2016; Michinov & Jeanson, 2021; Wilson, 2006). Grouping notes with similar themes together can highlight similarities and differences between individual notes, similar to a card-sorting task (Bussolon et al., 2006). These notes would then be visible on the whiteboard, allowing the facilitator and experts to further discuss the evolving themes.

Procedure

Before the main workshop, we conducted an online pilot session with six participants, who were all PhD candidates from the Human Factors and Safety research group at the Institute for Transport Studies, University of Leeds. The backgrounds of these pilot participants included psychology (N=1), design (N=2), control engineering (N=2), and modelling (N=1). The aim of the pilot session was to test the length and format of the main workshop and gather participants' views about the format and nature of our questions (see Appendix B). Ambiguous questions and instructions were modified following this pilot session, and we also simplified the procedure, and adjusted the time estimation for each session.

For the main workshop (which took place on 27th July, 2021), after welcoming all experts, the moderators provided a short introduction of the workshop, including its main aim, the topic to be discussed, an estimation of the likely duration of the event, and re-emphasised the anticipated academic paper as the output of the workshop. This was followed by a round-table session in which all experts introduced themselves, their backgrounds, and their expertise. The moderators then presented a brief summary of the state-of-the-art research on user comfort in automated driving, including an overview of the diverse descriptions and measurements used for comfort, and provided the list of research questions that were to be considered for the workshop discussions. A short tutorial on the use of the Miro whiteboard was provided. The workshop was divided into four separate sessions, in which different, but connected, topics were covered:

> **Session 1**: This session focused on a discussion of the terms used to describe comfortable and uncomfortable experiences when driven by currently available vehicles as a passenger, such as a taxi, bus or train. This was done for two reasons: first, it helped experts familiarise themselves with the topic by talking about currently available transport modes. Second, we wished to understand if there were any differences in the perceived comfort/discomfort of "being driven" by a taxi/bus/train, compared to that

of a Level 4 AV, because, in both cases, the user does not control the vehicle, and is also able to engage in NDRAs (Hecht et al., 2019).

Session 2: This session involved a discussion of any differences between being driven by a taxi/bus/train versus an AV, in terms of the experienced comfort/discomfort. This session was expected to connect with, and facilitate the discussions, in session 3.

Session 3: This session involved a discussion of terms used to describe comfortable and uncomfortable experiences of being driven by AVs. Discussions in this session were based on the previous two sessions. After reflecting on the unique characteristics of AVs in session 2, it was expected that experts would add or remove terms about comfortable/uncomfortable experiences of being driven by AVs, based on existing terms for a taxi/bus/train from session 1.

Session 4: This session focused on discussing the original conceptual framework for user comfort in automated driving (Figure 1), with an emphasis on how these are affected by different driving styles. After discussions in the preceding sessions, experts were expected to give constructive feedback on the original framework, in terms of complementing and revising relevant aspects and concepts, rather than clarifying concrete terms. Here, we explicitly instructed experts to take driving styles into consideration, compared to the preceding sessions, in which the term of "being driven" was used to implicitly remind experts of the driving scenario. However, we still encouraged discussions of broad but relevant concepts, in addition to driving styles.

Each session began with a verbal instruction provided by the moderator, including the topic of the session, the place to write notes, and the duration of the writing session. The workshop then began with writing and grouping notes on the Miro whiteboard, followed by a group discussion of the written notes and the patterns of the categorisations. For the note-writing, experts were advised to use one to two terms for each note, to keep descriptions succinct and easy to follow, so that other experts could read these through, within the limited time of a session. In order to get a comprehensive output, experts were encouraged to write as many notes as they could, and to avoid repetitions (i.e., to avoid writing a description that was already posted, allowing a maximisation of the number of concepts used). Instructions about the topic covered in each session was also shown on the Miro whiteboard, to remind experts of the focus of the current session. Along with writing, experts were instructed to move their notes closer to existing notes with similar meaning/themes. Figure 2 shows instructions of topics for discussions on the Miro whiteboard, the order of events and rough length of each session. Figure 3 shows the Miro whiteboard of session 1, as an example, which includes the written instructions, separated whiteboard areas for comfort and discomfort, the empty notes provided to experts, and an overview of the final notes provided by the experts. After the writing task, experts saw an overview of the whiteboard, and discussed the emerging patterns which were of interest to them. The Miro whiteboard screen was shared via Teams throughout the workshop, to ensure participants worked on and looked at the same area. All experts were thanked for their contribution after the workshop.

Both the pilot and the main workshop were moderated by the first two authors (CP and SH). These individuals also devised the questions and workshop format. For the main workshop, one moderator (CP) instructed and guided the discussion, while the other moderator (SH) monitored the online tools (e.g., timer setting and reminder in Miro).

Data analysis

For the two types of data (written notes and verbal discussions) collected from the workshop, we adopted different approaches to analysing data. For written terms describing comfort/discomfort of currently available transport modes and AVs (mostly from session 1 and 3), although experts have grouped most terms and discussed some patterns at a group level in the workshop, further categorisations were needed for two reasons. First, not all terms were moved into groups, while some groupings were roughly done with flaws, likely because, for example, experts overlooked some terms due to too much information on the whiteboard, and had insufficient time to refine these groups. Second, no explicit names were given to each group of terms to summarise the theme; however, it is important to identify the theme of a group of terms with similarities, because a theme summarises commonalities of these terms, and indicates one aspect of comfort/discomfort. Sorting text into meaningful categories is usually done by participants in group brainstorming (Clayphan et al., 2014), while it is also an approach of qualitative content analysis used after data collection (Ahmadpour et al., 2016; Hsieh & Shannon, 2005). Therefore, to complete the categorisation and highlight patterns of these terms, the categorisation was conducted as part of data analyses. The categorisation combined the theory-driven deductive approach and the data-driven inductive method (Berg & Lune, 2017; Duboz et al., 2022). To be specific, we tended to deductively categorise and name a group of terms, either based on frequently investigated psychological concepts (e.g., "perceived safety", "trust", and "engagement in NDRAs") in this area, or using terms used in currently available definitions for comfort/discomfort (e.g., "ease/unease", and "pleasantness"). We referred to these frequently used terminologies in academic literature rather than preparing a predetermined codebook based on existing research theories, because an elaborate theoretical framework of user comfort in automated driving is currently lacking. In the meantime, we categorised terms according to their similar meanings and themes, in an inductive way. Three individuals (CP, SH, RM) completed the categorisation (incl. grouping similar terms and naming the group) independently, and then discussed it in a team of four (the three raters, and NM). This team included moderators and experts from the workshop and thus had enough background knowledge for the categorisation. Other experts were given the opportunity to provide feedback at the time of writing. It is worth noting that the number of repeated notes was counted; however, we do not interpret the importance of a term according to the times it was repeated, because the purpose of the workshop was to have a comprehensive overview, and experts were instructed about this. Some terms were repeated because experts wrote in parallel, whereas monitoring the whole whiteboard in the meantime to avoid repetition was challenging.

For verbal discussions (from all sessions), the video recording was gone through and transcribed by the first two authors independently, and cross-compared to ensure no misunderstandings of the transcription. Then experts' discussions were summarised by the lead author. Summarising statements and discussions of experts is an approach used by some studies based on expert work, for example, expert interviews (Kyriakidis et al., 2019; Tabone et al., 2021) and expert round-table discussions (Elliott et al., 2019). All other co-authors also had a chance to comment on the statements and suggest amendments. Moreover, as the discussions added contextual information to the simpler notes, some categorisations of the written notes were then further revised.

The original conceptual framework was refined based on the workshop (see examples of using group discussions to refine conceptual frameworks: Agbali et al., 2019; Pettit et al., 2010). It is worth mentioning that, the output and discussions in both preceding sessions and session 4 were all relevant to the framework. Therefore, we combined results from all sessions to modify the conceptual framework, for example, categories of comfort/discomfort that were identified in session 1 and 3, discussed differences in user comfort in automated driving compared to a taxi (session 2), and experts' direct comments on the original conceptual framework (session 4). The refined version of the framework was drafted by the lead author and revised based on the co-authors' feedback.

Appendix B

Questions and instructions used in the pilot session

Session: Warm-up questions

Do you think understanding and defining driving comfort for AVs is important? (Slido)

Do you think it's easy to measure comfort in AVs? (Slido)

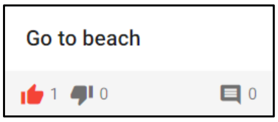
Do you think it's easy to manipulate driving comfort in AVs? (Slido)

Quick tutorial to Padlet

Session A: UNDERSTANDING DRIVING COMFORT (Padlet)

Imagine, you are being driven in a vehicle, e.g., taxi, train, and bus etc., not in control. A) During this journey, you feel comfortable ... B) During this journey, you feel uncomfortable ...

What terms can you use to describe these feelings? Use thumb up and thumb down reacting to all answers, for example,



How relevant is the term to describe comfort?

Session B: CREATING

First, let's talk about your experience and feelings about the existing automation functionalities... (Slido)

Have you experienced adaptive cruise control (ACC) in real cars or in prototype? - Y/N

Have you experienced Lane Keeping Assistance (LKA), in real cars or in prototype? - Y/N

Have you experienced any other ADAS functionalities, regarding vehicle motions or distances to other objects? - WordCloud

Regarding vehicle motions/distance to other objects, how does the system behave when you felt comfortable or uncomfortable? Why do you like it, or dislike it? (No tool; just discussion in Teams)

Imagine. You are being driven, not in control, don't need to monitor, can do NDRTs...

SAE LEVEL 3™ SAE LEVEL 4™

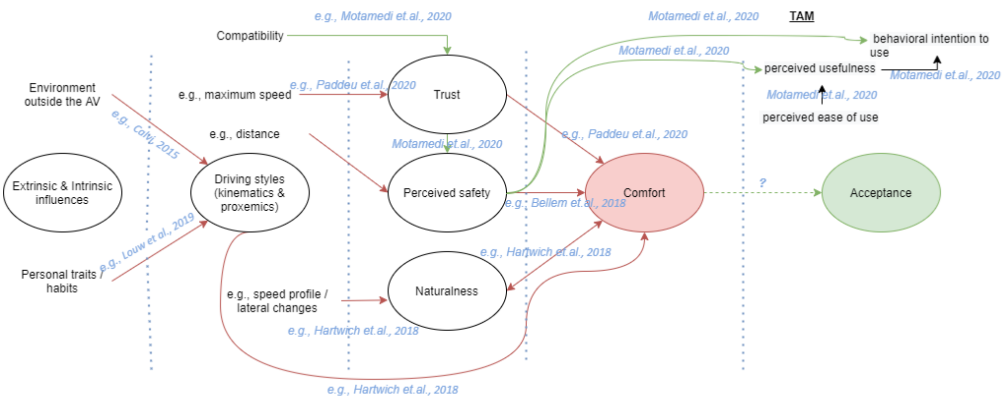
Regarding driving styles / environments, is there anything different in the L3/L4 automation, compared to the L1/L2 automation, about comfortable or uncomfortable experience?

Break

Consider the concepts - Trust, Perceived Safety, Naturalness, User acceptance - that are related to kinematics and/or proxemics, and this suggested conceptual framework...

Are there any other relevant concepts are missing? – add (Teams)

What are the relationships among them? – discuss (Teams)



Session C: LOOKING AHEAD

What else in this area, apart from kinematics and proxemics, are important to be understood? - Slido; word cloud
Are there any other different user groups that should be considered in this context? - If yes, please explain your answer – Slido

Session D: MEASURING

Among the range of measures to measure comfort in the driving context… Which one is most successful?

Feedback question