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Deliverable 2.6

Design guidelines for acceptable, transparent, and safe AVs in urban environments

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List of Associated Partners

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Note 1: The term Early-Stage Researcher (ESR) is used extensively in this document. The ESRs are PhD candidates funded by the SHAPE-IT project.

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List of Abbreviations

Acronym	Description
ACC	Automated Vehicle Adaptive Cruise Control
ADAS	Advanced Driver Assistance Systems
ADS	Automated Driving System
AI	Artificial Intelligence
AV	Automated Vehicle
EEG	Electroencephalography
ERPs	Event-Related Potentials
ESR	Early-Stage Researchers
HAI	Human Artificial Intelligence
HMI	Human Machine Interface
ITN	Innovative Training Networks
LC	Lane Change
ML	Machine Learning
NDRT	Non-Driving Related Tasks
ODD	Operational Design Domain
OEM	Original Equipment Manufacturer
SAE	Society of Automotive Engineers

Executive Summary

This Deliverable summarises the work of ESRs 1, 5, 7 and 12 of the SHAPE-IT project that considered how a range of human states such as attention, fatigue and mental workload are affected by SAE Level 2 and 3 automated vehicles (AVs), when compared to manual driving, and what this means for AV and road safety. The studies also consider how AV safety and acceptance can increase with Human Machine Interface (HMI) transparency, and what factors contribute to the improvement of this transparency. An investigation of what aspects of an AV's HMIs, its driving environment and driving style, contribute to the perceived safety, comfort and trust for its users is provided, and new methods and frameworks for enhancing these states are introduced. By considering how human factors concepts and knowledge should be embraced by software developers and AV engineers, ESRs 8 and 15 highlight the importance of a multidisciplinary approach to AV development. Finally, the work of ESR2 focuses on how AV trust, acceptance, and transparency changes with prolonged and repeated use of AVs, emphasising that successful deployment of AVs must embrace human factors knowledge during all stages of AV development. This work also highlights that as long as AVs require human interaction and intervention, including a diverse user group, and ensuring the appropriate level of trust is built at each stage of the interaction, will improve the correct and safe use of AVs.

1 Introduction

This Deliverable provides a summary of the work conducted by ESRs 1, 2, 5–8, 12, and 15, which was primarily based on studying the interaction of the user *inside* an Automated Vehicle (AV). However, since an urban environment contains a range of actors by default, the concepts defined here are also relevant to other road users (i.e., other drivers, pedestrians, and cyclists). It is also important to understand how the "sum of" these human factors concepts affect the overall flow and safety of all actors on the road. For example, how does increasing trust in the AV for the internal user affect other road users' trust of the AV. Understanding can be gained by observing all three actors: the internal user, the AV, and the other road users in a multi-actor setting. For example, ESR4 has considered how a driver and pedestrian interact with each other, and how this can help us with design of new internal and external interfaces for the AV, when the human is no longer in charge of the vehicle, but the AV still needs to communicate with the internal and external human actors. (see Deliverable 2.5 for more details).

The next section provides a short overview of the current understanding of the human factors theories and concepts studied by the ESRs when assessing what factors affect user trust and acceptance of AVs. A state-of-the-art review of the literature was used to guide each ESR's programme of research at the start of their studies. In some cases, the concepts have been updated based on the outputs of the project.

2 An overview of the psychophysiological concepts relevant to increasing user acceptance of AVs

From a human factors' perspective, concepts such as safety, trust, and acceptance of technologies are closely related to, and affected by, users and their characteristics (e.g., their demographics, personality, and experiences). Each of these concepts can also interact with a users' psychophysiological state. In other words, factors such as distraction/inattention, fatigue, and mental workload are known to affect users' interactions with AVs, which can in turn change users' perception of the AV. Importantly, this means that users' interactions with an AV can change not only with repeated use and over time, but also based on their psychophysiological state at the time of an interaction.

For example, if a driver is overloaded by a secondary or non-driving-related task, their performance on the primary driving task could be impaired, reducing safety, overall, and potentially affecting their trust in the AV's capabilities. On the other hand, if the vehicle is controlled by automation, the human is then less in control of the moment-to-moment task of driving, which could lead to driver boredom and underload. At higher levels of automation, drivers are allowed to engage in other tasks. But this situation may also lead to reduced safety if the human is suddenly and unexpectedly required to resume control of the AV (Louw & Merat, 2017; Louw et al., 2019), again affecting trust.

We begin by providing a short overview of why acceptance, safety, trust, and transparency are important for the design of AVs.

2.1 Acceptance and acceptability of AVs

A key factor to consider in the design and rollout of any automated driving function is its acceptability and ultimate acceptance by the end users. The term acceptability describes the prospective judgment of future systems/innovations, whereas acceptance defines users' attitudes, including their behavioural reactions, after the introduction of a new system (Schade & Schlag, 2003). *Willingness to use* is often employed as a proxy measure of user acceptance of automated vehicles. There have been hundreds of studies on the acceptability and acceptance of automated vehicles, measuring respondents' willingness to use these systems, both with and without any prior experience. However, most of these studies have focussed on highly automated vehicles (L4 and beyond), and only a very small number have considered conditional automation (SAE L3; Nordhoff et al., 2021). L3 AVs are likely to present different challenges from those operating at higher levels of automation since the former will only operate in certain ODDs. Thus, it is important to understand whether the factors influencing potential users of these vehicles are like those influencing users of higher- level AVs.

Results from the L3Pilot project, which included an online questionnaire with over 18,000 respondents across 17 different countries, provide several key insights into the factors which may impact the acceptability of L3 automated vehicles. For example, Nordhoff et al. (2020) found that the enjoyment (Hedonic Motivation) associated with using an AV, Social Influence, and Performance Expectancy all influenced drivers' intentions to use a conditionally automated car. There were also interrelationships between these factors, suggesting it is important for developers to take a holistic approach to designing L3 systems that promotes acceptance. This includes ensuring that they are enjoyable to use and perceived to be safe, comfortable, and efficient, while also considering how to encourage wide adoption within different social networks.

Louw et al. (2021) looked at intentions to use different automated driving functions (ADFs) and found that intentions to use were significantly higher for Parking systems than for Motorway, Traffic Jam, and Urban Road systems, although all four systems received high ratings. Interestingly, there was wide variation in intention to use ratings across different countries: respondents from countries with the lowest Gross Domestic Product (GDP) and highest road death rates showed higher intentions to use than respondents from countries with a higher GDP and lower road death rates. This research shows the multitude of factors which must be considered to understand the acceptability of L3 AVs.

Because of the low market penetration AVs, to date, only a small number of studies have considered what factors influence user acceptance, following real interactions. Results suggest that after users experience L3 automated systems (either in driving simulators or on real roads), perceived ease of use, usefulness, and trust all significantly affect users' intentions to use similar systems in the future. However, the relationships are not consistent across studies (Buckley et al., 2018; Lee et al., 2023; Xu et al., 2018). Other usability factors relevant to increasing user acceptance of L3 AVs include: the willingness to engage in other (non-driving-related) tasks, the level of information provided about system limitations, and the degree to which system expectations were met.

2.2 The effect of driver cognitive states on safety

Vehicle automation offers numerous potential benefits, including enhanced traffic safety, efficiency, and passenger comfort. However, it also redefines the driver's role. In traditional manual driving, drivers are fully in charge of vehicle operation. But as automation increases, vehicles take over a progressively larger share of control.

For instance, SAE Level 2 (SAE, 2016) vehicles can manage the lateral and longitudinal movements on the road. Drivers are required to continuously monitor the automated system and keep their hands on the steering wheel. However, at SAE Level 3, drivers can remove their hands from the steering wheel, and have the liberty to engage in non-driving-related tasks, such as reading a newspaper or using their phone. For this level, drivers can transition from active operators of the vehicle to passive supervisors of the automated system. However, unfortunately, Level 3 systems are not currently flawless. They are only effective within certain Operational Design Domains (ODDs); if they reach their operational boundary, they prompt drivers to resume control. Regulatory requirements suggest that drivers are given around ten seconds for these "planned" takeover requests (UNECE, 2021). On the other hand, for "unplanned events", such as sudden changes in the weather or unexpected debris on the road, a silent failure of the automation may occur, which involves an unplanned and unexpected disengagement of a limited or faulty automated system. For such failures, drivers are required to resume control with almost no warning. Many studies have shown the detrimental effects on safety of these automation failures (Bianchi Piccinini et al., 2020; Louw et al., 2019).

To truly reap the advantages of vehicle automation, it is important to design systems that support drivers in this new, more passive supervisory role. Prioritising a good understanding of human factors is essential when designing safe, user-centred automated vehicles that meet user preferences and expectations. Implementing designs with these priorities in mind requires a holistic understanding of the interactions between human drivers and automated systems across various automation levels, and how performance is different when compared to manual driving. Although a large body of research has been published on the topic of driver-vehicle interaction, several research gaps remain in our understanding of how drivers' physiological and cognitive states are affected by automated driving.

Most of the existing research is grounded in driving simulator studies. However, it is important to note that findings from driving simulators are not always in line with real-world outcomes (Wynne et al., 2019). For example, driving simulators may not always provide results with high ecological validity, making their direct application to real-world scenarios limited. ESR1's studies addressed this research gap by considering how a driver's cognitive state changes during automated driving in a test-track study (see Section 3.1). In the following section, an overview of some of the concepts which affect user safety, namely mental workload, attention allocation, and fatigue, is provided.

As outlined above, the task of supervising an automated vehicle imposes different demands on drivers, when compared to manual driving, because the vehicle takes over many of the perceptual and motor tasks traditionally managed by a driver. For example, the lack of steering control in automation disrupts drivers' perceptual-motor control of the vehicle (Mole et al., 2019), taking them "out of the loop" (Merat et al., 2019), which can result in later responses to critical events (compared to the response times in manual driving). Drivers of automated vehicles also tend to pay less attention to the forward roadway (Jamson et al., 2013), which results in reduced situational awareness (Merat & Jamson, 2009). During prolonged automation, drivers' ability to stay alert is impaired (Vogelpohl et al., 2019), reducing their overall capability to safely operate the vehicle (Higgins et al., 2017; Markkula & Engström, 2017). More details about the three concepts known to affect the safety of users in automated vehicles are outlined below.

2.2.1 Mental workload

Mental workload is the ratio of mental demands required to perform a task to the resources available to meet those demands (Kahneman, 1973). It is a multidimensional concept (de Winter et al., 2014), closely related to the Multiple Resources Theory (Wickens, 2002, Wickens, 2008). This theory posits that only a limited number of resources are available for processing information across different modalities. The overlap between two tasks therefore leads to greater interference, subsequently increasing mental workload.

The impact of vehicle automation on mental workload has been extensively studied, often using driving simulators instead of real vehicles on the road (see de Winter et al., 2014). These studies usually report that, compared to manual driving, Level 2 automation results in only a relatively small reduction in mental workload, while Level 3 automation results in a considerable reduction. However, since driving simulators do not accurately reproduce real-world experience, these results might be biased (Groh et al., 2019; Hock et al., 2018). In addition, since very few L3 systems are currently available in the real world, a direct comparison of both levels is only possible in driving simulators, and the effect of real world L2 and L3 driving on mental workload remains to be seen.

Perhaps due to practical and financial constraints, real-world studies are conducted less frequently. Results from these less controlled studies are also inconclusive or even in contrast with the findings from driving simulators. For example, a real-world study by Biondi et al. (2018) found that drivers have a lower mental workload during Level 2 automated driving, when compared to manual driving. In contrast, another real-world study by McDonnell et al. (2021) with a large group of participants (N = 71) reported that there was no noticeable change in mental workload between manual and Level 2 driving. Várhelyi et al. (2021) conducted an on-road experiment with Level 3 autonomous vehicles and found no difference in drivers' self-reported mental workload levels between SAE Level 3 and manual driving. However, Kim et al. (2023) observed that Level 2 drivers experienced a higher mental workload during real-world Level 2 driving compared to manual driving. Similarly, Banks & Stanton (2016) concluded that drivers of real Level 3 vehicles experienced a greater mental workload compared to when they drove manually. . Galante et al. (2018) examined the effectiveness of a driving simulator as a research tool for studying mental workload. They compared the performance-based and self-reported workload of participants who completed the same driving task both in the simulator and on an actual road. Their results are consistent with previous studies and provide mixed results about the validity of the results from a driving simulator, when compared to on-road studies. Although they suggest that simulator sickness and lack of familiarity with the simulator may have made this direct comparison with on-road results challenging.

Eriksson et al. (2017) posit that the disparity between results from simulator studies and real-world experiments might be due to the simulator's simpler driving environments (including the absence of other drivers on the road) or differences in driver behaviour. Carsten and Jamson (2011) further stress that risk perception is changed in a driving simulator, subsequently impacting drivers' experience and behaviour.

Prior experience with automation also appears to influence mental workload during real-world automated driving. Research by Stapel et al. (2019) showed that drivers familiar with Level 2 automation reported lower mental workload, while those new to the technology reported the same mental workload for both Level 2 and manual driving. Similarly, Lohani et al. (2020 & 2021) found that inexperienced Level 2 drivers had similar levels of alertness and cognitive load (measured by heart rate and brain activity) in both manual and automated driving.

Finally, some researchers note mismatches between actual (objective) and self-reported measures of mental workload (MW). For instance, Stapel et al. (2019) and Large et al. (2017) observed a difference in self-reported MW, but not in objective measures. Stapel et al. (2019) suggest that monitoring Level 2 driving demands as much attention as manual driving, implying that drivers might be underestimating the actual effort required.

2.2.2 Attention allocation

Attention is a core element of all human sensory and cognitive processes (Chun et al., 2011). It can be divided into external (bottom-up) or internal (top-down) attention. The former is spontaneously activated by our surroundings, based on the saliency and significance of an event or object, while the latter is steered by human intentions and objectives. For instance, when the car ahead flashes its brake lights, drivers' attention is instantly captured, showcasing bottom-up attention. In contrast, top-down attention is evident when drivers deliberately look for road signs. The drivers' understanding of the signs' significance, combined with a dedication to drive safely and legally, guides their focus amidst potential distractions. This intentional, goal-oriented behaviour serves as an example of top-down attention. The dynamic world of driving requires the integration of both bottom-up and top-down attention (Spence & Faraco, 2020).

Given that the human brain has a limited pool of attentional resources, different information must compete for processing space. Consequently, attention resources are utilised to process only the most behaviourally relevant events (Chun et al., 2011). While the saliency of an event often drives its selection, it can be modulated by top-down influences (Wang & Theeuwes, 2020). Attention allocation is closely related to mental workload, due to the limited capacity of processing resources.

With increasing automation, drivers are expected to focus their attention more inside the vehicle - due to the growing use of alerts, information, and warning signals inside vehicles, including auditory, visual, and tactile displays (Spence & Faraco, 2020). This applies especially for Level 3 driving, which allows drivers to disengage from the driving task and get involved in other activities. The shift in visual attention off the road has been proven to increase the risk of vehicle crashes (Liang et al., 2012; Simons-Morton et al., 2014). Moreover, automated vehicles will be equipped with sensors monitoring the environment, which could have further implications for how drivers allocate their attentional resources. To design future vehicles that will be supervised by potentially distracted drivers, it is crucial to get a better understanding of the drivers' attentional processes and how those processes differ for the different levels of automation.

2.2.3 Fatigue

Automated driving can be monotonous for the human, affecting their psychological satisfaction and user experience (Frison et al., 2019). Monotony can also lead to drivers becoming less alert over long stretches of automated driving (Vogelpohl et al., 2019; Bieg et al., 2020). As a result, drivers of automated vehicles might experience more fatigue compared to those driving manually (Kundinger et al., 2020; Michael & Meuter, 2006). Driver fatigue compromises vehicle safety (Higgins et al., 2017; Markkula & Engström, 2017). It also impacts a driver's attention (Boksem et al., 2005) and overall awareness (Bongo & Seva, 2022).

To monitor fatigue in drivers, researchers have developed techniques involving computer vision (Xiao & Sun, 2021; Dwivedi et al., 2014; Vural et al., 2008) and artificial intelligence (Karwowski et al., 2020; Vural et al., 2008). Tools using these methods measure eyelid movements and eye closure (Zhou et al., 2020; Chang & Chen, 2014), heart activity (Jung et al., 2014), and/or electroencephalography (EEG) (Morales et al., 2017; Salimuddin &

Panbude, 2018; Hu & Min, 2018). Notably, changes in EEG patterns can indicate fatigue and mental workload (Lohani et al., 2019). However, it is important to note that much of the research on driver fatigue has been done using driving simulators (de Winter et al., 2014). These simulators have their limitations and might not always reflect real-world scenarios (Hock et al., 2018). Often, the situations presented in these studies do not match what drivers might face in real AVs. For instance, critical events in driving simulators are more frequent than in natural traffic conditions (Klischat & Althoff, 2019), requiring a caveat about how results from these lab-based studies should be interpreted.

2.3 Perceived safety (risk) and Trust

Trust is an essential factor when using automation, as it is a key predictor of acceptance, leading to a positive user experience (Choi & Ji, 2015; Cysneiros et al., 2018; Detjen et al., 2021; Hoff & Bashir, 2015; Parasuraman & Riley, 1997; Wilson et al., 2020). Trust in automation refers to the assumption that the system helps users achieve their goals in situations characterised by uncertainty and vulnerability (Lee & See, 2004). Perceived risk captures the level of risk experienced in driving (Griffin et al., 2020); some researchers consider perceived safety as an antecedent of trust, while others suggest that perceived safety emerges from trust (Li et al., 2019; Nordhoff et al., 2021). In this project, we consider trust and perceived safety (or risk) to be closely related concepts in the context of the interaction between drivers and automated vehicles. Trust and perceived safety are primarily linked to the user's perception of the AV's performance in different driving conditions. User interfaces can help calibrate trust and perceived risk, as they can inform users of the (safe) operation of the automated vehicle and its ability to deal with the (dangerous) behaviour of other road users (Li et al., 2019). The ability of user interfaces to improve trust and the feeling of safety, which in turn help users accept AVs, has been shown in a recent study (Kim et al., 2021). ESR12's work seeks to extend the current understanding of trust and perceived safety for AVs, providing actionable insights for the design and implementation of more acceptable automated vehicles.

Perceived risk captures the level of risk experienced by drivers, which can differ from operational (or actual) risk (Griffin et al., 2020; Kolekar et al., 2020). A low perceived risk leads to feeling safe, relaxed, and comfortable, while high perceived risk results in cautious behaviour (Griffin et al., 2020). The advent of active safety and driving automation systems has reduced actual risk, but changes in drivers' risk perception are still observed. For example, drivers will perceive a high level of risk if the driving automation behaves inappropriately; leading to reduced trust and low acceptance, perhaps even refusing to use vehicle automation (Xu et al., 2018). In manual driving, the desire to maintain perceived risk below a specific threshold motivates drivers' as steering and braking behaviour (Summala, 1988). Consequently, misperception of risk during automated driving may cause drivers to distrust and intervene unnecessarily (if their perceived risk is high), while drivers may fail to recognise dangerous situations that require their intervention (if their perceived risk is low). Therefore, it is essential to comprehend and quantify drivers' perceived risk in driving automation, to design driving automation, which is not only technically safe, but is also perceived as safe.

2.4 User trust in AVs

Ensuring the appropriate level of user trust in AVs is a key factor influencing their acceptance (Ghazizadeh et al., 2012; Wintersberger et al., 2021; Zhang et al., 2019). Drivers' trust needs to be maintained at an appropriate level (Haspiel et al., 2018) to avoid both under-trust (or distrust) and over-trust (Lee & See, 2004). Over-trust can lead to misuse and unintended use of the system, which can be dangerous (O'Kane, 2020). Conversely, many (potential) users distrust vehicle automation, which may lead to their disuse (Smith & Anderson, 2017). These trust issues may result from a lack of information about the behaviour of a complex system (Norman, 1990). Low trust is partly related to system transparency, which is defined as the understandability and predictability of a system (Endsley et al., 2003). Transparency allows users to understand the intention and performance of automated processes (Chen et al., 2018). Automation system transparency is also considered valuable for trust calibration (de Visser et al., 2020; Gao & Lee, 2006; Hoff & Bashir, 2015; Lee & See, 2004; Lyons et al., 2017; Mercado et al., 2016).

To increase the trust in and acceptance of automated vehicles, transparent behaviour and a user interface that explains the vehicle's operations are crucial (Avetisyan et al., 2022; Chang et al., 2019; Hock et al., 2016; Koo et al., 2015; Ma et al., 2021; Petersen et al., 2019; Wintersberger et al., 2021). Information about the vehicle's surroundings and planned actions helps users understand what to expect, boosting trust and situation awareness (Hock et al., 2016; Petersen et al., 2019; Wintersberger et al., 2021).

Different kinds of information affect trust in varying ways. For example, Hock et al. (2016) found that providing information about surrounding vehicles and their manoeuvre increased trust and encouraged drivers to use automation. This kind of manoeuvre information, which also helps drivers to be more aware of their surroundings (Petersen et al., 2019), is valued by drivers, regardless of how much they trust the system (Wintersberger et al., 2021). However, not all studies agree on the effect of additional information on user trust. Koo et al. (2015) found that information about the AV's surroundings increased trust, but that manoeuvre information did not. On the other hand, Ma et al. (2021) have shown that using both types of information increased trust more than including just surrounding information. Finally, some research suggests that providing additional information about the surroundings and the AV's manoeuvres does not always increase user trust (Mackay et al., 2020; Chang et al., 2019).

The method by which information is provided to the driver is also important for establishing and building trust. Studies have used both visual and auditory stimuli for presenting information, and both have been effective in increasing trust during automated driving (Koo et al., 2015; Ma et al., 2021). For example, ambient light and auditory HMIs were found to elicit the same level of trust during an L3 automated driving simulator study (Gonçalves et al., 2023; Jouhri et al., 2022). However, there is a lack of detailed research on how the modality of the information provided by an HMI affects trust and perceived safety.

2.5 Transparency of the AV and its interfaces

Designing and building a vehicle that is automated, must also be accompanied by a safe and comfortable driving experience for the user. Despite all the potential benefits associated with automated vehicles (AVs), including a minimisation of human error, reducing the total amount of transport-related emissions, and even acting as a powerful tool during the pandemic (Othman, 2022), there are still critical issues to be solved before the era of the fully autonomous vehicle is realised. One of those issues is human users' confusion during interactions with AVs (Carsten & Martens, 2019, Wilson et al., 2020). Due to a regular transition between different levels of automation (SAE, 2021) during a drive, the responsibilities and tasks required of humans could alter many times. The main bridge between the AV and humans, the Human-Machine Interface (HMI), plays a considerable role in providing information to the driver and assisting with safety throughout the transitions. Hence, vehicle and road safety are reduced if the transmission of information from the AV HMI to the user is not clear or timely.

A range of HMI design guidelines have been proposed to ensure these interfaces are safe and effective, meeting the needs of human drivers and passengers. For example, Naujoks et al. (2019) proposed a set of principles to guide the design of AV HMIs, as well as introducing a heuristic evaluation method with a checklist to verify whether the HMI design matches the proposed guidelines. The checklist items are based on relevant research findings, ranging from the inclusion of multiple modalities, minimum requirements for the information content, and visual requirements such as position and colours of information presented.

When designing and building AV HMIs, designers and engineers are devoted to providing an AV that is comfortable, trustworthy, and easy to use. One of the constructs that could satisfy these requirements and allow safe driving is the *transparency* of HMI designs. In the literature, transparency is usually defined as the amount of information provided to help avoid false expectations and over-reliance on the system (Carsten & Martens, 2019). Transparency is also thought to increase decision accuracy, trust, and situation awareness (Bhaskara et al., 2020).

Transparency is thought to include different levels (Chen et al., 2014). For example, based on the **situational awareness-based agent transparency** (SAT) model, three levels of transparency exist: basic information (SAT Level 1), rationale (SAT Level 2), and outcomes (SAT Level 3). These levels clearly categorise the characteristics of the information provided but do not offer any indication of how *understandable* or clear the information is. Additional information might help promote a high level of transparency, but more research is needed to determine if this would then lead to an increase or reduction in users' workload.

Currently, it is difficult to evaluate the effect of the transparency of an AV HMI in different scenarios. For instance, increasing the amount of information provided, which should also be about increased transparency, should increase the human users' understanding of the automated system; because more information is provided about the AV, users can respond according to the current situation. On the other hand, redundant or irrelevant information might still indicate an increase in transparency (based on more information) but could lead to a higher workload (which typically is detrimental to safe driving), because the user might become confused by the extra information.

To clarify the ambiguous relationship between the amount of information provided to help increase the transparency of the AV and the effect of this information on the user in different scenarios, ESR7 has defined and validated the concept of **functional transparency** during his project. This concept represents an indicator which combines the subsequent workload and comprehension of AV HMIs (Liu et al., 2022). Functional transparency is also about the ease of understanding of AV HMI, without extra workload. Thus, an HMI design with high functional transparency would provide just enough information for the human user to understand the AV system and cope with a particular situation.

2.6 The effect of AV comfort on user acceptance

Experiencing a comfortable ride in an AV is thought to be crucial for the broad acceptance and uptake of these vehicles (Dichabeng et al., 2021; Siebert et al., 2013). A comfortable ride is especially the case for highly and fully automated driving (SAE Level 4 and 5; SAE, 2021), in which control is shifted from the human controller to the automated system, and the active driver becomes a passive passenger or rider. Without the need to control the vehicle, users can engage in non-driving-related activities (NDRAs), which reduces their situation awareness of any upcoming manoeuvres of the AV in response to surrounding traffic or changes in road geometry. Not being in control is regarded as a factor that threatens users' comfortable experience of AVs (Elbanhawi et al., 2015).

Although a commonly agreed-upon definition of user comfort in AVs has not yet been proposed, several definitions about comfort, in general, are outlined in the literature. Broadly speaking, Slater (1985) considered comfort as "a generic term for a pleasant state of psychological, physiological, and physical harmony between a human being and their environment". For user comfort in AVs, researchers specify the AV's driving environment as an important factor. Thus, comfort in AVs can be regarded as "the subjective feeling of pleasantness of driving/riding in a vehicle in the absence of both physiological and psychological stress" (Carsten & Martens, 2019), or "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). In these definitions, comfort is seen as a subjective, personal, and positive state during the drive, without any negative feelings such as stress, distress, or unease.

The effect of traditional factors influencing user comfort in vehicles, such as seat design, cabin temperature, noise, and vibration, has been widely investigated (Ahmadpour et al., 2016; Bryan et al., 1978; Qatu, 2012). Knowledge of these factors can also be applied to the design of more comfortable AVs. However, additional factors are thought to affect user comfort in AVs, such as the loss of control during system-generated trajectories, which can be unpredictable, leading to user discomfort. In addition to feeling uncomfortable with an unexpected manoeuvre, drivers may feel unsafe if the AV drives too close to other objects/vehicles. Discomfort can also arise if drivers engaging in NDRAs experience motion sickness due to a mismatch between the visual input and the vestibular perception of motion (Diels & Bos, 2015; Elbanhawi et al., 2015). Therefore, the driving style of an AV can be considered an important contributor to the level of comfort experienced by users.

In the context of manual driving, **driving style** is characterised by an individual's driving habits, which are gradually established over time. These habits include choice of driving speed, distance for overtaking other vehicles, distance to a lead vehicle, and whether there is tendency to break traffic rules (Elander et al., 1993). In the context of automated driving, the term "driving style" characterises how an AV drives. Researchers have investigated how to achieve a comfortable automated driving style for different groups of users.

While human drivers have different driving styles which can be influenced by their emotions and personalities (Eboli et al., 2017), an AV needs to ensure safety for the onboard, as well as surrounding, road users, while also obeying traffic rules. Therefore, there might be discrepancies between how the user expects the AV to drive and how the AV drives. During unpredictable AV manoeuvres, a human-like driving style which matches the user's own driving style is one method for enhancing user comfort. By increasing the predictability of an AV's driving style, users are likely to feel more comfortable with more familiar AV behaviours (Hasenjäger & Wersing, 2017; Li et al., 2022; Paschalidis et al., 2020).

Several studies have investigated the effect of different driving styles on user experiences in automated driving (Basu et al., 2017; Bellem et al., 2018; Dettmann et al., 2021; Griesche et al., 2016; Hartwich et al., 2018; Yusof et al., 2016). For example, Yusof et al. (2016) compared users' preferences for three driving styles (defensive, assertive, and light rail transit) with varying longitudinal, lateral, and vertical acceleration profiles. The authors suggested that the defensive driving style was preferred by both assertive and defensive drivers (see also Basu et al., 2017; Rossner & Bullinger, 2020). In contrast, Griesche et al. (2016) suggested that participants preferred a driving style like their own. Taking age into account, Hartwich et al. (2018) found that automated driving styles which felt familiar improved younger drivers' comfort, while older drivers preferred unfamiliar driving styles that were faster than their own (and more like that of young drivers). Bellem et al. (2018) investigated the effect of several manoeuvres, including lane change, acceleration, and deceleration, on comfort. They also manipulated the acceleration and jerk profiles for each manoeuvre to create a range of profiles. Based on their findings, the authors suggested minimising acceleration and jerk during acceleration manoeuvres and providing early motion feedback for lane changes to ensure user comfort.

The results from these studies are mixed and by no means comprehensive. Moreover, there are a few potential issues hindering any attempt to summarise these studies. First, a range of different psychological concepts other than comfort (e.g., enjoyment, trust, and feeling safe) are sometimes measured, while different concepts for reporting a positive experience are often used interchangeably. Second, not all studies provide a clear definition; but even when a clear definition is provided, the descriptions of comfort and subsequent evaluations of this concept vary greatly across studies. Finally, different kinematics are configured to create driving styles, and the tested scenarios (e.g., overtaking, lane changing) also vary across studies. All these variations make cross-study comparisons challenging.

3 Addressing the research gaps: Overview of work conducted by each ESR

3.1 Safety: Mental workload, Attention allocation and Fatigue (ESR1)

In the span of her PhD project, ESR1 conducted several experiments that targeted mental workload, attention allocation, and fatigue in automated driving. The goal of her project was to get a better understanding of the cognitive states and processes underlying the interactions between humans and automated vehicles. This knowledge is necessary to design future vehicles that are not only acceptable, transparent, and safe, but also desirable for the users.

The first experiment conducted by ESR1 (Figalová et al., 2022a) focused on the application of neuroergonomic methods in driver-vehicle interaction studies. The primary objective was to examine the impact of an ambient light indicating the current level of system reliability on drivers' take-over performance and mental workload. Furthermore, drivers' comprehension of the ambient light was evaluated using qualitative methods.

A between-group driving simulator study was performed: one group monitored a vehicle equipped with a four-stage ambient light indicating reliability, while the other group monitored a vehicle without this feature. The vehicle's jerk was analysed as an indicator of performance. Both perceived and objective mental workloads were assessed, the latter utilising electroencephalography (EEG).

The findings revealed that the introduction of the ambient light conveying reliability enhanced the take-over performance without increasing drivers' mental workload.

Driving simulators, while providing a secure and controllable environment for driver-vehicle interaction research, are known to present certain limitations, such as the potential lack of immersion experienced by drivers. To address the hypothesis, that a lack of full immersion influences mental processes, the oscillatory brain activity of drivers operating a Level 3 automated vehicle was measured, in a second experiment, using two versions of a driving simulator (Figalová et al., 2022b).

Participants were divided into two groups. The first group utilised a highly immersive simulator with a 190-degree field of view and a detailed replica of the vehicle interior. In contrast, the second group interacted with the same simulator, but only the front screen was displayed, thereby deliberately reducing the system immersion level. EEG recordings from the two groups were compared.

The findings indicate that the immersion level of a driving simulator influences a driver's oscillatory brain activity. Specifically, changes in the high-Beta bandwidth within the parietal and occipital regions and the Beta bandwidth at the Cz electrode were observed. However, no impact of system immersion was detected in the Theta, Alpha, and low-Beta bandwidths. These changes in psychophysiological activation suggest that system immersion can modulate driver arousal. This modulation has potential implications for drivers' cognitive and emotional states, perceived stress levels, and overall sense of presence in the simulated environment. The findings are relevant to our understanding of factors that affect drivers' acceptance, trust, and safety, as well as on the comfort of automated vehicles.

In a subsequent study (Figalová et al., 2023a; Figalová et al., 2023b), ESR1 used a prototype automated vehicle on a test track. This experiment compared the cognitive mechanisms underlying driver-vehicle interactions with SAE Levels 2 and 3 of automated driving to those with manual driving. Specifically, the aim was to discern differences in self-reported cognitive load and attentional resource allocation.

Throughout the three experimental conditions (manual, Level 2, and Level 3 driving), participants were presented with a passive oddball task. They were exposed to three types of task-irrelevant auditory cues: frequent beeps, infrequent beeps, and infrequent novel environmental sounds. The amplitude of the P3a event-related brain potentials elicited by novel environmental sounds, was evaluated as an indicator of the attentional resources dedicated to processing these auditory stimuli. P3a amplitudes were reduced during both Level 2 and Level 3 automated driving relative to manual driving.

Participants' self-assessments of cognitive load were collected after each driving session. The findings indicate that drivers perceived Level 3 automated driving as the least cognitively demanding. Interestingly, there was no significant difference in the self-reported cognitive load between manual and Level 2 automated driving. This reduction implies that drivers may allocate fewer attentional resources to processing environmental sounds during automated driving sessions. Moreover, drivers perceived high levels of fatigue when supervising the Level 3 system, while no difference in fatigue was observed between manual and Level 2 driving.

These findings have major implications for the design of user interfaces in Level 2 and Level 3 automated vehicles: they pinpoint different cognitive states and processes for drivers in the two levels of automation, and how these compare to manual driving.

In a subsequent study (Figalová et al., 2023c), the passive auditory oddball task was extended to examine the influence of mental workload manipulation on driver response. This exploration used the modified speed regulation n-back task introduced by Unni et al. (2017). The study utilised a driving simulator, where participants were subjected to both 0-back and 2-back task conditions.

Subjective mental workload was evaluated using the NASA Task Load Index. In addition, the P3a event-related potential component, which is elicited by task-irrelevant novel sounds, was analysed. This served as an indirect measure of objective mental workload. The findings revealed that participants perceived the 2-back condition to be more cognitively demanding than the 0-back condition. Discrepancies were observed between the two conditions in various facets of the NASA Task Load Index, specifically mental and temporal demand, effort, and frustration. Importantly, the P3a amplitude was notably reduced for the 2-back condition compared to the 0-back. Conclusively, the speed regulation n-back task shows promise as a reliable, valid, and reproducible instrument for manipulating mental workload in driving-focussed research. The task could be used in subsequent studies that aim to manipulate mental workload while retaining high realism and immersion in the driving experience.

During her project, ESR1 also extended her collaborations to explore other facets of driver-vehicle interaction (Pichen, Figalová, & Baumann, 2022). Specifically, using a collaborative approach, the investigation focused on the usability, acceptance, and user trust of Level 4 automated driving, using a driving simulator. Participants interacted with a *"Sneak Peek"* function, which offers drivers the ability to modify the vehicle's lateral position before accepting an overtake request. The study also contrasted the usability of the Sneak Peek function across two distinct interface modalities: the commonly employed touchscreen and a habituated interface with traditional manual driving controls.

The findings of this study underscore the practicality of the Sneak Peek function. It helped drivers assess the suitability of overtake suggestions proposed by a highly automated vehicle, which was particularly useful when the lead vehicle was obscuring the rider's view. Additionally, there was a higher preference for the familiar tactile experience of the habituated interface, such as a steering wheel, when compared to a touchscreen interface.

3.2 Perceived safety and Trust (ESR12)

This section delineates the results of three research studies conducted by ESR12, who focussed on trust and perceived risk in automated driving. The first study used a driving simulator to identify predictors of perceived risk and trust, revealing that relative motion with neighbouring road users significantly impacts these factors. The second work developed a computational model called PCAD, which can predict perceived risk for general two-dimensional motion based on potential difficulty of a avoiding a collision. The last study, which examined the role of user interfaces in enhancing trust and perceived safety, found that a complex User Interface, combining visual and auditory cues, was the most effective in boosting trust and reducing perceived risk. This work offers a comprehensive insight into human factors of automated driving, from predictive modelling to interface design.

Simulator experiment 1 – Perceived safety and trust in merging and hard braking

This simulator-based study aimed to identify the critical predictors that influence perceived risk and trust in automated driving systems, specifically focusing on SAE Level 2 driving automation (ACC + LC). The experimental setup involved 25 participants who were asked to monitor the driving automation system while encountering different types of events on a motorway, including merging and hard braking with varying levels of criticality.

The study employed stepwise regression models to predict event-based changes in perceived risk and trust. These models revealed that the relative motion with neighbouring road users is the most significant factor accounting for variations in both perceived risk and trust. Interestingly, the study found no substantial difference in perceived risk or trust between hard braking with merging and hard braking without merging.

Another important finding was the role of exposure and personal characteristics. Drivers were more trusting of the automaton system during their second encounter with similar events. The models also pointed to modest effects of personal characteristics on perceived risk and trust: experienced drivers were less sensitive to risk and trusted the automation more. Female participants perceived higher levels of risk compared to their male counterparts.

The study measured pupil diameter, and ECG signals as possible indicators for risk and trust in AVs. In addition, data were collected from a device (developed as part of the project) that is intended to measure continuous perceived risk. The results showed that continuous perceived risk closely aligns with participants' post-event verbal ratings, and the use of brakes is an effective indicator of high perceived risk and low trust. Pupil diameter was found to correlate with perceived risk during the most critical events. Although the events did increase the heart rate, no correlation was found with event criticality.

The findings of this study are particularly valuable as they not only shed light on the event-based dynamics of perceived risk and trust but also offer a roadmap for designing human-centred automation systems. The regression models and physiological measures can serve as tools to help with the design of AVs that reduce perceived risk and enhance trust, thereby making these systems more acceptable and safer for users.

Real-time 2D perceived risk modelling

This research introduces a novel computational model, the Potential Collision Avoidance Difficulty (PCAD) model, for assessing perceived risk in SAE Level 2 automated driving systems. This model was formulated to address the existing gap in our understanding of perceived risk dynamics, an area that is crucial yet underrepresented in the literature.

To develop the PCAD model, a computational approach incorporating both static and dynamic factors was employed. It uniquely uses the 2D safe velocity gap as the metric for potential collision avoidance difficulty, while considering the severity of potential collisions. The safe velocity gap signifies the 2D distance between the vehicle's current velocity and a safe velocity region. It quantifies the required adjustments in braking and steering, considering the behavioural uncertainty of neighbouring vehicles and the imprecise control of the subject vehicle. The model is designed to predict perceived risk, both continuously and by event.

The PCAD model underwent rigorous validation using two unique datasets: the Merging Dataset and the Obstacle Avoidance Dataset. PCAD was compared against three state-of-the-art models to evaluate its relative efficacy. The findings revealed that the PCAD model generally outperformed existing models in several key metrics such as model error, detection rate, and the ability to authentically capture human drivers' perceived risk tendencies.

However, it was noted that its superior performance comes at the cost of longer computation times.

Importantly, the study also highlights that perceived risk is a dynamic concept, influenced by the changing conditions of the surrounding traffic. The PCAD model, therefore, not only advances our understanding of perceived risk but also serves as a robust tool that can be applied across various levels of driving automation. Its insights are invaluable for both the design and safety evaluation phases of automated driving systems, making it an essential asset for enhancing public trust and acceptance of these technologies.

Simulator experiment 2 – Can UI enhance perceived safety, trust, and acceptance in partially automated vehicles?

This research focusses on the crucial role of user interfaces (UI) in shaping trust, acceptance, and perceived safety in partially automated vehicles. The study aims to uncover how UI design can positively impact these dimensions, while recognizing that trust and perceived safety are pivotal for acceptance.

The study employed a driving simulator to test four meticulously designed interfaces featuring varying levels of complexity. The levels were established by combining different types of automation information (either surrounding information alone or both surrounding and manoeuvre information) and modality (either visual or a combination of visual-auditory cues). The simulator was programmed to present scenarios in which a partially automated vehicle encountered merging and braking vehicles. Variables such as the merging gap and deceleration rate of the lead vehicle were manipulated to adjust the criticality of these events.

The findings indicate that the most complex UI, which conveyed both surrounding and manoeuvre information through both visual and auditory modalities, scored the highest in terms of trust, acceptance, and perceived usefulness, while also minimising perceived risk. Notably, manoeuvre information delivered via auditory cues was found to be particularly effective in enhancing trust and acceptance. These effects were generally consistent across different events, although it was observed that drivers did not feel entirely safe or trusting during the most critical events.

The study provides valuable insights into the multi-dimensional aspects of UI design for partially automated vehicles. It emphasises that an optimal UI should not just deliver the right information but also present it in the most effective modality. For instance, in complex driving scenarios, combining visual and auditory cues proves to be more effective, than either modality presented in isolation. This work concludes by offering actionable guidelines for UI designers, advocating for a blend of surrounding and manoeuvre information, delivered through visual and auditory channels to optimise trust and acceptance.

3.3 AV Transparency (ESR7)

To verify and validate the proposed functional transparency, an initial study was conducted with three HMI designs that were available on the market (Liu et al., 2022). The designs were chosen for their distinct interface elements. For example, the icons in HMI 1 were low contrast, violating the heuristic design principle, while the icons of HMI 2 were brighter and more distinctive. The different elements resulted in significant differences in the functional transparency of these HMIs. The automated driving system (ADS) experiences were also analysed and evaluated in this study; functional transparency was significantly different for the different ADS experiences. These significant findings gave us insight into the effectiveness of the proposed assessment method, which was then used for the subsequent studies.

The next step of the work involved extending the use cases into a more realistic driving environment. A simulator study was conducted to validate the assessment method in a dynamic interaction (Liu et al., 2023). Psychophysiological measures were adopted to provide real-time, objective workload measurements. Also, to have better control of the variables, we designed three HMIs based on heuristic design principles and the results of previous studies.

There are two relevant design principles. One specifies that the HMI should use clear, concise language and icons, making them easy to understand and respond to correctly. The HMI design obeying this principle will have higher functional transparency than one that does not. The second principle states that the HMI should provide accurate and prompt information (about the states of the AV system, for example). Even though providing more information does not necessarily increase functional transparency, prompt feedback is critical for human users to understand the current state of the system. One of the HMI designs used in this study provided direct feedback for an unsuccessful activation to SAE Level 2, while the other had indirect feedback for the failed activation and went silently back to the initial state. Results showed significant differences among HMI designs in terms of functional transparency. Furthermore, the electrocardiogram (ECG) and the electrodermal activity (EDA) were identified as suitable candidates for measuring differences in workload while interacting with HMI designs in a simulated environment.

3.4 Comfort (ESR5)

The work of ESR5 focussed on understanding and improving user comfort in highly automated driving, particularly from the perspective of the AV’s driving styles. Three studies were conducted, and are described below:

Study 1

To understand whether human-like driving styles are more comfortable and perceived as more natural by users, the first study investigated users’ subjective ratings of three highly automated driving styles (Peng et al., 2022).

Twenty-four participants experienced the driving style of three automated controllers in a high-fidelity, motion-based driving simulator and evaluated them in terms of their comfort and naturalness. The three driving styles presented by the controllers included two human-like driving styles (Defensive and Aggressive), created by recording the defensive and aggressive manual driving of two representative human drivers, respectively. These driving styles were then replayed back to a different group of participants. The participants' responses to these two driving styles were compared to that for a machine learning (ML)-based, (and therefore more machine-like), driving style (Solernou et al., 2020). The three AV controllers navigated a stretch of road in the UK divided into 24 sections, which included a variety of road geometries and road-side furniture, such as parked cars. Participants rated the comfort and naturalness of each controller for each road section, and provided an overall rating for each drive. Their risk-taking propensities were also measured using the Sensation Seeking questionnaire (Arnett, 1994).

Results showed that both human-like driving styles were perceived as more comfortable and natural than the ML-based AV controller. Furthermore, of the two human-like driving styles, the Defensive one, which was more conservative in response to curves and roadside furniture (e.g., slower speed), was rated as more comfortable. This was especially the case when the road environment became more challenging—for example, when the car negotiated sharper curves and drove at higher speeds. Participants with lower sensation-seeking scores rated the Defensive driving style as more natural than the Aggressive one. Conversely, high sensation seekers found the Aggressive driving style to be as natural as the Defensive driving style, although they considered the latter to be more comfortable.

Therefore, we concluded that participants could perceive differences between human-like and machine-like driving styles, and that a more defensive driving style was the most comfortable for both high and low sensation seekers, although high sensation seekers also felt that the aggressive driving style was natural. These results shed some light on the relationship between different, but closely related, psychological concepts. Specifically, a natural driving style does not necessarily lead to a comfortable experience.

Study 2

In the second study, to understand how AV driving styles affect user comfort and perceived naturalness, we investigated the influence of various kinematic and proxemic characteristics of an AV's driving style on subjective evaluations of both comfort and naturalness. We also explored the similarities between the automated driver style and users' own manual driving styles (as characterised by Euclidean distance) and the effect of such similarities on the subjective evaluations. In addition to the subjective evaluations of the three automated driving styles (Aggressive, Defensive, and ML-based), participants' own manual driving data along the same simulated road was included for comparison.

Linear mixed-effects models showed that the lateral and rotational kinematics of the AV's driving style had significant effects on both comfort and naturalness evaluations, while longitudinal jerk only influenced participants' comfort. In terms of similarities between automated and manual driving styles, Kamaraj et al. (2023) previously reported a positive relationship between objective similarity (characterised by speed) and subjective similarity (i.e., naturalness). We have built on these findings by confirming the positive association between similarity in speed and comfort evaluations. Moreover, we found that similarities in longitudinal jerk and yaw were also positively associated with comfort and naturalness. However, the association between similarity in lateral jerk and subjective ratings was found to be negative.

Study 3

As outlined above, at the start of the project there was a distinct lack of research detailing what exactly influences comfort in automated driving, how comfort is affected by the AV's driving style, how comfort should be evaluated, and what the relationship is (if any) between these closely related concepts (Peng et al., submitted).

Study 3 involved gathering insights via an online workshop involving nine internationally recognised experts with direct experience of AVs. Using the online whiteboard tool Miro and the meeting platform Microsoft Teams, these experts discussed the factors they found relevant to comfort and discomfort in current transportation options like taxis, buses, and trains. Furthermore, the experts compared these insights with those that apply to AVs.

Results showed that while terms used to describe comfort and discomfort in traditional vehicles are applicable to AVs, additional factors should be considered for AVs. These included the use of effective communication channels and a closer association between the vehicle's capabilities and user expectations. New, AV-specific factors influencing discomfort, such as riders' safety, privacy, and sense of control, also emerged. In fact, more descriptors were used by the experts for discomfort than for comfort, and comfort in AVs was not thought to be solely about reducing discomfort.

This study also contributed to a refined conceptual framework that outlines how AV driving styles and other (non-driving-related) factors affect user comfort. This refined framework offers a more thorough understanding and measurement of comfort, thereby aiding in the development and comparison of future empirical studies investigating AV comfort.

4 The impact of other concepts relevant to designing acceptable, transport and safe AVs

In this section, the work of ESRs whose projects were not directly linked to human factors concepts but are still relevant for influencing AV acceptance and trust, are outlined.

4.1 Safety and AV algorithms (ESR15)

It can be argued that safety should take precedence above all other considerations when designing AVs. A primary motivation for the development of AVs is their potential to reduce accidents and minimise injuries among all road users, including drivers, pedestrians, and cyclists. Given that human factors are thought to contribute to approximately 94% of accidents (NHTSA, 2015), many anticipate that AVs could significantly decrease or mitigate crashes caused by human error, ultimately improving road safety. However, the extent of an AV's safety performance, when compared to traditional manually driven cars, is still being investigated. The methods used to assess AV safety are crucial, as they play a central role in AV development and provide critical information for decision-making regarding deployment, as well as guiding policies and regulations (Sohrabi et al., 2021). In addition to the objective safety of AVs (their ability to navigate safely), their perceived safety, which pertains to how safe AV drivers and passengers feel, must be determined. Comprehensive guidelines for AV development should encompass various safety aspects, including design of a safe automated driving system, and guidelines and methods for how to assess safety. Perceived safety, which is related to the occupant's sense of safety (He et al., 2022), is covered separately in another section.

AVs cannot be considered in isolation: they coexist, and interact with, human drivers who need to adapt to AVs. The collaboration between humans and automation is of paramount importance (Christoffersen & Woods, 2002). The journey towards fully automated driving for AVs is expected to be extensive. During this development process, various human factors issues may arise. Understanding how drivers react to AVs in different scenarios is one pivotal issue which should be exploited to further improve AV design. This would in turn enhance safety and improve drivers' acceptance of AVs. Another issue, overreliance on automation, is a common challenge which can increase risk if the driver does not question the performance of AVs or does not sufficiently supervise an imperfect AV (Saffarian et al., 2012). One potential way to increase safety is to adopt human-centred, collaborative automated driving (Xing et al., 2021).

AV algorithms rely on object detection and tracking information provided by the AV's sensors. However, the sensors are not yet completely reliable under all circumstances. Uncertainties in sensor information influence the detection and tracking of objects, which in turn affect the decisions of AV algorithms, influencing driving safety. Sensor redundancy and high-quality perception are therefore crucial aspects of designing safe AVs, particularly for urban environments (He et al., 2020; Thandavarayan et al., 2020). Redundancy is achieved by equipping the AV with multiple sensors, either the same type (e.g., multiple cameras) or different types (e.g., lidar, radar, cameras, and ultrasonic sensors), that all serve the same purpose: detecting and tracking objects and obstacles in the environment. Redundant sensors provide fault tolerance. If one sensor fails (e.g., due to weather conditions such as heavy rain or fog), the AV can rely on the additional sensors to maintain perception capabilities. Different sensors have different strengths and weaknesses in various scenarios: for example, lidar is excellent at providing precise distance measurements but is easily incapacitated in heavy rain or snow. Radar can penetrate adverse weather but offers less detailed information. Cameras provide rich visual data but can be affected by low light or glare. Combining these diverse modalities enhances the AVs' robustness. High-quality perception involves ensuring that the data collected from sensors are accurate and reliable, which requires minimising sensor errors (such as calibration issues or sensor noise) and ensuring sensors are well-maintained.

Cybersecurity is another aspect that needs to be considered for ensuring the safety and ultimate trust and acceptance of AVs (Chowdhury et al., 2019; Petit & Shladover, 2015; Schmittner & Macher, 2019). This is especially because AVs are heavily reliant on software, communication systems, and data sharing. This reliance makes AVs susceptible to cybersecurity threats. If AVs are hacked, their functionality could be controlled and/or destroyed. The consequences of this interference could be severe, for example leading to accidents or malicious takeovers. Therefore, is it essential to safeguard AVs against cybersecurity threats, both during their development and also their operation.

The assessment of AV safety relies on specific evaluation methods. The precision and efficiency of these assessments can have a substantial impact on the advancement of AV technology. Such assessment can occur when the system is in production, such as the Euro-NCAP rating program for consumers. (Euro NCAP, 2022; Ratingen et al., 2016). However, during the development of conflict and crash avoidance systems, car manufacturers often employ virtual safety assessments due to the high costs associated with physical experiments. This decision is particularly common in the early stages of safety system development. Scenario (crash) generation plays a vital role in this process, as it can encompass all potential scenarios for an evolving system's safety assessment (Cai et al., 2022; Khastgir et al., 2017; Stark et al., 2020). Additionally, efficient sampling methods (part of ESR15's contribution in SHAPE-IT) are utilised during safety assessments, to ensure efficient assessment while facilitating accuracy and precision in the assessment (Imberg et al., 2023). Efficient sampling enables virtual assessments to conclude substantially earlier than if no sampling is employed.

Various methods exist for generating different scenarios for virtual safety assessment, one of which is crash causation model-based scenario generation. Note that although AVs may be automated, the virtual assessment of AVs needs to be compared to something – the baseline. Consequently, baseline crash generation is a core component of virtual AV safety assessment. While crashes occur for various reasons, research, such as that conducted by Knipling et al. (1993), has identified driver inattention as a major factor in rear-end collisions. Several studies have explored how driver glance behaviour causes crashes, and how to utilize glance behaviour-based crash causation models in generating baseline scenarios. However, it is important to note that driver glance behaviour may vary across different levels of AVs. For instance, research by Bärgman & Victor (2019) shows that driver glance behaviour differed across levels automation and investigated the safety impact of this behaviour change though virtual simulations. When driver behaviours are included in AV safety assessments, it is crucial to investigate how these behaviours may be influenced by the presence of advanced driving systems and higher levels of automation. Future research should also investigate what the actual safety impact is of driver monitoring systems.

AVs coexist with human drivers, and knowledge of driver behaviours can be invaluable for enhancing both AVs and scenario generation for AV performance assessments. Understanding how humans typically respond in various traffic situations helps improve AV decision-making algorithms and creates realistic scenarios for AV testing. In the practical implementation of AVs, sensor redundancy and high-quality perception are vital for ensuring accurate environmental awareness. These aspects collectively contribute to the safe and effective integration of AVs into real-world environments, where safe human-machine interactions are paramount concerns. Considering these aspects in the development of AVs will likely enhance their safety, and lead to higher trust and acceptance of these new forms of mobility.

4.2 Human Factors in Artificial Intelligent (ESR8)

To harness the full potential of AVs and address automation-related issues (Biever et al., 2020), human factors experts emphasise the importance of incorporating human-centric knowledge into the AV design process (Hancock, 2019; Wickens et al., 2018; Navarro, 2019). Human factors research focusses on understanding human abilities and constraints and applying this knowledge to system designs to enhance performance, safety, and comfort (Human Factors and Ergonomics Society, 2023). For effective automation design, human factors insights should be integrated at an early stage in the development process (Calp & Akcayol, 2019; Chua & Feigh,2011; Håkansson & Bjarnason, 2020). Traditionally, these insights have been included in the system requirements specified up-front forming the foundation for subsequent design work (Royce, 1987). The process of defining, analysing, and validating these requirements is termed Requirements engineering (RE) (Kotonya & Sommerville, 1998).

However, the automotive industry's shift towards agile development methodologies has altered the significance of RE. Agile methods prioritise rapid, iterative development by collaborative teams (Moniruzzaman & Hossain, 2013). These methods aim for quicker market delivery, but often sideline aspects like human factors. Since agile approaches don't emphasise processes, integrating RE becomes challenging (Kasauli et al., 2021). The absence of a defined role for RE in agile methods, coupled with limited research on how to integrate human factors into agile development, means that practitioners are left without clear direction on how to incorporate human-centric knowledge in this new development landscape.

Therefore, the primary goal of the work conducted by ESR8 has been to explore methods for the efficient introduction of the requirements derived from human factors knowledge to AV developers within a large-scale agile AV development process. To achieve this goal, a comprehensive exploration of the domain was established, and a detailed examination of the issues relevant for meeting the end goal was performed. A set of initial solutions to address the core issues, serving as a foundation for the final resolution of the research project, is outlined below.

4.2.1 Requirements Engineering

The International Requirements Engineering Board (IREB) describes requirements as the portrayal of clients' and users' needs and wishes for creating new or enhancing existing products (IREB, 2020). Requirements can be categorised as:

- Functional requirement: a specific outcome or behaviour the product should exhibit.
- Quality requirement: aspects not addressed by functional requirements, such as performance, security, and reliability.
- Constraint: further limitations on solutions to satisfy functional and/or quality requirements.

Requirements engineering (RE) involves recording these requirements in accepted documents that guide all subsequent tasks (Leffingwell & Widrig, 2000). IREB sees RE as the practice of shaping and overseeing system requirements to ensure that the final systems align with stakeholder expectations (IREB, 2020).

Historically, RE was a linear process comprising requirements elicitation, analysis, specification, and validation (Kotonya & Sommerville, 1998). Elicitation involves gathering stakeholder requirements through methods like storyboarding or prototyping. Next, in the analysis phase, requirements are scrutinised for gaps, and any overlaps or conflicts are settled. The specification phase then formally or informally documents these requirements. Lastly, the requirements undergo validation for coherence and thoroughness (Kotonya & Sommerville, 1998).

However, the integration of traditional RE with modern development approaches has been challenging, especially in agile environments. This has led to the understanding that traditional methods may not effectively cater to evolving user values and that requirements might be better developed in tandem with the system rather than being predetermined (Boehm, 2006).

4.2.2 Agile Development

Agile methodology has gained traction among development firms due to its adaptability and product success rates, which are greater than those of traditional methods (Serrador & Pinto, 2015). Agile practices embrace changes affordably and deliver superior products swiftly (Meyer, 2014). A distinct advantage of agile is its user-centric approach, ensuring regular feedback and mirroring customer values.

Typically, agile is recommended for compact teams of six to eight members (Meyer, 2014; Beck, 1999). The Agile Manifesto (Beck et al, 2001) underscores the essence of agile: prioritising human interactions to produce effective software in tight collaboration with clients, while downplaying the significance of processes, tools, and extensive documentation.

In agile, the exhaustive requirements of traditional methods are replaced by ongoing dialogue with stakeholders (Meyer, 2014). Initially, agile teams draft user stories (brief notes detailing client needs). However, some critiques of agile include its tendency to overlook initial planning and its restriction to functional requirements illustrated by ideal scenarios (Meyer, 2014).

Originally, agile methods were designed for small teams. However, in recent times, these techniques have been embraced by larger corporations (Larman, 2010). 'Large-scale agile' refers to the application of agile methodologies within extensive teams or multi-team projects (Dingsøyr & Moe, 2014). According to the classification of scale in agile software development, large-scale agile describes projects with more than two teams (Dingsøyr & Moe, 2014). If an organisation has over nine teams, it is on a very large scale. Yet, Dikert et al. have stated that large-scale agile development can be defined as agile processes involving over six teams (Dikert et al., 2016).

Numerous guidelines and frameworks have been crafted to implement agile principles in areas beyond software development, like business strategies or operations, and within bigger entities. The Scaled Agile Framework (SAFe; Kasauli, et al., 2020) stands out as the most prevalent framework for large-scale agile development, particularly in the automotive sector. SAFe structures teams into broader units known as agile release trains, which regularly develop and roll out their contributions to deliver value to end-users (Leffingwell, 2010). Additionally, SAFe introduces a model for requirements wherein multiple user stories are merged into a single epic, signifying medium- to long-term goals for team clusters. This model also incorporates additional stipulations as quality (non-functional) requirements (Leffingwell, 2010).

4.2.3 Requirements Engineering in Agile

Agile Requirements Engineering (RE) or RE tailored for agile development is generally seen as an agile approach, although a universally accepted definition is yet to be established (Heikkilä et al., 2015). Several conventional RE practices—including direct communication, customer engagement, prioritising requirements, review sessions, acceptance testing, and managing changes—are adaptable to agile RE (Ramesh et al., 2010; Inayat et al., 2015).

As noted, implementing RE within an agile framework comes with a set of challenges. These encompass overlooking non-functional requirements, ensuring client availability, fostering team collaboration, facilitating knowledge transfer, maintaining adequate documentation, and achieving a mutual understanding of customer values (Dikert et al, 2016); Inayat et al., 2015; Kasauli et al., 2017).

Research from initial efforts to resolve some of these RE challenges in agile environment suggests an integration of traditional RE practices with agile RE (Inayat et al., 2015; Paetsch et al., 2003). This approach addresses dilemmas such as determining the right amount of documentation (Hoda et al., 2010) to ensure the collective grasp of customer values. While existing RE methodologies seem promising for addressing many agile-related challenges, there's a clear need for more research to tackle RE-specific issues in the agile context.

4.2.4 Human Factors for Effective Engineering

It is crucial to understand how design and development experts perceive human factors, especially in multidisciplinary studies which involve requirements from various engineers working with human factors experts). Often considered as "soft factors", human factors encompass non-technical attributes and skills. They are vital in any work involving humans, including AV development. Hence, defining a specific term for a particular subject, such as AV design, becomes essential. ESR8 used the following definition for her work: *"The field of Human Factors in AV Development aims to inform by providing fundamental knowledge about human capabilities and limitations throughout the design cycle so the product will meet specific quality objectives*" (Muhammad et al., 2023). Given the diverse views on human factors, it is evident that these factors represent core values in software and road transport development (Wickens et al.,2018; Pirzadeh, 2010).

In AV development, human factors are an integral part of both software and hardware design. Software-related human factors might involve lane-keeping (Xu et al., 2017; Miller & Boyle, 2019), communicating with external road users (Ackermann et al., 2019; Faas et al., 2020) or software-based human-machine interfaces (HMI) (Carsten & Martens, 2019), and human-AV interactions (Ackermann et al., 2009). Hardware design aspects range from seating ergonomics and the influence of AV capabilities on car interiors (Salter et al., 2019) to the design and positioning of HMIs.

These examples underscore the extensive human factors knowledge needed for effective engineering. Other researchers also emphasise the importance of integrating human factors in development (Hancock, 2019; Wickens et al., 2018; Navarro, 2019). Yet, the pace of human factors research lags that of AV development, raising questions about engineers' awareness of human factors in their designs. It is imperative to devise strategies to consistently integrate human factors into development. Preliminary studies suggest introducing human factors early in the development process (Chua & Feigh, 2011; Håkansson & Bjarnason, 2020). However, the best approach to embedding human factors knowledge in the initial stages of agile AV development remains ambiguous.

4.3 Long-term changes in acceptance, transparency, trust, safety, and comfort of AVs (ESR2)

Automation is currently changing the way we think about driving. Many Original Equipment Manufacturers (OEMs) are currently in the process of advancing their automated driving systems (ADS), with level three automation (L3, SAE J3016_202104) set to hit the market in the imminent future. Thus, more research is needed to measure the long-term effects of automation and users' experiences over time. Special attention should be given to how the design of an AV affects its transparency, trust, acceptance, safety, and comfort for the user.

An understanding of how these factors may change over time, following repeated and long-term Human-Automation Interaction (HAI), is also important.

In essence, there is a need to understand the user experience (UX) with automation, from its first introduction to long-term use. Although considerable thought has been given to human factors-related challenges arising from interactions with automation, little attention has been devoted to any changes in behaviour encountered during long-term exposure to these systems. Since research on HAI is usually short-term, it is difficult to study situations where the user is habituated to interacting with automation. Therefore, it is important to investigate any changes in behaviour as users gradually experience the system and learn to use it. Thus, more long-term research methods and approaches are warranted, and human factors researchers should consider performing long-term studies. These are typically neglected in empirical work, probably because these studies are time-consuming, expensive, challenging, and complex. Indeed, a precise definition of what constitutes a long-term study is also currently lacking (Portouli et al., 2006; Metz et al., 2021; Mbelekani & Bengler, 2023).

Gruel and Stanford (2016) argued that long-term effects of technology are rarely considered, and seldom examined in the literature. Thus, the potential impacts, which could encompass both positive and negative outcomes with direct and indirect effects, are unknown. As a result, whether technology brings overall benefit or damage to society is far from clear (Gruel & Stanford, 2016). The lessons learned from this type of research suggest that studies should consider the interaction process in behavioural terms rather than only technical terms. Moreover, assessing how the interaction changes a user's mental model over time is also valuable. Bloomfield et al. (1998) observed changes in user performance after a long period of travel on an automated highway system. Inconsistencies in automation capabilities and limitations also mean that there will be considerably different effects of automation for different users, especially over repeated usage (Metz et al., 2021). Essentially, factors such as automation transparency, how much users trust automation (Lee & See, 2004; Molnar et al., 2018), as well as its use, misuse, disuse, abuse (Parasuraman & Riley, 1997) play an important role in this discussion.

Controlling (and ideally preventing) problems posed by AV technologies requires awareness of the issues and their timing. As with any other innovative technology, an automation system takes several seasons to build the credibility needed for users to become accustomed to it and accept it. In this context, transparency plays an important role. We assume that with long-term exposure or repeated usage, users learn to understand the messages presented by a human-machine interface (HMI). Learning is also a continuous process, with users becoming more familiar with the design of a system after repeated and gradual exposure. As with any foreign or unfamiliar entity, humans may take time to fully comprehend the AV's distinct transparency, and research suggests that advanced, agile transparency may be a fundamental requirement for user trust and acceptance of automated systems (Ososky et al., 2014; Körber et al., 2018; Oliveira et al., 2020; Liu et al., 2022). Importantly, to be inclusive, user studies on AV interactions must include results from a more diverse population than has been achieved to date.

To understand how long-term interaction with automation affects user trust, one must understand how repeated exposure with a system affects cognitive aspects of behaviour. Moreover, different users may have different experiences with automation, which in turn affects their trust over time. For example, if a user has a negative experience, this may reduce their trust in that and similar systems. Positive prior experience may also be problematic, as it can lead to complacency and over trust (Lee & Seppelt, 2009; Lee & See, 2004) with long-term use. To harness the potential of automated systems, humans need to learn how to use them safely and appropriately and, as a result, develop a sense of safety-induced trust in the automation. To fulfil safety requirements in system usage, users may need to experience the system in different situational and environmental contexts, among other factors. As users experience the system in different situational contexts, their behaviour-based safety may be enhanced over time. However, it is important to note that this may also have the reverse effect, with behaviour-based risk being the outcome.

Overall, the current interaction design strategies require a level of smartification when designing for long-term HAI experience, to ensure users' safe use and assimilation of, and interest in, AVs. For the interaction between humans and automation to be considered successful, the automation must be able to observe its position, make decisions, and behave ergonomically. The human experiencing this interaction should consider it satisfying, comfortable, and enjoyable, even over time.

5 New Design Guidelines and Methodologies

In this section a short overview of the design guidelines and conclusions for each concept explored by the project's ESRs is presented, with a focus on how this work has transformed the state of the art.

5.1 Transparency (ESR7)

Transparency is a critical concept for achieving a safe and understandable AV HMI. To better evaluate and estimate the ease and comprehension of HMI designs, ESR7 defined the term **functional transparency** and verified and validated a proposed assessment method for the concept. This method led to the identification of the HMI designs that were more accurate and easier to understand. The proposed method could also be used to for identifying components of the HMI design that would increase or decrease functional transparency, either facilitating or hindering users' understanding and correct use of AV HMI. Further research is still needed to create a more comprehensive list of factors that are relevant for the interaction between humans and AV HMI. However, the proposed method could efficiently and systematically assist with this work.

5.2 The effect of driver cognitive states on safety (ESR1)

The experiments showed that drivers' roles change with increasing levels of automation. The new roles pose different demands on drivers, particularly when compared to the demands of manual driving. The new demands are reflected in changes in cognitive states and processes. Therefore, when developing future user interfaces and in-vehicle environments, designers should consider these changes in drivers' experiences and states across the automation levels. While driving Level 2 vehicles can be considered relatively demanding and, up to a point, comparable to manual driving, driving Level 3 vehicles is significantly different. When supervising a Level 3 system, drivers are allowed to be involved in other, non-driving related tasks. They pay less attention to their environment, and they might experience high levels of fatigue.

Due to the high fatigue and inattention, advice and warning cues should be timely and salient. Drivers need to shift their attention towards the road, regain situation awareness, re-calibrate their perceptual-motor control loop, and perform a successful, safe transition of control.

Communicating the AV's current level of reliability by means of a peripheral ambient light appears to be a feasible solution for increasing the predictability of potentially safety-critical situations.

Changes in drivers' cognitive processing also call for reliable driver monitoring systems. If the drivers' fatigue and attention allocation are correctly identified, the AV can provide support to the drivers before a system limitation is reached. ESR1's work identified the need for adaptive user interfaces that dynamically change over time, to provide the best possible support to drivers in any specific moment. Ideally, intelligent user interfaces should be designed that monitor and support drivers' performance, managing their attention.

Finally, the results of the work stress the need for real-world testing. Although simulator studies provide a safe, efficient way to collect data in driver-vehicle interactions, the applicability of the results to the real world is limited. Real-world experiments are the only way to understand how drivers really interact with an automated system. Moreover, such studies should also consider the long-term effects of interaction with automation, as the experience of novice drivers might be different from that of experienced drivers.

5.3 Perceived safety and Trust (ESR12)

5.3.1 Modelling and Measuring Perceived Risk & Trust

New regression models for perceived risk and trust are being developed, providing a quantitative framework that integrates both subjective and objective measures. These models represent a significant advancement over traditional methods by offering a more holistic view of the variables that influence perceived risk and trust in automated driving systems.

5.3.2 Factors Influencing Perceived Risk and Trust

The relative motion of neighbouring road users was found to significantly influence perceived risk and trust. This is a crucial finding, as it underscores the dynamic nature of driving environments and the need for automated systems to be highly adaptive. Demographic factors also play a role; experienced male drivers tend to be less sensitive to risk, compared to inexperienced female drivers, indicating that perceptions of automated driving technology can vary widely among different user groups.

5.3.3 Physiological Indicators

The value of physiological measures for quantifying perceived risk was demonstrated. For example, pupil dilation was found to be a reliable indicator of perceived risk, especially when the event was sufficiently risky. Events involving merging and braking led to increased heart rate among participants, reinforcing the emotional and cognitive load associated with these scenarios.

5.3.4 Perceived Risk Characteristics

Findings confirmed that perceived risk is not a static, unidimensional concept; it is dynamic and multidimensional. For the first time, perceived risk can be reliably predicted, and it displays a non-linear increase as the distance to surrounding vehicles decreases.

5.3.5 User Interface (UI) Design

The work also delved into the impact of UI design on drivers' trust and acceptance. The different UIs had different effects on trust and acceptance. The most effective UI, which displayed information both visually and audibly, was associated with the lowest levels of perceived risk and the highest levels of trust and acceptance. Moreover, the inclusion of manoeuvre information via the auditory modality significantly enhanced drivers' trust and acceptance, indicating a need for current partially automated vehicles to include additional auditory information for a better user experience. These recommendations could serve as the basis for the next generation of user-centred, trustworthy, and safe automated vehicles.

5.4 Comfort (ESR5)

The work of this ESR has resulted in new definitions for comfort and naturalness of AVs. The work distinguished between a comfortable driving style “a driving style that does not cause any feeling of uneasiness or discomfort”, and a natural driving style as “a driving style that is closest to your own driving”. Further, comfort was defined as the absence of discomfort. The methodology was found to be useful in capturing participants’ experiences and distinguishing different psychological concepts (see also Peng et al., 2022).

A refined conceptual framework was developed which provides an overview of how AV driving styles affect user comfort, from both physical and psychological perspectives, by integrating concepts that are either related to driving style (e.g., trust, perceived safety, expectations, naturalness) or not (e.g., privacy concerns). With such a comprehensive list of factors, the measurement of comfort and discomfort can be more precise as different aspects can be measured—and in particular the features of automated driving can be taken into account.

The three studies conducted by this ESR provide new design guidelines for increasing the comfort of AVs. Results showed that human-like driving styles are more natural and more comfortable than the less human-like, machine-learning-based driving styles. Regarding personalisation of automated driving, results showed that individual personality traits, such as the sensation-seeking score, were in line with drivers' preferences for a particular driving style. Although the high sensation seekers' driving style was most like the aggressive controller, both low and high sensation seekers considered the defensive driving style more comfortable. Therefore, an automated driving style that is similar and more familiar to an individual's own driving style may feel more natural but is not necessarily the most comfortable.

5.5 Design of more acceptable AVs from an engineering perspective (ESR8)

This PhD research explored the effective methods for conveying human factors knowledge to AV developers within large-scale agile environments. ESR8 tackled this challenge through an RE lens.

The work has led to a working definition of human factors tailored to AV development, which will enhance comprehension in this area. The definition led to an exploration of the intricacies of agile methodologies and human factors within AV development. Significant implications for agile development, human factors, and requirements engineering were identified, which can guidance for researchers and industry experts. These insights are valuable for human factors specialists and AV engineers, particularly for conveying HF requirements during development. Previous research emphasises the need to incorporate human factors into the RE process; the current findings support this, but also spotlight the challenges when human factors is applied in agile contexts. Additionally, it should be noted that new areas in AV development, such as AI-driven features, require a focussed approach to human factors integration. Overlooking this need could result in missing the human implications of AI-centric approaches.

Moreover, the findings emphasise the significance of incorporating human factors expertise within development teams. However, the intermittent demand for such expertise and the limited availability of human factors experts in numerous agile AV teams present challenges. The swift, iterative character of agile methodologies might not always be conducive to the comprehensive experiments that human factors experts deem necessary to ensure user-centric quality.

Additionally, to address the challenges of integrating requirements into agile development, preliminary solutions are presented in the form of a requirements strategy template. The research highlights an urgent call for more in-depth studies in this crucial area, with the expectation that these initial insights will contribute meaningfully to the ongoing discourse.

In the future, this ESR will explore the integration of HF requirements within agile methodologies, focusing on their inclusion in sprints and daily operations. The roles and responsibilities associated with HF requirements will be examined, along with the methods used for recording and managing these requirements. For a comprehensive perspective, a qualitative survey will be broadened to include a diverse range of companies and participants. This approach aims to provide diverse insights and a comprehensive dataset of current practices and challenges. A detailed case study in an automotive company is also on the horizon, with the goal of creating a practical requirements strategy that promotes the integration of HF knowledge across organisational levels. This case study is especially pertinent since many requirements originate from Original Equipment Manufacturers (OEMs) and get passed on to suppliers.

6 Final Conclusions

The research conducted by ESRs 1, 5, 7, and 12 has covered a range of human factors concepts which can ultimately improve user trust and acceptance of AVs. The work shows how user states such as attention, mental workload, and fatigue are affected differently by SAE Level 2 and 3 automated vehicles, compared to manually driven vehicles. A range of new methods for measuring these states are provided, helping designers to ensure that their users do not have unrealistic expectations from the vehicle's systems. New guidelines for increasing user comfort and perceived trust in AVs are provided, and methods for increasing HMI transparency are outlined. ESRs 15 and 8 provide an overview of how AV AI and algorithms should consider human limitations and capabilities, and how human factors should be embedded and considered in the agile development of automated vehicles. Their work highlights the need for a multidisciplinary approach to AV development, which must go beyond the knowledge of software development and software engineering for its developers. Finally, ESR2's work has focussed on defining and investigating how long-term and repeated interactions with AVs affects user trust, acceptance, and behaviour. Since real AVs are not yet available to a large proportion of drivers, work in this area is particularly challenging. In addition, the technology used for these vehicles in not yet foolproof, and humans remain responsible for their operation. Therefore, some considerations are provided about how human factors knowledge can ensure a calibrated level of trust in AVs, to ensure their safe use for the foreseeable future.

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