



Understanding driver monitoring systems

Public awareness, attitudes
and expectations

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Disclaimer

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Foreword

Drivers have long since become accustomed to the various ways automotive designers have sought to make the driving task easier and safer by augmenting and informing their actions – from power steering and ABS braking through to sensors alerting them to the presence of obstacles and other road users, low temperatures (and the risk of icy roads), even windscreen wipers triggered automatically by raindrops. But what of technology that doesn't monitor the vehicle or the road environment but observes the human driver? The latest batch of vehicle safety regulations envisage systems that detect and trigger alerts if the driver is observed to be unduly distracted or appears to be drowsy. Such systems are surely to be welcomed if they reduce the risk of drivers losing control, in principle, but drivers aren't always as welcoming of the systems designed to scrutinise their behaviour (telematic insurance policies requiring installation of 'black boxes' to monitor and record driver behaviour having had at best a mixed reaction).

Looking ahead to the point surely not too far ahead when self-driving options will be offered to car buyers the risk we have long since flagged is of the vehicle wishing to hand control back to the human driver but at a point where the human is not ready to re-take the wheel (if, say, on a long, dull motorway journey they have succumbed to sleep). Vehicles with conditional automation that can be turned on and off will surely require systems to be installed that allow the vehicle to establish whether the human in the driving state should have control returned to them.

That is why we thought it important to pursue the research documented in this report to get a better understanding of how drivers feel about driver monitoring systems, their rationale and the factors that would make them more or less acceptable. We commend the recommendations on page 83 to automotive designers and regulators alike.

Steve Gooding

A handwritten signature in black ink, appearing to read 'Steve Gooding', with a stylized flourish extending from the end.

Director, RAC Foundation

Executive summary

Driver monitoring systems (DMS) are increasingly being integrated into modern vehicles as part of broader efforts to improve road safety and support the safe deployment of advanced driver assistance and partially automated driving technologies. These systems use sensors, cameras and algorithms to assess aspects of driver behaviour and state – such as fatigue, distraction or impairment – and provide feedback or intervention when risks are detected. As vehicles move towards conditional automation, DMS are also expected to play a critical role in assessing whether drivers are capable of safely retaking control of the vehicle when required. Despite their growing prevalence, relatively little is known about how drivers understand these systems, how acceptable they find them, and how this may influence behaviour and system use.

This research examined public awareness, attitudes and expectations regarding DMS in the UK. The study was conducted in three stages. Firstly, a review of academic literature, regulations and industry guidance was combined with interviews with stakeholders from automotive, regulatory and road safety organisations. This established the current technological and regulatory landscape and identified priority applications of driver monitoring. Five representative scenarios were subsequently defined for further study: driver fatigue, driver distraction, cognitive decline, driver intoxication, and data surveillance and sharing.

Secondly, a focus group study involving 30 UK-licensed drivers explored how people interpret and understand driver monitoring concepts. Using visual storyboards to represent the aforementioned scenarios, participants discussed what they believed the vehicle was detecting, how the system might work and why it was being used. Findings revealed that most drivers have limited awareness of existing monitoring technologies and often rely on personal judgement to assess their own fitness to drive. Participants generally viewed monitoring as beneficial when it supported safety through advisory feedback, but expressed concerns when systems appeared intrusive, overly controlling or unclear in their purpose. Issues of privacy, trust and autonomy emerged as important considerations. The focus groups also revealed that drivers interpret DMS as comprising distinct functional roles, rather than as a singular, unified technology.

Thirdly, insights from the focus groups informed the design of a large-scale online survey involving 477 UK drivers, which measured the perceived acceptability of different DMS conceptualised as a set of functional capabilities. An additional driving performance scenario was included in the survey to reflect broader performance-related monitoring, while cognitive decline was reframed more generally as ‘fitness to drive’ to encompass a wider range of health-related conditions. Results showed that acceptance varied considerably depending on the function and level of system authority. Monitoring associated with immediate and clearly understood safety risks – particularly fatigue and intoxication – was viewed most positively. In contrast, more intrusive or speculative applications, such as emotional monitoring or extensive data collection and sharing, generated substantially greater concern.

Depending on the scenario, a significant minority of respondents (approaching one in five drivers) remained strongly opposed to driver monitoring in any form, and many (up to one in three drivers) indicated reluctance to purchase vehicles equipped with the systems under evaluation.

Overall, the research suggests that drivers may be more accepting of monitoring technologies than is sometimes assumed. While a minority expressed strong opposition to all forms of monitoring, many participants viewed DMS positively when systems were clearly linked to improving safety and supporting the driver rather than controlling them. Concerns emerged when monitoring appeared intrusive, disproportionate or unclear in its purpose, with issues of privacy, trust and autonomy becoming particularly important.

This highlights that acceptance of DMS is shaped less by monitoring itself and more by how monitoring is implemented, communicated and justified to drivers. Drivers are likely to be more supportive of systems that provide proportionate, safety-oriented assistance and less accepting of technologies perceived as surveillance or unnecessary behavioural control. This distinction is particularly important in the context of future conditional and higher levels of automation, where vehicles may need to continuously assess driver readiness to resume control. Understanding what influences acceptance of DMS is therefore likely to become increasingly important for vehicle manufacturers, regulators and policymakers.

The research also suggests that regulation alone may not guarantee successful or publicly acceptable DMS implementation. Although current regulatory approaches are intended to improve vehicle safety, there is a risk that manufacturers adopt a compliance-focused or 'tick-box' approach that satisfies technical specifications while overlooking broader human factors (HF) considerations. The findings instead indicate that DMS designed around HF principles – including transparency, contextual sensitivity, appropriate levels of system authority, and respect for driver autonomy and privacy – are more likely to achieve both effective safety outcomes and long-term public acceptance.

Based on these findings, the report proposes a set of ten design recommendations, recognising the distinction between DMS as a sensing and monitoring technology, and the broader set of advanced driver assistance systems (ADAS) or automated interventions that may act on DMS-derived outputs. Collectively, the recommendations emphasise prioritising safety-critical applications, ensuring transparency in system operation and data use, respecting privacy boundaries, and designing systems that support rather than unnecessarily police the driver. Such approaches are likely to maximise both the safety benefits and societal acceptance of driver monitoring technologies.

1. Introduction



The term ‘driver monitoring systems’ (DMS) is commonly used to describe advanced in-vehicle safety technologies that employ cameras, sensors and algorithms to monitor a driver’s alertness, head position and eye behaviour in order to detect states such as drowsiness, distraction or inattention. When such states are identified, DMS may issue warnings or, in some cases, initiate vehicle-based interventions (e.g. limiting system functionality or applying braking) to mitigate risk and enhance road safety. As vehicles become increasingly automated, the role of effective driver monitoring has become more critical, particularly in ensuring appropriate driver engagement during partial automation. As a consequence, DMS functionality (also referred to as ‘occupant status monitoring’) is now explicitly incorporated into vehicle safety assessment frameworks, including the European New Car Assessment Programme (Euro NCAP), which mandates that all new cars must include systems that warn about drowsiness and distraction in their Safe Driving Driver Engagement Protocol (see: Euro NCAP, 2026a). In addition, DMS have attracted substantial research attention across domains such as human factors (HF), computer vision and artificial intelligence (e.g. Öztürk et al., 2026).

Although contemporary discourse often frames DMS as a relatively recent innovation, more rudimentary forms of driver monitoring have existed for decades. Early examples include seatbelt reminder systems introduced in the early 1970s, which monitored basic aspects of driver compliance rather than the driver's cognitive or attentional state.

In addition, today, the notion of 'monitoring drivers and their driving behaviour' extends well beyond regulated, closed-loop, camera-based systems. Modern vehicles routinely collect extensive data on driver behaviour, vehicle usage and performance through a range of embedded sensors and connected services (Caltrider, Rykov and MacDonald, 2023). As a result, current DMS implementations vary substantially in terms of the type, granularity and volume of data collected, the methods used to collect and process this data, the level of feedback or support provided to drivers, and the manner, timing and authority with which interventions are delivered.

This diversity is especially evident when comparing early systems with contemporary DMS. For instance, early fatigue-related systems relied on simple heuristics such as journey duration, and provided non-prescriptive feedback – often in the form of a dashboard 'coffee cup' icon – to suggest that a break might be advisable. In contrast, state-of-the-art DMS employ driver-facing cameras and sophisticated AI-based algorithms to continuously analyse eye movements, gaze direction, blink rate and head position to infer the driver's attentional state. In certain vehicles, these systems are now tightly coupled with advanced driver assistance and automation features, such that access to, or continued use of, these systems is conditional on the driver demonstrably maintaining attention to the driving task (e.g. Ford Motor Company, n.d.).

Beyond safety-critical applications, there is growing interest in more expansive, user-centred conceptions of driver monitoring. Emerging research and industry visions describe 'smart' vehicle interiors capable of inferring drivers' emotional state, stress levels or general wellbeing, and even posit the use of in-vehicle monitoring to detect early indicators of neurodegenerative conditions such as Alzheimer's disease or Parkinson's disease (Baraniuk, 2021). While such developments promise potential benefits, they also necessitate the collection and interpretation of increasingly sensitive personal data. This escalation in monitoring capability raises significant ethical, legal and societal questions concerning data minimisation, consent, transparency, ownership and secondary data use – particularly in light of evolving data protection regulations and the involvement of third-party service providers.

From the driver's perspective, this rapidly evolving and heterogeneous DMS ecosystem can be difficult to comprehend. Drivers may have limited awareness of what data is being collected, how this data is processed and stored, who has access to it, and how system outputs are generated or acted upon. This lack of understanding and transparency has important implications for trust, system acceptance and appropriate reliance. Drivers may subsequently over-rely on DMS for support beyond their intended design, ignore or override system feedback at critical moments, or unknowingly consent to the sharing and nefarious repurposing of their personal data with third parties. Such mismatches between system capability, driver understanding and driver behaviour present significant safety and ethical risks.

Given the current situation, the overall aim of this research is to examine drivers' understanding of DMS and to explore the implications of this understanding for driving behaviour, system use and driver-vehicle interaction, more broadly.

1.1 Programme of Work

The current research was conducted in three stages:

1. Literature review and stakeholder interviews
2. Focus groups
3. Online survey

In stage one, we reviewed academic, technical and regulatory materials and conducted key stakeholder interviews to establish the current state-of-the-art with respect to DMS technologies and driver monitoring, more generally. This enabled us to define DMS and its use in different driving contexts and to develop exemplar use-case scenarios, which could be used as communication tools during the focus groups discussions that took place in stage two.

In stage two, we conducted a focus group study, in which five driver monitoring scenarios were presented to 30 participants in the form of black and white storyboards. The scenarios were: driver fatigue, driver distraction, cognitive decline, driver intoxication, and data surveillance and sharing. The scenarios were not intended to represent any specific DMS, but rather to demonstrate the underlying concept of driver monitoring at increasing levels of complexity, intervention and futurism, as informed by stage one. Participants were asked to consider what was happening, how they thought it was happening and why they thought it is happening.

In stage three, we used the findings from the focus groups to inform the design of an online survey, capturing 477 responses. The aim of the survey was to understand wider public attitudes towards the acceptability of the different driver monitoring scenarios. For the survey, an additional scenario focusing specifically on driving performance was also included to better represent general performance-related monitoring. The term 'cognitive decline' was also broadened to 'fitness to drive' to encompass a wider range of health-related conditions. As the design of the survey had been informed by the focus groups, it explored distinct functional roles rather than measuring acceptance of DMS as an individual technology, thereby enabling us to interpret acceptance at different levels of system authority.

Finally, outputs from all activities were synthesised to support the development of guidelines and recommendations to inform the design and implementation of DMS, with the aim of improving public acceptance, which are presented in section 5.

2. Literature Review and Stakeholder Interviews: Defining Driver Monitoring



2.1 Introduction

To gain a better understanding of the current and evolving DMS landscape, and to define specific driver monitoring scenarios to be taken forwards into further research activities, we conducted a review of the current academic literature together with existing guidelines and regulations (the EU's General Safety Regulation (GSR2), Euro NCAP etc.). The literature review aimed to establish a theoretical foundation for the research and to define how DMS are currently defined and understood. This was followed by exploratory interviews with key stakeholders, aiming to capture their professional and practical insights into technology development, regulatory influences and real-world implementation. The literature review is presented below, followed by the stakeholder interviews.

2.2 Literature Review

The term ‘driver monitoring systems’ can be applied to any type of technology that detects aspects of the driver’s behaviour or state, such as seatbelt detection at a very basic level, to more complex visual, postural, physiological or emotional state monitoring. The detection of the non-optimal driver behaviour or state is then communicated to the driver, and indeed other vehicle occupants, through warnings. Broadly speaking, DMS refers to the tools, either embedded or purpose-built, which collect data to assess the competency of the vehicle operator to undertake the driving task in a safe and effective manner (Hayley et al., 2021).

Descriptions for DMS in academic literature largely concur, highlighting the detection of driver states such as distraction or fatigue (e.g. Coyne et al., 2024; Neuhuber et al., 2020) through the continuous acquisition of operator and vehicle data, and the provision of real-time feedback notifications (Hayley et al., 2021). It may also be possible for DMS to exist separately to the vehicle; smartphones may be used to monitor the driver using inbuilt sensors (i.e. rear and front cameras, accelerometer, microphone) with the advantage of mobility, meaning the device can be moved with the driver and so used in any vehicle (Levshun et al., 2022). Although some authors may classify these systems as driver assistance, in the same manner as systems like adaptive lane keeping (Neuhuber et al., 2021), the important distinction is the requisite collection of data about the driver, such as facial expression, driver performance/style, physiology, speech, steering-wheel inputs, secondary tasks, etc. Work by Jannusch et al. (2021) classified DMS into three categories: Type 1 which use vehicle motion data, Type 2 which use non-intrusive sensors (e.g. cameras) and Type 3 which use intrusive biometric sensors such as a fingerprint or electrocardiogram (ECG). The intrusiveness of these varies – for example, detection using a fingerprint would be momentary, whereas the ECG requires continuous monitoring with direct contact with skin.

There is some inconsistency in the definitions and terms used by manufacturers for DMS, which may result in confusion for consumers. Manufacturers use a range of names and descriptions to refer to their systems, with varying detail provided about the underlying technology. For example, Jaguar Land Rover (n.d.) refers to a *Driver Condition Monitor* system as part of its wider advanced driver assistance systems (ADAS), which monitors steering, brake and throttle inputs to detect drowsiness. It also highlights an upcoming *Driver Monitor System*, developed with Seeing Machines and Intel, which specifically addresses the monitoring of eye and facial movement for inattentiveness, to be implemented in future vehicles (Jaguar Land Rover, 2026). Volvo refers to a *Driver Understanding* system, which uses “real-time sensing technology” to identify whether a driver is impaired or distracted, with interventions “up to the point of stopping the car” available (Volvo Cars, 2024). Volvo also advertises an *Occupant Sensing* system, which monitors the full cabin using radar and claims to “sense submillimetre scale movement, such as the soft breathing of a baby” (Volvo Cars, 2020). However, it is unclear which data is collected and analysed for any of these systems. Other terminology used by vehicle manufacturers include *Driver Attention Camera* (BMW), *Driver Monitoring* (Mercedes), *Driver Alert Monitor* (Ford) and *Intelligent Driver Alertness* (Nissan). Additionally, some of these monitoring systems are

conditional, e.g. only monitoring when certain driver assistance modes are used. This creates a confusing situation for users, who may have limited awareness or understanding of what the system does, why and how it does so, and what this means for them.

There are currently several regulations available that provide guidance to support the development and assessment of DMS. GSR2, developed by the EU and adopted in part in the UK after leaving the EU (DfT, 2026), was updated in 2019 and now mandates additional safety features for new vehicles sold in the EU, with some of these elements also adopted for the UK market. GSR2 includes the requirement for Intelligent Speed Assistance (ISA), which warns the driver when the speed limit is exceeded, drowsiness and attention warnings, and a form of a black box to monitor and capture vehicle data before, during and after a collision. Additionally, it includes a provision for Alcohol Interlock Installation Facilitation, allowing for the aftermarket addition of a breathalyser lock which could prevent repeat offenders from drink-driving. These regulations are mandatory for the production and sale of new vehicles, with phase one applied from July 2022. Phase two was applied to existing vehicle models from July 2024 and mandates certain ADAS features, including ISA. Phase three will apply from July 2026, and includes both drowsiness and attention warnings and alcohol interlock, as well as some other features. Therefore, in most new vehicles drivers will soon be experiencing driver monitoring in several different states. It is therefore important for users to understand the capabilities (and subsequent limitations) of these systems and respond appropriately in order to maximise the benefits and improve road safety.

In addition, Euro NCAP published its *Vision 2030* (in 2022), which mandates the assessment of technology that monitors driver impairment and cognitive distraction, and the testing and assessment of assisted and automated driver support systems (Euro NCAP Newsroom, 2022). The possible rating points (which are then aggregated into an overall star rating) have recently been increased from two in the 2023 protocol to 25 in 2026, when assessing DMS, covering both transient and non-transient driver states. Transient driver states address shorter-term influences on driving, such as distractions and phone use, whereas non-transient states address impaired or unresponsive drivers. To support this, Euro NCAP assessment now covers long and short distractions, phone use, states of impairment (including those caused by drugs or alcohol), drowsiness and microsleep, and other unresponsiveness (Euro NCAP, 2026a). There is also a section within the testing protocol for increased occupant monitoring – for all users of the vehicle, not just the driver. This includes the *correct* use (not just *use*) of seatbelts, detection of the presence of children within the vehicle – including whether they are left unsupervised in the vehicle – and the reliability of airbags that are able to adapt to the occupant's size and warn in the event of the occupant being out of position (Euro NCAP, 2026b).

Whereas basic DMS, such as seatbelt detection, were introduced in the 1970s to support driver safety, the rapid advances in technology and increased focus on driver and occupant safety during intervening years mean that DMS now extend well beyond the immediate driving experience. As development of DMS continues, there is the potential for them to be used in more sophisticated ways to support drivers. For example, simple corrective actions can be achieved through instructions to the driver such as “eyes on road” and “hands on

wheel”, or by monitoring the driver’s gaze or pressure on the steering wheel. Today, these technologies (supported by complex AI algorithms) can be used to infer fatigue (Lu et al., 2022), or to identify emotion or increased cognitive workload (Hidalgo-Muñoz et al., 2018), e.g. through heart rate variability. It is therefore expected that more detailed and specific monitoring could provide more specific and personalised advice and warnings to drivers, further improving their safety and driving ability.

DMS have also been proposed and developed to address issues caused by other advances in technology. The introduction – and arguably, overcomplication – of in-vehicle infotainment systems raises significant concerns of driver distraction; DMS can identify these occurrences of distraction, via gaze monitoring systems, and redirect the driver’s attention to the road, as necessary (Lachance-Tremblay et al., 2025). Additionally, non-vehicle distractions, such as mobile phone use (Ortiz et al., 2018), can be identified directly by gaze monitoring systems or inferred based on systems linked to the vehicle. It has also been proposed that mobile phones could be used as driving aids for older vehicles, extending the lifespan of vehicles either by repurposing technology already present within the phone or by linking in-vehicle technology to the phone (Papatheocharous et al., 2023).

Currently, and indeed for the foreseeable future, the driver remains responsible for the safe control of their vehicle operating Driver Control Assistance System (DCAS) technology at level 2, and potentially elements of level 3, of the SAE levels of automation (SAE International, 2021). However, if drivers are removed from elements of the driving task – particularly if they are permitted to remove their hands from the steering wheel and/ or their feet from the pedals for significant periods of time – they may become “out of the loop” (Heinrich et al., 2025). As increasingly automated DCAS systems are introduced, the removal of the driver from the ‘loop’ can also lead to distraction and ‘mind wandering’, as the vehicle controls some – but not all – of the driving task. There may also be some demographic considerations associated with increasing levels of automation. For example, in a study by Neuhuber et al. (2020), older participants (50–77 years) reported a significantly higher level of difficulty in understanding and interacting with DCAS, even at level 2 vehicle automation. These users may subsequently require additional support to ensure or feel that they are using the new technology correctly. DMS can potentially be utilised to monitor the driver’s engagement, e.g. through gaze monitoring (Schnebelen et al., 2020). As drivers are not experiencing full automation, they consequently need to remain attentive to take over control if necessary (Kashevnik et al., 2021). Research suggests that drivers may glance away from the road for longer in assisted driving (e.g. Gaspar & Carney, 2019) and reduce their overall visual attention to the forward road (e.g. Pipkorn et al., 2022). DMS may subsequently use advisory (e.g. through prompting the driver to return their eyes to the road or reduce their speed) or corrective methods (e.g. through ISA intervening to reduce the speed of the vehicle itself (Day et al., 2023)).

DMS may also be utilised to monitor a vehicle’s users and occupants, and indeed other road users, perceived to be ‘at risk’, e.g. enabling parents to monitor their children’s driving habits (McCartt et al., 2010). However, such use raises legal and ethical issues relating to data collection and sharing. Driver monitoring may also be used to identify a reduction

in driving skills, over long or short periods of time. For example, as people age, they may experience reduced capacity and cognitive functions (Salthouse, 2009), with older drivers demonstrating greater vulnerability to dynamic hazards and less awareness of what is behind their vehicles (Key et al., 2016), compared to younger drivers (Kaber et al., 2012). Therefore, DMS can be used to identify when it may no longer be appropriate for somebody to drive or to identify the need for further support, both for their safety and that of others.

DMS may also be used to monitor those who have medical conditions that could affect their driving capabilities (Manstetten et al., 2021) by providing early warnings of an episode based on biometrics or other monitored data. Longer-term monitoring could also be used to provide medical information to drivers, including progression of existing conditions. Driving with advanced vehicle technology may be perceived by older drivers as providing a sense of comfort in supporting their driving abilities with increased feelings of safety, convenience and ease of use (Gish et al., 2017). Consequently, the introduction of DMS may increase not only the comfort and confidence of the individual in their own driving, but also the safety of those around them.

Increasingly, DMS claim the potential to infer more abstract concepts such as the driver's emotional state, with the implication that vehicle systems could mitigate poor or undesirable emotional states using alerts, interactions and changes in the vehicle cabin environment. Consequently, we are likely to see an increasing prevalence of 'intelligent', user-centred vehicle environments that claim to enhance the driver's wellbeing. For example, future vehicle systems may be able to recognise that a driver is in a state of heightened stress and activate calming ambient features to relax them. Vehicles may also actively support drivers and/or passengers to 'de-stress' through interactive relaxation exercises. It may also be possible for DMS to monitor physiological driver states, including alcohol and drug intoxication. For example, Celaya-Padilla et al. (2021) investigated a system using alcohol sensors fitted to the interior of the vehicle that could reliably detect the presence of alcohol in the air of the vehicle cabin. DMS may also extend beyond systems attached to the car – for example, via wearable health and fitness monitoring devices it may be possible for the vehicle systems to link to additional data about the driver, such as sleep patterns and activity levels prior to driving, to further inform predictive analysis (Manstetten et al., 2021).

The integration of DMS into vehicles may be met with concern from potential users. Concern may stem from a lack of correct knowledge about whether and how DMS are integrated into vehicles currently on the road. For example, research conducted by Nees & Liu (2022) suggested that 10% of study participants were unsure if they had ever used a vehicle with DMS capabilities. Their conclusions highlighted that work may need to be done to correct the mental models of drivers regarding system performance and capabilities. The perceived capability of DMS may also influence their acceptance among users: Nees & Liu (2022) investigated the perceptions of different generic monitoring systems and their findings indicated that participants were sceptical about the ability of DMS to detect adverse mental states compared to monitoring core, recognisable aspects, such as gaze position and in-cabin movement. Additionally, some participants also believed that their console or mobile phone interactions were monitored directly, and that they consequently could 'beat'

the DMS by avoiding interactions with these devices. In other studies, users also raised concerns with the ‘future use’ of data, relating to legal consequences or ‘commodification’ of their data, without their knowledge or consent (Coyne et al., 2024).

The design of DMS and the related vehicle warning and/or intervention systems may also lead to challenges to uptake and acceptance by users. In a study by Smyth et al. (2021), the “effort expectancy” of potential users (indicating that the system is expected to be easy to learn and use, enabling drivers to interact with it effectively) was shown to be a strong influence on their intention to use DMS. Drivers also report their preference for driving for enjoyment and could therefore suspect DMS will impair their experience by suggesting and/or enforcing stricter adherence to regulations (Coyne et al., 2024). A further concern is that the implementation of any warning systems inherently adds more distraction challenges, due to the greater number of in-vehicle alerts (Koniakowsky et al., 2025). More frequent alerts may also compete for the driver’s attention against other warning stimuli in the driving environment, such as emergency vehicles’ lights (Forster et al., 2024). Context is also critical in the design of DMS, as the attentional demand and the available spare capacity of the driver vary based on environmental factors such as weather, traffic, road type, etc. (Kujala et al., 2021). This may be particularly relevant if warnings were to occur during high-demand manoeuvres (Forster et al., 2024), compared to more mundane (monotonous or lower-demand) periods of driving. Consequently, systems that can intelligently adapt to the driving environment, as well as the characteristics of the driver, may improve user acceptance.

Due to the novelty of DMS, there is limited research about the longitudinal impact of these systems on understanding and acceptance. There are some likely consequences of longer-term use, including the potential for over-reliance on DMS which could lead to lapses in attention or vigilance; this has already been noted as a concern by potential users (see: Coyne et al., 2024). Additionally, the advances in technology mean that drivers could be presented with different systems and different levels of monitoring over a comparatively short period of time, with different makes and models of vehicles employing different systems. As a consequence, drivers may learn and rely upon certain familiar systems and may even lose driving skills that are no longer required, but when faced with a different vehicle (for example, a hire car with a lower level of DMS), they may struggle to readjust. The converse is also true: if a driver moves from a vehicle with little or no monitoring to a vehicle with significant levels of monitoring, they are likely to be surprised or confused by warnings and interventions while driving. Users may also choose to challenge the DMS, or if they are unclear or unsure about what a warning means, they may purposely act non-optimally to try to activate the warning again in order to test the system or increase learning speed (Forster et al., 2024). There may also be challenges with assessing the effectiveness of DMS itself, with research by Koniakowsky et al. (2025) suggesting that task complexity and experience significantly influence the effect of DMS on glance behaviour. The authors consequently recommended that DMS should not be assessed in isolation (Koniakowsky et al., 2025).

Concerns around data collection will also be a challenge in the acceptance of DMS. Coyne et al. (2024) explored several concerns regarding storage and handling of DMS data, including the risks of data breaches and sale to third parties. Extensive monitoring by DMS

was also perceived as an invasive form of surveillance, with participants feeling they would have little control or choice over the data collected. Work by Picco et al. (2023) suggested that issues around data collection may be addressed by considering the perceived costs versus the perceived benefits for users, ensuring that the users of the technology could understand the benefits clearly. The work also suggested that trust in the collection of data could be improved by allowing users partial or total control over the type and quantity of information collected.

Summary of Literature Review

The literature review highlighted five principal sets of issues which can be grouped as follows: Definition, Terminology and Scope; Strategy and Vision; Regulation and Compliance; Consumer Perception and Privacy; and Future Developments. These are summarised below.

Definition, Terminology and Scope

DMS broadly encompass technologies that collect and analyse driver-related data to assess a driver's ability to operate a vehicle safely. These systems range from basic functions, such as seatbelt detection, to advanced monitoring of gaze, posture, physiology, emotion and cognitive workload. Feedback is typically provided through warnings or, in some cases, direct vehicle intervention. Academic definitions largely converge on the continuous monitoring of driver state (e.g. distraction, fatigue, impairment) using vehicle data, non-intrusive sensors (e.g. cameras) or intrusive biometric sensors (e.g. ECG). However, terminology varies considerably across manufacturers, potentially creating confusion for consumers regarding system capabilities and limitations.

Strategy and Vision

DMS are rapidly evolving from basic safety aids to comprehensive driver and occupant monitoring platforms. While regulatory factors and technological innovation are accelerating implementation, user understanding, trust, system design and data governance appear critical to ensuring safe, effective and socially acceptable deployment.

Regulation and Compliance

Regulatory frameworks are accelerating DMS adoption. The EU's GSR2 mandates features including drowsiness and attention warnings, ISA and event data recorders in new vehicles. Similarly, Euro NCAP *Vision 2030* (Euro NCAP Newsroom, 2022) expands assessment criteria for driver and occupant monitoring, significantly increasing the weighting of DMS in vehicle safety ratings. As a result, driver monitoring is becoming standard in many new vehicles.

Consumer Perception and Privacy

Despite the opportunities associated with DMS, significant challenges remain. Users often lack clarity about what DMS monitor and how data is used, raising concerns about privacy, data security, surveillance and potential legal consequences. Acceptance is influenced by perceived usefulness, effort expectancy and system intrusiveness. Poorly timed warnings may increase distraction, and over-reliance on DMS may degrade driving skills. Effectiveness may also vary depending on driving context and task complexity.

Future Developments

Technological advances, including AI-driven analytics, enable increasingly sophisticated inference of fatigue, distraction, emotional state and even potential medical conditions. DMS may also support drivers in partially automated (SAE level 2–3) vehicles by monitoring engagement and mitigating ‘out-of-the-loop’ effects. Beyond safety, systems are being explored for broader applications such as health monitoring, parental oversight and occupant protection.

2.3 Stakeholder Interviews

The literature review examined the current and evolving landscape of DMS based primarily on academic literature and emerging regulatory frameworks. While this helps to inform our understanding of the present capabilities and potential future developments of DMS, many aspects of these technologies – particularly the design, deployment and real-world use – are largely shaped by automotive manufacturers, technology developers and suppliers, rather than academic research. Incorporating a stakeholder perspective therefore helps to ensure that the research reflects practical realities, technological constraints and market considerations.

We therefore designed a study involving stakeholder interviews, aiming to capture stakeholders’ professional insights and unique perspectives on DMS. Stakeholders approached for the interviews included vehicle manufacturers, technology providers, transportation research and motoring groups, an automotive risk intelligence organisation, and a specialist user experience (UX) and human factors consultancy. The stakeholder interviews aimed to develop a wider understanding of the legislative, regulatory and industry-specific contexts and concerns around DMS introduction and implementation in the UK, from those who are directly involved. These insights are important to inform subsequent research activities in the current programme of work, but they also have their own intrinsic value in informing policymakers and industry bodies when selecting the most effective methods for introducing and adopting DMS.

The stakeholder interviews had two specific objectives:

1. To explore stakeholders’ understanding and attitudes towards DMS.
2. To define exemplar DMS scenarios and use-cases to facilitate subsequent data collection activities.

Method

Participants

Seven key stakeholders from transport-related organisations and vehicle manufacturers were recruited by email using the authors’ existing network of contacts. In addition, participants were asked to recommend or share information about the study with other potential stakeholders. Recruitment targeted stakeholders from industry, regulatory bodies, UX and safety practitioners and advisors who had practical experience or direct involvement

with DMS. Potential stakeholders with only theoretical or academic perspectives were not included in the study. Anonymity and confidentiality were preserved to encourage honest and rich data-sharing and to minimise social desirability bias (i.e. the tendency for people to provide socially acceptable responses instead of those that are reflective of their true feelings and beliefs) (Grimm, 2010; Kaiser, 2009).

At the start of the interview, participants were asked to describe their experience and expertise in, or associated with, the automotive industry, including their professional interest in DMS. In response to this, participants described their experience and expertise as: 1) OEM system development, implementation and UX; 2) Road safety and human factors research; 3) Vehicle safety science, investigations and regulation; 4) Product research, development and testing; 5) Vehicle safety, security and sustainable repair; 6) Insurance risk modelling; and 7) UX design.

The study design was approved by the Faculty of Engineering ethics committee at the University of Nottingham.

Data Collection

Interviews took place online using Microsoft Teams between June and September 2025. The focus of the interviews was on driver monitoring as a concept, not any specific sensing technology, interface or intervention, and the interviewer used additional prompts and probes to refocus attention if necessary.

Informed by the findings from the literature review, the interview was structured around the following five principal areas: Definition, Terminology and Scope; Strategy and Vision; Regulation and Compliance; Consumer Perception and Privacy; and Future Developments. The following questions were used, with further prompts if replies were short or limited information was forthcoming (see Appendix A for further details):

1. What do you understand by the term driver monitoring systems (DMS)?
2. Do you see DMS as a regulatory requirement or a value-added safety feature?
3. Do you think that DMS should be mandatory and regulated?
4. How do you balance privacy concerns with the safety benefits of driver monitoring systems?
5. How do you see DMS evolving with AI and autonomous driving?

Interviews were recorded and transcribed using Microsoft Teams and each lasted approximately 30 minutes. Transcripts were manually checked and edited to ensure accuracy and anonymity. Participants were also provided with the opportunity to view and redact any sensitive content prior to analysis.

Data Analysis

An inductive thematic analysis was conducted on the interview data to identify recurring patterns in how DMS were understood, justified, experienced and critiqued by stakeholders across industry, regulation, UX and safety domains. A realist approach was taken to coding and analysing, in that stakeholder perspectives were taken as representative of their beliefs (Brooks et al., 2015). The analysis followed an inductive (or ‘bottom-up’) approach, allowing

themes to emerge from participants' language rather than imposing predefined categories (see: Braun & Clarke, 2006). A HF lens was applied to interpret the emerging themes and to relate these to established HF principles, including human–automation interaction, workload and attention, trust and acceptance, individual differences, usability, and socio-technical system design.

Results

Summary of Stakeholder Interviews

The interviews captured a wide range of expert perspectives on DMS, focusing on their purpose, implementation, and impact on safety and UX.

Overall, DMS were widely understood by our expert stakeholders as systems intended to monitor driver state – such as attention, fatigue, distraction and impairment – but it was also generally understood that DMS were most commonly implemented to satisfy regulatory and vehicle rating requirements, rather than to deliver clear user-facing value.

Stakeholders consistently expressed concerns that many current DMS implementations were poorly calibrated, overly rigid and intrusive, leading to annoyance, mistrust and, in situations where it was possible, drivers disabling the system altogether. A recurring issue was the mismatch between system judgements and drivers' own perceptions of their state and fitness to drive, which was compounded by a lack of personalisation and insufficient consideration of individual differences. In contrast, indirect and unobtrusive interventions (e.g. a coffee-cup icon to indicate driver fatigue) were generally thought to be viewed more positively and as more acceptable to drivers, though arguably lacked efficacy.

From a broader perspective, the interviews highlighted tensions between regulation, safety potential, privacy and consumer acceptance. While there was broad agreement that DMS have the potential to improve road safety and support other driver assistance systems, the interviews suggested that their effectiveness depends heavily on human-centred design, thoughtful and meaningful integration with other vehicle systems, and careful communication with drivers.

Thematic Analysis of Interview Transcripts

Six themes merged from the data (see Table 1). These were:

1. DMS as a Compliance-Driven System
2. Misalignment with Drivers' Mental Models
3. Lack of Personalisation
4. Intrusiveness and Annoyance
5. Trust and Acceptance
6. DMS as Part of a Broader Socio-Technical System

Further details of each theme and the implications for design are discussed below.

Table 1: Themes emerging from the thematic analysis with illustrative quotes from participants

Theme	Subthemes	Codes (examples)	Further Comments and Implications
DMS as a Compliance-Driven System	Compliance focus	"Regulatory requirement", "tick the box", "Euro NCAP-driven"	Risk of technology-centred design; HF criteria must extend beyond minimum regulatory requirements
Misalignment with Drivers' Mental Models	Misclassification	"Annoying alerts", "gets it wrong", "I'm not tired"	Reduced trust; need for explainable and context-aware system behaviour
Lack of Personalisation	Individual variability	"Too rigid", "one size fits all", "we're all different"	Supports adaptive systems and consideration of individual differences
Intrusiveness and Annoyance	Disengagement	"People switch it off", "too intrusive"	Alarm fatigue; importance of graded, low-intrusion interventions
Trust and Acceptance	Subtle feedback, trust erosion	"Unobtrusive coffee cup works", "bad implementation ruins ADAS reputation"	Reinforces HF principles of minimal interruption and supportive feedback; trust calibration critical to sustained safety benefit
DMS as Part of a Broader Socio-Technical System	System interaction	"Helps other ADAS", "integration matters"	Need for holistic HF evaluation across systems

Theme 1: DMS as a Compliance-Driven System

A dominant theme across interviews was the framing of DMS as a regulatory and rating-driven requirement, rather than a system designed primarily around driver needs or capabilities. Participants repeatedly described DMS as something OEMs "have to do" to satisfy EU regulations or Euro NCAP scoring, with limited perceived incentive to exceed minimum requirements. This compliance orientation naturally leads to systems that are narrow in scope, minimally functional and optimised to pass tests rather than to support drivers effectively.

From a HF perspective, the findings reflect a technology-centred rather than human-centred design paradigm. Foundational HF theory emphasises that safety systems are most effective when they are designed around real human behaviour, limitations and contexts of use (Norman, 2013). When systems are built to satisfy external metrics rather than user needs, they risk poor usability, reduced acceptance and compensatory behaviours, such as disabling the system (Dekker, 2016). Results from the current study mirror classic HF findings from alarm fatigue and poorly designed safety-critical automation, where compliance with standards does not guarantee safe or effective human interaction, or, indeed, successful implementation (Hollnagel, 2018).

Theme 2: Misalignment with Drivers' Mental Models

Stakeholders consistently highlighted the potential for frustration when DMS outputs do not align with drivers' subjective experience or situational understanding – for example, if a driver is warned of fatigue shortly after starting a journey or flagged as distracted when their

behaviour is contextually appropriate. This mismatch can lead drivers to perceive the system as inaccurate, intrusive or unfair.

Effective human-machine interaction depends on the system's logic being understandable and predictable to the user. When drivers cannot reconcile why a warning occurs, trust degrades and the system is more likely to be ignored or disabled (Parasuraman et al., 2000). Several stakeholders explicitly noted that repeated false or poorly timed alerts are more detrimental to safety than no alerts at all, because they can condition drivers to disregard genuine warnings – seminally identified as “the alarm problem” by Woods (1995). This theme also directly relates to mental model alignment, a core HF concept (see: Johnson-Laird, 1983), as also highlighted by Rasmussen (1983) and Endsley (1995), whose work predicts that mismatched system behaviour or unclear system logic disrupts cognition and diminishes situation awareness.

Theme 3: Lack of Personalisation

Stakeholders criticised the use of rigid, one-size-fits-all thresholds for fatigue, distraction and attention. They repeatedly highlighted that drivers differ substantially in baseline behaviour, driving style, tolerance for workload and physiological markers. Systems that rely on absolute thresholds are seen as poorly calibrated and insensitive to individual norms.

This aligns with HF theory on individual differences and adaptive systems. Human performance varies both between and within individuals and over time, and systems that fail to account for this variability – and adapt to operator state – tend to produce higher error rates and lower acceptance (see: Parasuraman et al., 1992; Wickens, 2008). Several participants explicitly advocated for systems that learn a driver's ‘normal’ state and detect meaningful deviations, rather than enforcing population-level averages. This aligns with HF theory on individual differences and adaptive systems (see: Parasuraman et al., 1992; Wickens, 2008).

Theme 4: Intrusiveness and Annoyance

Stakeholders frequently described current DMS implementations as “annoying”, “nagging” or “in your face”, with frequent auditory alerts cited as particularly problematic. Intrusiveness is strongly associated with negative attitudes, system deactivation and technology rejection. In contrast, indirect or subtle interventions (e.g. a coffee-cup icon) were widely viewed as more acceptable and even appreciated by drivers.

This reflects HF research on workload, interruption management and alarm design. Excessive or poorly timed alerts increase cognitive load and frustration, particularly in already demanding driving contexts (Wickens, 2008). The data clearly shows that perceived intrusiveness is not solely about frequency, but also about timing, modality and perceived justification. This reflects classic HF research on workload, interruption management and alarm design (see: Wickens, 2008; Czerwinski et al., 2000; Woods, 1995).

Theme 5: Trust and Acceptance

A recurring concern highlighted by the stakeholders was that poorly designed DMS can encourage drivers to disable the system entirely, eliminating any potential safety benefit.

Participants drew parallels with other ADAS/DCAS features (e.g. lane-keeping assist) that have suffered reputational damage due to intrusive or unreliable behaviour. Trust in DMS was therefore described as fragile and difficult to rebuild once lost.

This theme is well established in HF literature on automation trust and misuse/disuse (Parasuraman & Riley, 1997). When systems are perceived as unreliable or overly controlling, users either over-rely on them inappropriately or disengage completely. The interviews strongly suggest that current DMS implementations risk the latter.

Theme 6: DMS as Part of a Broader Socio-Technical System

Stakeholders frequently situated DMS within a wider ecosystem, including other ADAS/DCAS features, insurance models, regulatory bodies, privacy concerns and future automation. Several noted that DMS can positively influence other systems (e.g. adjusting Automatic Emergency Braking (AEB) sensitivity based on driver state), but only if integration is handled carefully.

From a HF perspective, this shows that safety and performance emerge from interactions between people, technology, organisations and regulation. This reflects a socio-technical systems view (see: Emery & Trist, 1960) – a foundational concept in HF, organisational theory and safety science, which describes how people (the ‘social system’) and technology (the ‘technical system’) interact within a broader organisational and environmental context, and argues that all elements must be designed jointly; isolated optimisation of DMS without considering the broader socio-technical system risks unintended consequences (see: Reason, 1990; Rasmussen, 1997).

Implications for Design

Several preliminary design recommendations emerge directly from the six themes:

- To avoid ‘checkbox’ DMS implementations, regulatory frameworks and assessment protocols should incentivise quality of interaction, not just detection performance. Designers should treat regulation as a baseline and explicitly incorporate HF goals such as usability, driver trust and behavioural effectiveness into system requirements.
- DMS should prioritise context-sensitive interpretation of behaviour and provide feedback that supports drivers’ understanding of why an alert is triggered. Explanatory or graded feedback, rather than binary alerts, can help align system behaviour with driver expectations and preserve trust.
- The design of DMS should move towards adaptive and personalised models, where feasible and ethically acceptable. From a HF perspective, adaptation should be transparent, bounded and reversible to avoid unpredictable behaviour or loss of user control. Calibration periods, driver profiles and adjustable sensitivity settings can support individualisation without overwhelming users.
- DMS alerts should follow HF principles of graded escalation, minimal interruption and modality appropriateness. Systems should intervene only when necessary and proportionately to risk, preserving driver autonomy wherever possible. Subtle visual cues or context-aware prompts may be more effective than repetitive auditory alarms.

- Designers should treat trust as a primary design objective, not a by-product. This includes consistency, transparency, controllability and demonstrable benefit. Allowing drivers limited, well-designed control over sensitivity or feedback style may improve long-term acceptance.
- DMS should be designed and evaluated as part of an integrated human–vehicle system, with attention to cross-system interactions, privacy expectations and long-term behavioural effects. Early HF involvement in design and development is essential to avoid downstream usability and acceptance problems.

DMS Scenario Development

One of the aims of the stakeholder interviews was to develop a set of exemplar DMS use-case scenarios to be employed during the focus groups and online survey. The interviews highlighted that DMS sit at the intersection of technology development, safety research, regulation and UX. As such, research into DMS must address both immediate road safety needs and longer-term mobility challenges.

Based on the interview findings, the following five areas were identified as priorities for further study:

1. In-Cabin Monitoring for Driver Safety

In-cabin monitoring of driver state, such as attention and alertness, represents a core application of DMS with direct safety benefits. By enabling the detection of conditions associated with increased crash risk, these systems have the potential to reduce both collision occurrence and injury severity. There is strong alignment across industry deployment, safety research and regulatory interest, indicating that this application is both feasible and likely to deliver high impact. As vehicles increasingly incorporate advanced driver assistance and partial automation, real-time understanding of driver readiness becomes essential to ensure safe transitions of control. The involvement of regulators further suggests that this application could shape future mandatory safety standards, amplifying its broader societal value.

Driver fatigue was chosen as an exemplar of this application.

2. Driver Monitoring in Support of Regulation and Compliance

DMS are increasingly relevant as tools for meeting regulatory requirements related to driver attention, safety and the oversight of automated driving functions. The growing regulatory momentum in this area suggests that such systems may become mandatory or increasingly standardised across markets. Early research and development can help shape system designs that not only comply with regulatory requirements but are also acceptable and understandable to drivers. In this way, driver monitoring serves as a bridge between technical innovation, policy objectives and real-world deployment, helping to ensure that regulation translates into genuine safety improvements.

Driver distraction was chosen as an exemplar of this application.

3. Driver Monitoring to Support Health and Wellbeing

DMS also offer opportunities to support health and wellbeing by detecting indicators such as discomfort, stress or other ‘medically relevant expressed behaviour’ and adapting the vehicle environment accordingly. Extending monitoring beyond safety-focused interventions may increase perceived consumer value and acceptance, particularly if benefits are experienced directly during everyday driving. Health- and wellbeing-oriented applications may also encounter fewer behavioural resistance issues than systems perceived as enforcing or policing driver behaviour. Importantly, it is anticipated that these features can be developed using the same underlying sensing and software infrastructure as safety systems, allowing OEMs and technology providers to differentiate their products without substantial additional technical complexity.

Cognitive decline was chosen as an exemplar of this application.

4. Driver Monitoring as the Arbiter of Human Behaviour

With rapid advances in technology, it is becoming increasingly feasible that DMS will be able to make a quick and accurate judgement of ‘fitness to drive’, e.g. in situations of excessive driver fatigue, intoxication etc. Such systems could potentially preclude a driver who is over the legal blood alcohol level from even getting behind the wheel. The effectiveness of DMS in this application is strongly influenced by how they interact with drivers, positioning them as critical human-machine interaction tools as well as sensing technologies. Poorly designed UX can undermine even technically proficient systems, leading to annoyance and misunderstanding. Research-led human-machine interface (HMI) design is therefore essential to avoid unintended consequences and to ensure that DMS deliver real-world safety benefits rather than merely annoying drivers.

Driver intoxication was chosen as an exemplar of this application.

5. The Misuse of In-Vehicle Technology for Content Delivery

As vehicles become increasingly digital environments, DMS may become seamlessly integrated with other digital devices, such as the driver’s mobile phone. By adapting or restricting infotainment and content delivery based on the driving context, monitoring systems could play an important role in managing interaction with non-driving-related content, but this also raises concerns of data privacy and confidentiality (lack of consent, misuse of data etc.). This application reframes driver monitoring not only as a means of detecting unsafe behaviour but also as a way of monitoring the driver’s digital footprint. Given the rapid expansion of in-car digital services, this represents a timely response to emerging data privacy concerns associated with modern vehicles.

Data surveillance and sharing was chosen as an exemplar of this application.

2.4 Conclusions and Next Steps

The literature review provided a theoretical foundation for the research, defining DMS as technologies designed to assess a driver's ability to operate a vehicle safely by collecting and analysing driver-related data. It also highlighted how increasing regulation – such as the EU's GSR2 and Euro NCAP safety ratings – is accelerating the adoption of DMS in new vehicles. This is occurring in parallel with advances in sensing technologies and AI that are expected to expand the capability of DMS, and support partially automated driving and even health or occupant monitoring applications. However, the review also highlighted some of the challenges that remain around consumer understanding, privacy, data security, system intrusiveness and the risk of over-reliance, meaning that trust, transparency and effective design will be essential for safe and acceptable implementation.

Informed by the literature review, the stakeholder interviews provided an industry perspective, revealing practical insights into technological development, regulatory influences and real-world implementation. The interviews demonstrated clear multi-stakeholder involvement in and engagement with DMS, including OEMs, Tier 1 suppliers, researchers and regulators, underlining the systemic nature of DMS development and deployment. Findings show that current DMS implementations often fall short of HF best practice due to compliance-driven development, limited personalisation, poor mental model alignment and intrusive interaction design. While the stakeholders broadly agreed on the theoretical safety potential of DMS, they also highlighted that any real-world benefits are highly contingent on how each system interacts with the driver. From a HF perspective, future DMS development should therefore prioritise adaptive, transparent and minimally intrusive designs that respect individual differences and support, rather than police, the driver.

The interviews also identified five principal application areas for future research – driver fatigue, driver distraction, cognitive decline, driver intoxication, and data surveillance and sharing – used to inform the focus group study reported in the next chapter.

3. Focus Group Study: Exploring Understanding of Driver Monitoring



3.1 Introduction

The stakeholder interviews identified five principal DMS applications, representing current scenarios and expected near-future developments: driver fatigue, driver distraction, cognitive decline, driver intoxication, and data surveillance and sharing. Core safety applications such as monitoring fatigue and distraction directly address immediate crash risks and are increasingly essential as vehicles adopt advanced DCAS, where the safe handover and co-ordination between the human driver and automated system depends on accurate assessment of driver readiness. At the same time, DMS are emerging as key enablers of regulatory compliance, shaping how policy translates into real-world safety outcomes. Beyond safety and compliance, the same sensing and software technologies can support driver health and wellbeing – offering

added consumer value with, potentially, minimal additional technical complexity. Looking further ahead, DMS may act as arbiters of fitness-to-drive in cases such as intoxication, making human-machine interaction design critical to ensure trust and acceptance. Finally, as vehicles evolve into digital spaces, DMS are increasingly implicated in managing in-car content and data use, raising important questions around privacy and consent. Together, the five scenarios reflect both current technological trajectories and the broader societal challenges facing contemporary and future mobility.

However, drivers may have limited awareness of such systems, beyond what may be reasonably deduced by the language used to describe them – although even this can differ between automotive suppliers and technology providers, giving rise to further confusion. This lack of understanding and transparency has important implications for trust, system acceptance and appropriate reliance, but to evaluate this, we must first understand precisely what drivers think is occurring. To capture drivers' tacit knowledge and current understanding, the five scenarios were translated into elicitation prompts and employed in a focus group study. The focus group study aimed to explore drivers' understanding of DMS applications. This was then followed by a large-scale online survey, informed by the findings of the focus group study and reported in the next chapter.

The focus group study had two specific objectives:

1. To uncover drivers' tacit knowledge and current understanding of DMS.
2. To translate this understanding into question prompts for use in an online survey.

3.2 Methodological Challenge

Findings from previous driver surveys (for example, see: Durbin, 2016) suggest that many drivers do not know what technology their car has, do not accurately understand how it works and therefore do not use it properly. Our ambition was to explore what this means with regard to DMS. Specifically, we wanted to uncover precisely *what* drivers thought was happening, *how* they thought it was happening and *why* they thought it was happening.

This presents an interesting challenge in that in order to capture drivers' current understanding of and attitudes towards DMS, the applications and concepts must be communicated in clear and concise terms. However, using specific terminology in descriptions (e.g. "a fatigue monitoring system") or referring to a specific technology (e.g. "a driver-facing camera") can lead or prime participants and therefore bias their responses. In addition, we wanted to depict possible future applications of DMS, such as detecting driver intoxication, for which no commercial system currently exists. We therefore decided to avoid referring to any particular system, brand or technological solution, and instead decided to use visual prompts that could communicate a series of unfolding events, depicting the actions and consequences of DMS, rather than the DMS themselves.

Inspired by a concurrent research project (see: Harvey et al., 2026), we used generative-AI to create visual prompts, in the form of storyboards, each of which depicted a different driver monitoring scenario. In this manner, we ensured that the focus group materials lacked

technical specificity but were still capable of communicating the desired aspects of driver monitoring. Chat-GPT was used to generate the storyboards during July 2025. Text prompts were designed to contextually situate the scenario. They specifically avoided the use of the terms ‘monitor’ and ‘driver monitoring system’, and avoided any terms referring to specific technologies, such as a ‘driver-facing camera’. All descriptions were presented in the third person to avoid superiority and social desirability bias during discussions. The former is a cognitive bias describing situations in which people overestimate their own abilities, knowledge, traits or behaviour compared to others (a common predilection in driving). The latter is a response bias whereby people answer questions in a way they think will be viewed favourably by others, rather than answering truthfully, which can lead to over-reporting of socially acceptable behaviours and under-reporting of socially unacceptable behaviours.

For example, the following Chat-GPT prompt was used to generate the storyboard for ‘driver fatigue’, which is shown in Figure 1:

“Please create a black and white storyboard in comic-strip style with 4 images to show the following situation. Rob works in a factory and has just finished a long shift. Rob looks very tired when driving the next day. Part-way into the journey, the car suggests that Rob takes a break.”

Figure 1: Storyboard created for driver fatigue scenario



As a further example, the following Chat-GPT prompt was used to generate the storyboard for 'cognitive decline', which is shown in Figure 2:

"Please create a black and white storyboard in comic-strip style with 4 images to show the following situation. Roger is an older driver. Roger is driving to an appointment at the hospital. At a junction, Roger looks very confused and has difficulty concentrating. After a long time waiting, the car asks if Roger would like help with his driving."

Figure 2: Storyboard created for cognitive decline scenario



In a similar manner, storyboards were created for driver distraction, driver intoxication, and data surveillance and sharing scenarios (all shown in Appendix B).

It is worth highlighting that composing the correct text prompt to generate the storyboards can be complicated, not least because the wording of AI prompts implicitly embeds the writer's assumptions about human behaviour, task design and socio-technical contexts. Moreover, text prompts must have enough detail to guide the generative-AI model clearly, but not so much detail that the prompt becomes restrictive or contradictory. Indeed, too little detail often leads to vague or generic outputs, or hallucinations because the AI model must fill in many gaps using general statistical patterns. In practice, this means that AI image generation often requires several iterations, with minor changes made to the prompt between attempts, to achieve the desired result – please refer to Harvey et al. (2026) for more details.

3.3 Method

Following generation of the five storyboards depicting driver fatigue, driver distraction, cognitive decline, driver intoxication, and data surveillance and sharing, a focus group study was designed in which participants were asked to consider what they thought was happening in each scenario, how they thought it was happening and why they thought it was happening. The study design was approved by the University of Nottingham Faculty of Engineering ethics committee.

Participants

Thirty participants were recruited using purposive sampling (in particular, to target specific age groups). Participants were then distributed across ten focus groups based on their age profile, effectively differentiating older and young drivers (see Table 2). The mean age across all participants was 42.4, with ages ranging from 20 to 79.

Age plays an important role in driving – both in terms of the practical accomplishment of the task of driving and in an individual's attitudes towards other drivers in age groups different to theirs. For example, young drivers (aged 17–25), especially males, are generally considered to be riskier due to inexperience and impulsivity, resulting in more road traffic collisions (Clarke et al., 2006; DfT, 2024), with older drivers often referring to this group as 'boy racers'. In contrast, older drivers face physical and cognitive challenges and impairments that can impact on aspects of their driving, resulting in collisions at intersections, commonly due to failing to give right of way (Clarke et al., 2010; DfT, 2024); young drivers can therefore often be equally critical of older drivers. It is, of course, noted that driving ability is not just about age but about the combination of experience, health and risk awareness. However, by broadly segregating young and older drivers during recruitment for the focus groups, we aimed to avoid any unnecessary tensions and possible emotional outbursts when inevitable age-related attitudes and opinions arose.

All participants held a valid UK driving licence and were active drivers, with the mean number of years holding a driving licence reported as 23.2 yrs (responses ranged from 1 year to 62 years). Typical annual mileage (median value) was reported as 10,001 to 15,000 miles. When asked (after completion of the focus group discussions to avoid biasing earlier discussions), participants reported limited experience of using DMS or DCAS, with only six participants describing specific systems. Of these, two participants reported that they had had a 'black box' fitted to their vehicle, which they stated provided ratings for "fatigue, speed, time of day and smoothness" after each journey. In addition, one participant mentioned that their car had a lane-departure warning sensor. Another participant stated that they had heard about ADAS that track steering, blinking and head movements to detect fatigue and alert the driver, but they had had no direct experience of using such a system. Finally, one participant, who declared their profession as a delivery driver, stated that the delivery vans they used were fitted with "a tracker, cameras and sensors to detect speed and braking behaviour", and one of the aforementioned black box users explained that they also used a works vehicle that was fitted with the Netradyne Driver-I DMS system (<https://www.netradyne.com/uk/products/driver-i-hub-x>), although they commented that the associated app "isn't very accurate".

Table 2: Participant demographics and details of focus groups

Focus Group	Participants – Gender, M/F (Age)	Age Profile	In Person or Online
1	M(54), M(62), F(59), F(53)	Older	In Person
2	M(25), M(20)	Younger	In Person
3	F(74), F(79), F(76)	Older	In Person
4	F(22), F(22), F(23)	Younger	In Person
5	M(65), F(59), F(58)	Older	In Person
6	F(66), M(66), F(60), M(60)	Older	In Person
7	F(27), F(22)	Younger	Online
8	F(26), M(23), M(24)	Younger	Online
9	M(23), M(30), F(22)	Younger	Online
10	F(26), M(23), F(23)	Younger	Online

Data Collection

Focus groups were conducted either in person or online using Microsoft Teams (see Table 2), based on the availability, location and preference of participants, with Microsoft Teams used to record and transcribe the dialogue in all situations. In each focus group, the five scenarios were presented to participants in the form of black and white storyboards. The order of presentation of scenarios remained the same during each focus group to support narrative and cognitive flow. In other words, the use-cases had been specifically selected to represent increasingly futuristic and intentionally controversial applications. The earlier storyboards – depicting contemporary applications – therefore set context for the later ones, and by considering current, less contentious applications first, we avoided any emotional carryover from the potentially more contentious examples.

Each storyboard was shown in turn to participants, who were then asked a series of questions, inspired by critical decision method (CDM) interview probes (Klein et al., 1989) (see Table 3 and Appendix C). The CDM is an interview technique that is particularly effective at uncovering how people actually think and decide, typically in complex, time-pressured domains, not just what they say they do and think in general. An overview of the CDM-inspired probes is shown in Table 3. Essentially, these were used in the focus group study to uncover *what* participants thought was happening, *how* they thought it was happening and *why* they thought it was happening.

Table 3: Overview of the CDM-inspired questions and probes used in focus groups

Main Question	Follow-Up Prompts and Probes	CDM Category
What do you think is happening in this situation?	Confirm that situation has been interpreted correctly and redirect, as appropriate.	Context
What specifically do you think the car is trying to achieve in this scenario?	Consider short-term versus long-term goals/implications.	Goal
What information or data do you think is being captured?	Consider the type of data (e.g. driver behaviour versus car performance data) and how accurate this might be and/or what else it might mean.	Cue/Knowledge
How do you think this information or data is being captured?	Consider what technology could be used and if there are any practical, ethical, legal and/or societal issues.	Information
What do you think happens to this data?	Consider how and where the data will be analysed and stored, and what else it might be used for (including issues of consent).	Information
How accurate and reliable do you think the system will be?	Consider whether they think the system will always interpret the data correctly and make the correct decision or recommendation.	Errors
What do you think are the potential outcomes in the scenario? In other words, what do you think happens next?	Consider how the system knows if the driver has responded appropriately and what 'responding appropriately' means in this context. Consider what should happen next, if the driver doesn't respond. Consider if the system should adapt over time, and if so, how? Consider if the system is fair, inclusive and respectful, and if not, why not? Consider if drivers should be given the option to 'opt in' or 'opt out'?	Action

The storyboards were designed to convey clear and distinct DMS concepts. However, if a participant misinterpreted the scenario but their interpretation was broadly as intended (for example, driver fatigue was interpreted as low driver mood), the discussions were allowed to continue in this manner. In situations where a dubious interpretation was made and this differed significantly from the intended meaning, participants were gently guided back on track, e.g. by asking them to consider another possible interpretation of the storyboard. Each focus group lasted approximately one and a half hours, and each participant received a £20 online shopping voucher for taking part.

3.4 Thematic Analysis

Dialogue was automatically transcribed using Microsoft Teams. All transcripts were manually checked and edited to correct any errors or omissions, and to ensure that each transcript conveyed an accurate sense of what was said. The transcripts were then analysed using inductive thematic analysis using a 'bottom-up' approach in which the themes are derived directly from the raw data (see: Braun & Clarke, 2006).

This approach ensures that the analytical focus is on finding meaningful patterns, rather than just counting the occurrence of words, and is particularly useful for exploratory research where limited theory exists. Following data familiarisation (i.e. reading through the transcripts to gain an overview), phrases and sentences were labelled using open coding – this is the foundational first pass of thematic data analysis where the researcher breaks down qualitative data (transcripts, field notes, text) into smaller, meaningful segments and assigns labels (codes) to them. It is defined as ‘open’ because the researcher begins without a predefined codebook or set of themes, allowing the codes to emerge directly from the data in a ‘bottom-up’ or ‘data-driven’ approach. Related codes can then be clustered together to identify broader themes. These themes are then reviewed and refined to ensure that they represent distinct and coherent patterns and can also be applied to the broader data set. Finally, an appropriate name is chosen for each.

Using this approach, three HF experts initially coded the same transcript independently. Then, using an iterative, qualitative process of comparing and discussing coded data to clarify and resolve any discrepancies, an agreed consensus was achieved and a common coding rubric adopted. All transcripts were then coded using this bespoke rubric. The final themes are shown below, with each one having several subthemes and coding elements:

1. Driver Physiological and Affective State
2. Contextual Factors Shaping Understanding
3. Attitudes Towards DMS Concepts and Scenarios
4. Driver Monitoring and Inferred States
5. Human–Machine Interface and Intervention Design
6. Driver Response to Monitoring, Feedback and Intervention
7. Data Governance, Interpretation and Secondary Use
8. System-Level Trust, Fairness and Reliability
9. Human-Centred Expectations and Boundaries for DMS
10. Driver Engagement, Use and Adaptation to DMS
11. Perceptions of Other Drivers’ Acceptance and Use of DMS

3.5 Overview of Themes

Drivers recognised that their physiological, cognitive and emotional state (e.g. fatigue, illness, distraction, stress or confidence) affected their capability and readiness to drive. Self-assessment subsequently played a central role in how drivers perceived, understood and responded to DMS: people often judged their own fitness to drive, which can result in the DMS being seen as either supportive or intrusive depending on whether it aligned with their own judgement – regardless of whether their own judgement was correct or not.

Understanding DMS was strongly shaped by context. Journey conditions, personal circumstances, vehicle behaviour and the driver's broader life situation all influenced how participants interpreted system alerts and interventions. Participants evaluated DMS not just as a technological add-on but as something operating within the practicalities of everyday driving (i.e. traffic, weather, work pressures, time constraints etc.).

Attitudes towards DMS revolved around trust, autonomy and control. Participants were more positive when systems were seen as advisory or assistive, but indicated greater resistance when interventions appeared mandatory or overruled their authority or agency. Concerns included surveillance, data privacy and unclear purpose, but were mediated by the recognition and acceptance of potential safety benefits.

Participants differentiated strongly between what was measured directly and what was inferred. They considered driving performance indicators (steering, speed, reaction time), attention cues (gaze, secondary device use) and physiological signals (heart rate, stress) as ways DMS might measure or infer driver capability. However, acceptance was also expected to depend largely on how feedback was delivered (timing, modality etc.). These factors (timing, modality, escalation and personalisation) are also likely to impact on workload, frustration and compliance.

The discussions highlighted that drivers would not remain passive in response to DMS but would be likely to negotiate their relationship with the system, potentially ignoring alerts, testing system limits and/or adapting their behaviour. Findings suggest that DMS could therefore support learning and safer driving habits and behaviour over time, but might also create irritation or over-reliance, or encourage drivers to find workarounds.

Broader data governance and societal issues were also a central theme. Participants balanced safety benefits against risks such as data misuse, profiling, discrimination and external monitoring by employers, insurers or authorities. Acceptance is therefore likely to depend not only on usability but also on fairness, transparency and perceived legitimacy.

Finally, expectations regarding desired system roles, anticipated personal use and social norms frequently featured in discussions; these are also likely to affect acceptance. In particular, perceptions of how other drivers might respond – including common stereotypes about age, experience and risk-taking – influenced personal attitudes, often amplifying resistance or justification for opting-out of systems. These findings highlight that acceptance is dynamic, socially situated and influenced by first-hand experience.

Overall, the thematic analysis suggests that acceptance of DMS is likely to be less about the capability of the sensing technology and intervention, but more about its perceived purpose, user autonomy, trust and ethical handling of data. Drivers are more likely to accept supportive systems that are transparent, proportionate and safety-focused, but resist systems perceived as punitive, intrusive or controlling.

Full details of the themes, subthemes and coding elements are shown in Table 4.

Table 4: Themes and subthemes describing drivers' current understanding and interpretation of DMS

Theme	Subthemes	Codes	Driver's Interpretation
Driver Physiological and Affective State <i>Transient physical, cognitive and affective states influencing driving capability and self-assessment</i>	Physical and Medical Condition	• Age-Related Factors • Physical Symptoms (e.g. Faintness, Headache, Visual Impairment) • Fatigue and Tiredness • General Malaise ("Not Feeling Right") • Medical or Health-Related Conditions	My physical health, age and bodily conditions, and how they impact on my ability to drive safely and comfortably
	Cognitive and Psychological State	• Cognitive State (Confusion, Reduced Mental Capacity) • Lack of Understanding or Situational Awareness • Emotional State • Distraction	My mental, emotional and cognitive state, and how it impacts on my driving performance and decision-making
	Perceived Capability and Readiness to Drive	• Perceived Readiness to Drive • Job Satisfaction	My self-assessed ability, preparedness and motivation to perform driving tasks effectively
Contextual Factors Shaping Understanding <i>Situational, personal, environmental and vehicle-related moderators of driver behaviour and system perception</i>	Contextual and Situational Factors Associated With the Journey	• Current Journey Characteristics • Driving Environment (e.g. Road, Traffic, Weather Conditions) • Circumstances Prior to Driving	The situational context and conditions surrounding a specific journey or trip
	Driver State and Personal Circumstances	• Driver's Current Physiological and Psychological State • Driver's Broader Life Situation • Driver's Needs and Preferences	My internal state, personal context and motivations
	Vehicle and System Factors	• Vehicle Status and Operating Conditions • Vehicle Actions and System Responses	The state and actions of my vehicle

Theme	Subthemes	Codes	Driver's Interpretation
Attitudes Towards DMS Concepts and Scenarios <i>Trust, perceived control, autonomy and moral alignment with DMS intervention concepts</i>	General Technology Orientation and System Appraisal	• Overall Positivity Towards Technology • Acceptance Versus Non-Acceptance of DMS • Attitudes Towards Storyboard Scenarios • Comparison With Existing Technologies	My general attitudes towards DMS technology
	Understanding, Purpose and Functional Framing of DMS	• Perceived Rationale for DMS Use • Lack of Understanding of the Technology • Technology as a Diagnostic or Decision-Support Tool	My perception, understanding and interpretation of the purpose and functions of the DMS
	Control, Autonomy and Governance of Use	• Driver Responsibility and Autonomy • Human-in-the-Loop Considerations • Opt-In Models • Opt-Out Models • Mandatory Use (No User Choice)	How my control, autonomy and decision-making are shaped by different governance models and the extent of mandatory or voluntary use of the system
	Risks, Consequences and Ethical-Societal Concerns	• Dangerous Driving Behaviours (As Justification or Concern) • Perceived Wider Consequences of DMS Deployment • Data Privacy and Protection Concerns • Perceived Surveillance or Intrusion	The potential risks, ethical issues and societal implications of DMS

Theme	Subthemes	Codes	Driver's Interpretation
Driver Monitoring and Inferred States <i>Physiological, behavioural and contextual signals used to infer driver capability and intent</i>	Driving Behaviour and Vehicle Control Performance	• Observable Driving Behaviour • Longitudinal Control (Acceleration and Braking Behaviour) • Lateral Control (Lane Position and Stability) • Speed Regulation and Speed Variability • Distance Travelled and Exposure • Steering Control and Grip Force • Hand Placement on Steering Wheel • Reaction Time to Events and Hazards • Behavioural Intent and Anticipatory Actions • Indecision and Hesitation • Double-Checking Behaviours • Driving Capability and Task Competence	Measurable aspects of my behaviour and vehicle control, reflecting my skill, performance and decision-making while driving
	Attention, Interaction and Task Engagement	• Gaze Direction and Visual Attention • Blink Rate and Eye Closure Patterns • Head Position Relative to Driving Task • Interaction with Mobile Devices and In-Vehicle Interfaces • Interaction with In-Vehicle Interfaces (duplicate but conceptually same) • Speech Characteristics During Driving	How my attention, engagement and interactions with the vehicle or devices reflect my focus and involvement in the driving task

Theme	Subthemes	Codes	Driver's Interpretation
Driver Monitoring and Inferred States <i>Physiological, behavioural and contextual signals used to infer driver capability and intent</i>	Physiological and Affective Driver State	• Cardiovascular Signals (Heart Rate, Pulse, Blood Pressure) • Skin Conductance, Sweat Response and Temperature • Breath-Based Indicators • Blood Alcohol Estimation • Brain Activity Signals • Driver Emotional State • Stress and Arousal Indicators • General Health Indicators • Wearable-Derived Physiological Data • Driver Movement Within the Seat and Postural Stability	My physiological and emotional state, including bodily signals, health indicators and affective responses, as they relate to driving performance and wellbeing
	Contextual, Identity and Data Ecosystem Factors	• Deviation From Individual Baseline Behaviour • Driver Age and Identity Characteristic • Gait and Action Outside the Vehicle (Pre/Post Journey) • Generic Facial Feature Analysis • Journey Duration and Time-on-Task • Location and Route Information • Vehicle Access to Personal User Data • External Monitoring Systems (e.g. Employer, Insurer, Law Enforcement) • Integration of External Data Sources	How contextual factors, my identity and the broader data ecosystem –including personal, vehicle and external data – affect my driving behaviour and system interactions

Theme	Subthemes	Codes	Driver's Interpretation
Human–Machine Interface and Intervention Design <i>Design of information, alerts and interventions that affect trust, workload and emotional response</i>	Feedback Philosophy and System Role	• Advisory Feedback (Information Without Control) • Non-Physical Intervention (Warnings, Prompts, System Messages) • Feedback Encouraging Behaviour Change • Graduated Feedback and Escalation Thresholds and Strategies • Physical Vehicle Intervention (Steering, Braking, Speed Limitation) • External System Feedback (e.g. Apps, Employers, Insurers) • Post-Journey Reflective Feedback and Feedback Consistency	The design, purpose and types of feedback provided by the system, including how it informs, guides or intervenes in my behaviour
	Feedback Design, Delivery and System Intelligence	• Feedback Modality (Visual, Auditory, Haptic) • Timing and Context Sensitivity of Feedback • Feedback Design Quality • Personalisation and 'Smart' Feedback Behaviour	How feedback is designed, delivered and tailored, including modality, timing, quality and intelligent personalisation to support my understanding and response
	Perceived Effectiveness, Usefulness and Need	• Feedback Effectiveness and Task Support • Perceived Usefulness of the System • Perceived Need for Intervention	My perceptions of how effective, useful and necessary the system or its feedback is for supporting driving performance
	User Experience, Trust and Perceived Risks	• Attitudes Towards Automated Feedback and Intervention • Negative User Experiences and Frustration • Risk of Undermining Driver Authority • Potential for Intervention-Induced Harm	My experiences, trust and concerns regarding automated feedback and interventions, including frustration, perceived risks, and potential impacts on my authority or safety

Theme	Subthemes	Codes	Driver's Interpretation
Driver Response to Monitoring, Feedback and Intervention <i>Adaptive and learning-related responses to system feedback</i>	Driver Engagement and Attitudes Towards Assistance	• Concern or Reluctance to Seek Assistance • Compliance with DMS Feedback • Active Ignoring of System Feedback	How I perceive, accept or resist system support
	Driver Interpretation and Judgement of System Alerts	• Driver Judgement in Response to Alerts • Observable Driver Response to Alerts • Incorrect or Unsafe Driver Responses	The cognitive evaluation of alerts and decision-making that follows
	Behavioural Adaptation and Performance Outcomes	• Identifiable and Measurable Behavioural Changes • Return to Task-Appropriate Driving Behaviour	Measurable changes in my driving behaviour after system interaction
	Learning, Skill Development and Capability Building	• Driver Education and Skill Development	Longer-term improvement and learning effects
Data Governance, Interpretation and Secondary Use <i>Perceived risks and benefits of data collection, ownership and downstream use</i>	Data Governance and Control	• Data Consent and Permissions • Data Sharing and Privacy Concerns • Data Storage and Data Location • General Data Use • Data Analysis and Interpretation Practices	Rules, processes and transparency around how my data is handled
	Benefits and Value of Data Use	• Manufacturer Benefits • Insurance-Related Use of Data • Third-Party Benefits • Personal and Societal Benefits • Emergency Response Support	Positive outcomes and incentives tied to data use
	Risks, Ethics and Fairness	• Data-Driven Discrimination Risks • Data Sharing and Privacy Concerns • Behaviour and Lifestyle Profiling	Ethical tensions, misuse and fairness issues

Theme	Subthemes	Codes	Driver's Interpretation
Data Governance, Interpretation and Secondary Use <i>Perceived risks and benefits of data collection, ownership and downstream use</i>	Contexts of Data Application	- Crash and Incident Analysis - Legally Relevant Driving Performance - Professional or Occupational Monitoring - Rental Vehicle Contexts - Prior Experience with Data Monitoring	Situations and domains where my data becomes relevant
System-Level Trust, Fairness and Reliability <i>Overall evaluations of system competence, equity and role allocation</i>	Perceptions of the System	- Perceived Usefulness of DMS - Perceived Fairness of DMS - Perceptions of the Monitoring System - Perceptions of System Feedback	My evaluations, trust and system experience
	Ethics, Agency and Responsibility	- User Consent and Agreement - Perceived Responsibility and Accountability - Perceived Respectfulness of the System	My control, autonomy and ethical acceptability
	Value and Practical Trade-Offs	- Perceived Safety Benefits - Cost Considerations	My practical justification and value judgements
	Social and Contextual Influences	- Evolving Attitudes Towards Technology - Contextual Influences on System Use - Influence of Other Road Users	Broader situational and social influences
Human-Centred Expectations and Boundaries for DMS <i>Drivers' expectations regarding adaptive support, authority and transparency</i>	Adaptive and Responsive System Functions	- Responsiveness to Driver State - Adaptation to Driving Behaviour - Support for Drivers Unfit to Drive	System sensitivity and tailoring to me and my driving
	Safety Enforcement and Intervention	- Prevention of Unsafe Driving - Activation of External Interventions	Direct safety actions and escalation

Theme	Subthemes	Codes	Driver's Interpretation
Human-Centred Expectations and Boundaries for DMS <i>Drivers' expectations regarding adaptive support, authority and transparency</i>	Feedback and Behaviour Change	• Provision of Driving Feedback • Support for Long-Term Driving Improvement	Learning, coaching and habit change
	Transparency and Acceptable Limits	• System Transparency and Clarity • Perceived System Boundaries and Limits	What makes the system understandable and acceptable to me
Driver Engagement, Use and Adaptation to DMS <i>Drivers are not passive users; they experiment, resist, rely, ignore, and negotiate their relationship with the system over time</i>	Acceptance, Adoption and Willingness to Use	• Immediate Acceptance of DMS • Future Acceptance of DMS • Voluntary Adoption of DMS • Advocacy for DMS Use by Others	My willingness to use, timing and social influence
	Trust, Reliability and Accuracy	• Perceived Superior Self-Knowledge • Risk of Reduced Driver Engagement • Potential Over-Reliance on DMS • Perceived Inaccuracy of DMS • Failure to Intervene When Necessary	My trust, reliability and risks of dependence
	Interaction and Compliance	• Direct Compliance with DMS Guidance • Indirect Attention to DMS Feedback • Active Disregard for DMS • Attempt to Circumvent the DMS • Deliberate Testing of DMS	My behavioural responses, engagement with, and manipulation of, the system
	Perceived System Experience	• Perceived Feedback Invisibility • User Irritation with DMS • Perceived 'Distractiveness' of DMS • Perceived Unfairness and Exclusion Awareness of Personal Driving Limits • Consent to Data Collection	My subjective experience, usability, ethics and personal boundaries

Theme	Subthemes	Codes	Driver's Interpretation
Perceptions of Other Drivers' Acceptance and Use of DMS <i>DMS acceptance is shaped not just by individual usability, but by identity, norms, stigma, fairness and perceived legitimacy</i>	Driver Demographics and Characteristics	• Older Drivers • Younger or Inexperienced Drivers • Drivers Experiencing Illness or Impairment • Overconfident Driver Behaviour • Unsafe or Illegally Behaving Drivers • Risk-Taking/Reckless Drivers	Personal characteristics that affect how other drivers interact with DMS
	Perceptions and Attitudes Towards Monitoring	• Perceptions of Surveillance and Control • Drivers Accustomed to Monitoring • Drivers Who Perceive DMS as Unnecessary • Drivers Concerned About Personal Device Monitoring	Other drivers' attitudes, beliefs and concerns about monitoring systems
	Driver Acceptance and Compliance	• Conditional Acceptance of DMS • Drivers Likely to Opt Out of DMS • Drivers Likely to Resist or Be Angry at DMS • Drivers Likely to Ignore DMS • Deliberate Non-Compliance by Drivers • Drivers Rejecting DMS • Drivers Misusing or Abusing DMS	Other drivers' willingness to accept, follow or resist DMS
	Perceived Effects of DMS on Drivers	• Drivers Potentially Improving Behaviour with DMS • Drivers Perceiving DMS Benefits • Drivers Valuing Safety Benefits • Drivers Feeling Negative Impact From DMS	How DMS might influence other drivers' behaviour, safety and wellbeing

3.6 Discussion

The first aim of the focus group study was to uncover drivers' tacit knowledge and current understanding of DMS. The findings from the thematic analysis clearly show that DMS cannot be evaluated solely as sensing technologies but instead as something that operates within a socio-technical system in which human behaviour, environmental context, system design and data governance jointly determine real-world effectiveness. Participants consistently framed DMS not simply as safety aids but as technologies affecting autonomy, responsibility and social trust. As a result, system acceptance and behavioural responses may depend less on detection accuracy than on compatibility with drivers' expectations, values and lived experiences.

Participants described driving capability as dynamic, transient and multi-dimensional, shaped by fatigue, emotional condition, discomfort, distraction and general wellbeing. Importantly, impairment was often experienced subjectively as a gradual or ambiguous change ("not feeling right") rather than a discrete condition. These accounts challenge implicit assumptions underlying many DMS implementations that driver fitness-to-drive can be classified using threshold-based criteria. Human-performance research has long established that vigilance, reaction time and decision-making fluctuate continuously rather than categorically (Hancock, 1989). Fatigue, in particular, degrades attention and hazard perception (Williamson et al., 2014), while emotional stress and cognitive load affect situational awareness (Endsley, 1995). Consequently, a binary classification approach risks misalignment between system output and driver experience. Indeed, participants in the focus groups indicated that disagreement between their own judgement and the system's assessment would undermine system credibility: *"If that happens when you're not tired, you'd lose faith."* (Focus Group 2 – Scenario 1) This finding aligns with research on trust in automation showing that perceived reliability depends on consistency with user expectations (Lee & See, 2004). Indeed, even technically proficient systems may be rejected if their decisions appear inconsistent with the driver's lived experience.

From a HF perspective, DMS may subsequently be most effective when designed to support drivers' awareness rather than replace their judgement. Systems that communicate uncertainty and provide graduated feedback may align better with drivers' perception of fluctuating capability. In other words, DMS might act best as a decision-support tool rather than an authoritative fitness-to-drive classifier.

Participants repeatedly emphasised that the meaning and risk of their driving behaviour depended on context. For example, fatigue, distraction or reduced alertness were viewed differently depending on road type, traffic density and journey purpose. A uniform intervention was therefore perceived as inappropriate or unfair: *"If my car was telling me to take a break while I'm in the middle of a standstill traffic queue, it'd probably be quite aggravating."* (Focus Group 4 – Scenario 1) This finding reflects ecological approaches to human performance, which conceptualise behaviour as emerging from interactions between a person and their environment (Vicente, 1999). Driving is a dynamic control task requiring adaptation to changing environmental demands (Summala, 2007). Monitoring driver state

alone therefore provides only a partial representation of safety risk. Automation research similarly shows that adaptive systems that account for task demand are both more effective and more acceptable (Parasuraman et al., 2000). The findings from the focus groups suggest that drivers implicitly evaluate DMS interventions according to context of use and situational appropriateness: *“There’s all sorts of reasons why his driving might be different [...] there might be an accident, there might be a lot of traffic, there might be road works.”* (Focus Group 1 – Scenario 3) Systems that intervene identically across different conditions risk being interpreted as insensitive or lacking understanding. This suggests that effective DMS should integrate environmental and behavioural data to assess risk, rather than relying solely on driver physiology or gaze behaviour. Context-sensitive interventions may improve not only safety but also perceived fairness, which in turn is likely to support acceptance.

Drivers’ expectations of DMS were strongly influenced by their understanding of how the system worked. Participants formed mental models regarding system capability, authority and accuracy, and these models shaped anticipated compliance. Mental model theory suggests that users predict system behaviour using simplified internal representations (Norman, 1983). When the system behaviour violates these expectations, trust deteriorates (Lee & See, 2004). Indeed, several drivers indicated concerns about unclear system boundaries, particularly when the system inferred psychological or cognitive states such as emotion or fitness to drive: *“Autonomy in terms of if you’re not adhering to this message that the car is giving, the car does not automatically stop. It still allows you to drive.”* (Focus Group 9 – Scenario 1) A clear distinction emerged between directly observable measurements (e.g. speed or steering) and higher-level inferences. Monitoring driving behaviour was generally accepted, whereas unclear or unsubstantiated inferences were perceived as intrusive or unjustified.

This finding reflects broader issues in algorithmic decision-making: trust depends not only on accuracy but also on explainability. Trust in automation is best understood as graduated rather than as a binary measure of acceptance or rejection (Hoff & Bashir, 2015). Under-trust can subsequently lead to non-use, while over-trust leads to complacency. Participants’ responses suggest that transparent feedback explaining system reasoning could support appropriate trust and reliance: *“If it had some way where it could, like, show you how you’re performing badly, then maybe you’d be more likely to stop.”* (Focus Group 1 – Scenario 1); *“It could go back to the driver’s phone and therefore when he gets out of the car after driving, he could have a notification: ‘So, you seem tired. This is the analysis to back up why we think you were tired’.”* (Focus Group 8 – Scenario 1) Providing understandable explanations of why an alert occurred may therefore be as important as improving acceptance.

The tone, timing and modality of feedback strongly influenced drivers’ reactions. Frequent alerts were seen as annoying and distracting, whereas supportive and proportionate feedback was viewed positively. This aligns with alarm fatigue research, which shows that excessive or poorly designed warnings degrade attention and compliance (Wickens et al., 2021). Participants expressed a preference for advisory and coaching-style systems, rather than punitive or authoritative interventions: *“It’s not a statement. It is actually suggesting, it’s not telling.”* (Focus Group 3 – Scenario 1) Informative feedback was perceived as helpful,

while judgemental feedback provoked resistance: *"The car's not acting as a policeman."* (Focus Group 6 – Scenario 4) Feedback intervention theory suggests that constructive feedback promotes behavioural change, whereas evaluative feedback reduces motivation (Kluger & DeNisi, 1996). The findings suggest that DMS may influence long-term behavioural change only if drivers perceive the system as a supportive co-driver rather than a surveillance tool. Escalation strategy was a particularly sensitive area, with poorly timed interventions seen as potentially counterproductive or even harmful. Participants were wary of forceful interventions, such as automatic vehicle control, especially when the system's reasoning was unclear: *"It's trying to make me do something which I don't want to do."* (Focus Group 3 – Scenario 5) Poorly timed takeover requests in automated driving have previously been shown to increase workload and degrade performance (Banks & Stanton, 2016). The present findings suggest similar concerns apply to control-based DMS interventions.

Attitudes towards DMS were closely linked to perceived autonomy. Drivers generally supported systems that provided assistance but resisted systems perceived to override them or impose mandatory monitoring. Drivers' desire to remain 'in control' was a recurring theme: *"Ultimately, you can't force the driver to stop."* (Focus Group 6 – Scenario 1) HF research emphasises the importance of meaningful human control in automated systems (Sheridan & Parasuraman, 2005). When users feel their authority is reduced without a corresponding transfer of responsibility, they may disengage or attempt to circumvent the system. Participants also expressed concern about ambiguity of responsibility, whereby drivers remain legally responsible for their vehicle while the system could be considered to be responsible for their behaviour: *"If you went through a red light, you should not be able to send that to the police or his insurance or anyone, really, because, yeah, he's gone through the red light, but your car isn't policing you."* (Focus Group 6 – Scenario 3); *"At what point do you feel your car's responsible for your driving? And at what point are you taking full responsibility for the driving?"* (Focus Group 5 – Scenario 2) This reflects a well-known challenge in partially or conditionally automated driving, where unclear role allocation leads to confusion and can impact on safety (Banks & Stanton, 2016). The findings suggest that DMS designers should explicitly communicate the division of responsibilities between system and driver. Maintaining the driver as an active participant rather than a passive subject could therefore be important to achieve acceptance of DMS.

Privacy and data use emerged as a central factor shaping attitudes. Participants were concerned about insurers, employers, legal liability and potential discrimination – both by the system itself (*"If you're giving your age and your gender, and maybe the numbers of years you've been driving, there could be an element of bias"*) (Focus Group 4 – Scenario 3)) and from potential recipients of the data (*"An insurance provider could charge them more because they are more likely to have an incident, if you are constantly panicking when you're driving"*) (Focus Group 2 – Scenario 3)). These concerns are likely to affect acceptance even among drivers who recognised and welcomed safety benefits. Research into technology adoption shows that perceived legitimacy and fairness strongly influence compliance (Tyler, 2006). Unlike conventional vehicle safety systems, DMS collect behavioural and biometric data, making them resemble surveillance technologies. Consequently, trust in the institutions responsible for safeguarding their data becomes inseparable from trust in the device.

Participants indicated that acceptance would depend on transparency, purpose limitation and user control over data.

This suggests data governance should be treated as a HF design parameter rather than a purely regulatory issue. If not, systems that are perceived as technically effective but socially ignorant or morally misaligned may be resisted or disabled.

Finally, drivers anticipated that they could adapt to DMS over time, but that this might require them to test the system limits, ignore alerts and/or learn from feedback: *"I can imagine people pressing [the button] that allowed them to drive the car."* (Focus Group 5 – Scenario 4) Such behavioural adaptation is consistent with risk compensation theory (Wilde, 1998), which predicts that users rarely interact with safety technologies exactly as designers intend. Importantly, participants indicated that although supportive systems could encourage safer habits, punitive systems might encourage avoidance or circumvention: *"I think when you try and control people in the sense where you don't give them the option to do something they don't want to do, they start to behave in the opposite way."* (Focus Group 7 – Scenario 5) As a consequence, research exploring short-term use of DMS may overestimate effectiveness as patterns of use would likely evolve over longer-term exposure. Designing for realistic use requires anticipating non-compliance and misuse. Robust systems should therefore tolerate imperfect human behaviour rather than assume ideal adherence.

Considered together, the findings show that drivers evaluated DMS across three dimensions:

1. Intelligibility – *Does the system make sense?*
2. Respect for autonomy – *Does it treat me fairly?*
3. Usefulness – *Does it genuinely help me?*

Failure in any of these dimensions, in the opinion of the individual driver, is likely to reduce acceptance, regardless of technical performance, as the system must make sense to the user and be perceived as both fair and genuinely helpful. These dimensions map closely to established determinants of trust in automation – predictability, controllability and perceived benefit (Lee & See, 2004) – and suggest a conceptual shift from driver monitoring to co-operative assistance. The findings therefore suggest that DMS should be designed not as enforcement tools but as collaborative safety partners, or 'co-drivers', supporting driver awareness and self-regulation.

3.7 Conclusions and Next Steps

The focus groups uncovered valuable insights about drivers' tacit knowledge and current understanding of the application of DMS across different scenarios, suggesting that acceptance is likely to be shaped by the complex, uncertain and context-dependent nature of driving, in which drivers' physiological and psychological states, self-assessments, goals, and the surrounding conditions continually fluctuate.

Participants viewed rigid, authoritative or opaque systems as poorly aligned with lived driving experience, particularly where system judgements conflicted with personal judgement or

ignored uncertainty and context. In contrast, DMS are likely to invite the highest level of trust and acceptance if they are transparent, explainable, respectful and advisory in nature, keep the driver meaningfully in the loop, and frame monitoring and feedback as supportive, fair and learning-oriented rather than punitive.

From a HF perspective, these findings indicate the need for context-sensitive, uncertainty-aware and ethically governed DMS designs that calibrate authority carefully, communicate limits clearly, and recognise acceptance as dynamic, socially situated and experience-dependent. The findings from the focus groups were then translated into question prompts to evaluate acceptance in an online survey.

4. Online Survey: Measuring Acceptance of Driver Monitoring



4.1 Introduction

The focus group study uncovered drivers' tacit knowledge and current understanding of DMS. It also provided valuable insights to inform the development of an online survey to explore acceptance in greater depth and with a larger sample of participants.

The online survey had one main objective:

1. To capture drivers' attitudes and opinions, operationalised as 'acceptability', in response to different applications of DMS.

The results from the online survey could then be combined with the findings from the stakeholder interviews and focus groups to inform recommendations to improve the design, implementation and acceptance of DMS.

4.2 Measuring Acceptance

When considering the acceptance of technology, researchers are typically interested in exploring not only whether a user will try using the technology, but also whether they actually adopt it, trust it and keep using it as part of their normal behaviour. Technology acceptance is therefore both psychological and behavioural in nature.

The most widely applied approach is to use the Technology Acceptance Model (TAM) (Davis, 1989), which aims to predict whether a person will adopt a particular technology based on two key beliefs: Perceived Usefulness (PU) (*“Using this will improve my performance or life”*) and Perceived Ease of Use (PEOU) (*“This is easy to learn and operate”*). These shape the user’s attitude, which in turn influences their intention to use the system and eventually their actual usage. It is also important to recognise that technology acceptance is not just about usability. A system can be easy to use and useful, but still be rejected (e.g. Google Glass (Weidner, 2024)). This is because acceptance also depends on trust, social meaning and perceived consequences.

The TAM measures users’ attitudes by asking structured questions (often presented as Likert scales, inviting responses from ‘Strongly Disagree’ to ‘Strongly Agree’). Findings are then typically substantiated by collecting behavioural data such as adoption rate, frequency of use and retention over time. Together, survey responses and usage data show whether users have truly accepted the technology rather than just tried it once, or think they may use it.

Measuring acceptance of speculative or future technology is therefore particularly challenging as real-world usage data does not yet exist. Instead of observing behaviour, researchers therefore typically estimate likely adoption using anticipated acceptance, often referred to in the academic literature as ‘acceptability’. In academic research, acceptance and acceptability are related but distinct concepts (although for the purpose of this report, the terms may be used interchangeably). In contrast to acceptance, defined above, acceptability refers to users’ evaluative judgement before or during initial exposure to a technology – whether they believe it is appropriate, trustworthy, ethical or suitable for their needs. It is therefore mainly attitudinal. However, it is worth highlighting that a technology can be seen as acceptable in principle (people approve of it) but not necessarily accepted in practice (people do not actually use it).

4.3 Survey Development

Our ambition was to use the findings from the focus groups to measure drivers’ acceptance of DMS. Although several popular survey-based methods exist, such as the aforementioned TAM (Davis, 1989), these are aimed at evaluating a particular technology. In contrast, the focus groups revealed that drivers associate distinct functional roles with DMS. Therefore, a bespoke solution was required to measure acceptance. We therefore translated qualitative focus-group insights – each representing a specific functional role or attribute of DMS – into measurable survey constructs, retaining the functional meaning and as much of the specific

language used by focus group participants as possible. Each statement thus represented a distinct, imagined capability of DMS. To further avoid any association with a specific technology, each capability was assigned to the vehicle itself (e.g. *"My car monitors me and my driving to determine if I am too tired to drive safely"*), rather than using technology-specific statements (e.g. *"A driver-facing camera is used to detect signs of fatigue"*). The level of acceptability associated with each of the statements could then be captured using a five-point Likert scale, labelled from 'Completely Unacceptable' to 'Completely Acceptable'. The survey therefore measures acceptance of distinct functional roles, rather than measuring acceptance of DMS as a single technology.

Importantly, because DMS technology is still evolving, the items measure anticipated behavioural acceptance rather than actual usage. The statements provide participants with concrete scenarios that approximate experience, reducing abstraction and allowing respondents to evaluate consequences they might not otherwise consider. As a result, the survey captures not only whether drivers are likely to accept DMS, but also which types of DMS they accept and why, revealing how acceptance changes as the system moves from a safety feature (*"My car detects when I have taken my hands off the steering wheel"*) to monitoring (*"My car monitors my emotions"*), decision-making (*"My car will not allow me to resume driving until I have had an adequate break"*) and data-sharing authority (*"My car shares data on my driving behaviour with my family and friends"*).

Furthermore, by comparing responses across advisory (*"My car provides information and suggestions based on my phone's browsing history and/or social media use"*), assistive (*"My car monitors my driving performance and behaviour and provides assistance to make my driving safer"*) and enforcement (*"My car takes over control of driving if I do not look back at the road when alerted"*) functions, the survey enables us to interpret acceptance at different levels of system authority. This effectively identifies a 'threshold of acceptability', representing the point at which safety assistance becomes perceived surveillance or coercion. For example, drivers may accept warnings about tiredness but reject automated vehicle takeover or long-term behavioural profiling. This allows acceptance to be modelled on a graduated scale rather than a binary outcome.

Operationalising acceptance also often encompasses intention to use or buy. We therefore added 'likelihood to choose' as a specific set of questions relating to each scenario – for example, *"How likely or unlikely are you to choose a car in the future that monitors you and your driving to determine if you are too tired to drive safely?"*.

Finally, discussions within the focus groups revealed a marked divergence between self-directed attitudes and beliefs about other drivers. Although this distinction warrants further investigation, adequately examining it would require replicating the full survey with modified referents (e.g. substituting "me" or "my car" with "other drivers"). Such duplication would substantially increase the length and respondent burden of the survey. Consequently, this line of inquiry was deferred for future research.

The survey and study design were approved by the Faculty of Engineering ethics committee at the University of Nottingham.

4.4 Survey Structure

The survey contains four main sections (outlined below). In each section, respondents were presented with a number of statements or questions and asked to rate each of these using the scales provided. Respondents were told that the survey explored their attitudes towards systems and technology that monitored them and their driving, but it made no reference to any specific technology or commercial solution. They were reminded to answer honestly and informed that their responses would be combined with those of others, ensuring that individuals could not be directly identified from the data.

Section 1 – Driver Behaviour Questionnaire

The Driver Behaviour Questionnaire (DBQ) (Reason et al., 1990) measures driver behaviour by asking drivers how often they engage in various aberrant driver behaviours using six-point Likert scales (from '0 = Never' to '5 = Nearly all the time'). It measures three behavioural categories, namely, violations, errors and lapses. Violations are deliberate acts, such as intentionally disregarding the speed limit. Errors are acts that fail to get the intended outcome, such as misjudging the speed of a moving vehicle when overtaking. Finally, lapses are unintentional acts, such as failing to read road signs correctly when exiting from a roundabout and selecting the wrong road.

Drivers' responses to the DBQ have been used to identify high-risk drivers, evaluate safety interventions and predict accidents based on reported violations, especially among young drivers. In addition, responses can be used to categorise respondents (for example, as low, medium or high risk) to help evaluate and interpret other data.

The DBQ has been used extensively in research. However, the full DBQ contains 27 items and can be time-consuming and tedious to answer. This can impact on the completion rate because participants may find it overwhelming and decide not to answer all the questionnaires (De Leeuw et al., 2012). This heightens the risk that people will refuse to participate in the study, leave out questions entirely or partly, or respond with biased or random answers. Martinussen et al. (2013) consequently developed the mini-DBQ, which reduces the original DBQ to the shortest possible version, maintaining its scale integrity, construct validity and predictive power. The mini-DBQ has nine statements (see Appendix C, Section 1). The mini-DBQ was used in the current study to explore respondents' driving behaviour.

Section 2 – Affinity with Technology Interaction Scale

Initially proposed by Franke et al. (2019), the affinity for technology interaction (ATI) is a scale that measures a user's tendency to actively engage with (or avoid) new and emerging technologies. It acknowledges the concern that people who volunteer to take part in research studies may naturally prefer to engage with technology more strongly than the target audience in general (i.e. they have a higher ATI), and that this can impact on the generalisability of results. While the survey in itself cannot overcome this concern, being able to provide an understanding of respondents' affinity with technology – when used as part of a larger data collection exercise – can help interpret findings and identify trends in attitudes and behaviours.

For similar reasons to those highlighted above, a shorter version of the ATI has been proposed (by Wessel et al., 2019), namely, the ATI-Short, or ATI-S, which provides a reliable and valid assessment in situations in which the full ATI scale cannot be used. In the ATI-S, four items are used. Responses are collected using six-point Likert scales (from '1 = Completely Disagree' to '6 = Completely Agree'), with two items reverse-coded to minimise response bias and force respondents to read each statement carefully. The ATI-S was used in the current study to explore respondents' ATI.

Section 3 – Attitudes towards DMS and Intention to Use

The main part of the survey contained 62 declarative statements relating to DMS. These were extracted directly from the focus groups and covered the following DMS scenarios: driver fatigue, driver distraction, cognitive decline, driver intoxication, and data surveillance and sharing. Following the focus groups, an additional scenario – driving performance – was added to reflect more general performance-related monitoring, advice and interventions; also, cognitive decline was more broadly termed 'fitness to drive' to incorporate other health-related scenarios.

The aim of the survey was to capture drivers' attitudes towards the acceptance, or acceptability, of each proposed application or statement. High-level statements directly addressed each scenario, reflecting a singular technological construct, e.g. *"My car monitors me and my driving to determine if I am too tired to drive safely."* Further statements highlighted distinct functional roles, with understanding and, where appropriate, specific language and terminology, taken directly from the focus groups, e.g. *"My car keeps reminding me to take a break if I am tired"* and *"My car will not allow me to resume driving until I have had an adequate break."* In this manner, we were able to explore acceptance of distinct functional roles rather than measuring acceptance of DMS as a single technology; it also enabled us to analyse acceptance at different levels of system authority.

Statements covered aspects of monitoring, advising and assisting/controlling, but intentionally avoided any mention of a 'driver monitoring system' or specific technology (other than in the case of a breathalyser to measure driver intoxication).

The order of the statements was randomised, with each presented alongside a five-point Likert scale (labelled from '1 = Completely Unacceptable' to '5 = Completely Acceptable'). Drivers were asked to indicate the level of acceptability they associated with each statement.

Finally, respondents were asked to indicate how likely (or unlikely) they would be to choose a car in the future that monitored their driving in line with the six scenarios, e.g. *"How likely or unlikely are you to choose a car in the future that monitors you and your driving to determine if you are too tired to drive safely?"* For these final questions, responses were collected using a five-point Likert scale (labelled from '1 = Extremely Unlikely' to '5 = Extremely Likely').

Section 4 – Participant Demographics

Lastly, respondents were asked to provide demographic information, including their age, gender and driving experience, and to document any prior experience of DMS and DCAS. Additional information, such as employment status, was provided by Prolific (www.prolific.com), the online platform used to recruit and remunerate participants.

4.5 Method

Participants

The survey was designed and developed in Microsoft Forms. Participants were recruited and remunerated through Prolific (www.prolific.com) during January and February 2026. Participants were screened for Nationality ('England or Wales or Scotland or Northern Ireland'), Driving licence ('Yes') and Current Country of Residence ('United Kingdom'). The study was distributed as a standard sample, i.e. to all available participants meeting the screening criteria. The median time to complete the survey was 12:05 minutes and participants received a fixed reward of £3 following submission, corresponding to a mean reward per hour of £14.89. Several attention-check questions (ACQs) (e.g. "How many hours are there in a day?") were also included in the survey to identify inattentive respondents, filter out careless data and ensure data quality.

In total, 488 participants began the survey. After filtering responses and validating submissions, data from 477 participants was retained. These comprised 237 females, 237 males, 1 other and 2 prefer not to say. Ages ranged from 18 to 84 (mean = 43.5). On average, participants had held their driving licence for 22.2 years (minimum = 6 months; maximum = 60 yrs) and drove 6772 miles per year.

Age Categories

In UK academic and policy research, 'younger drivers' are most commonly defined using age bands that reflect both legal driving eligibility and elevated crash risk observed in the data. A typical threshold – used by the Department for Transport (DfT) in its statutory road casualty factsheets – defines younger car drivers as those aged 17 to 24 years, reflecting the minimum legal driving age (17) and higher collision rates up to the mid-twenties (DfT, 2022). This age range is also widely adopted in academic studies and safety analyses of youthful driving behaviour, where 17–24 captures the period of both novice status and comparatively high accident involvement (Andrew & Kinnear, 2009).

In contrast, there is no single agreed chronological definition of 'older drivers'. Instead, thresholds typically reflect both research design choices and policy frameworks, rather than a universally accepted biological boundary for ageing. Many studies treat drivers aged around 55 or 60 years and above as 'older' in comparative analyses of behaviour or technology use, with thresholds depending on the context of the research question and the datasets available; for example, a UK review of ADAS noted that the youngest age at which participants were classified as 'older' was 55 years, while many studies used 65 years and above, and some used 70 years as the cut-off (Burridge et al., 2020). In contrast, official statistical analyses by the UK DfT regularly define 'older drivers' for casualty reporting as those aged 70 years and over (DfT, 2025). At this age, drivers must renew their licence every three years and are required to declare that they are medically fit to drive. Although drivers in this age bracket may drive less, they are recognised as a group with increasing safety risks due to frailty and potential physical/cognitive decline. However, 70 is not a strict scientific demarcation of cognitive or physical change. In practice, age-related changes – such as reduced vision,

hearing and slower reaction times – can begin to impact driving skills gradually, often starting during the mid-50s. This justifies the selection of a lower ‘older driver’ age threshold than 70.

By default, ‘mid-aged’ drivers occupy the intervening years between young and older drivers. This group often acts as the baseline for comparison in safety studies, representing experienced drivers, and typically exhibits lower accident rates than younger or very old drivers.

For the current study, we therefore define ‘young’ drivers as those aged between 17 and 24, and ‘older’ drivers as those aged 60 or above. Drivers between 25 and 59 were subsequently classified as ‘mid-aged’ (see Table 5).

Table 5: Age profiles and number of respondents in each category

Age Category	Defined as	Number of Respondents
Young	Aged 17 to 24	106
Mid-aged	Aged 25 to 59	270
Older	Aged 60 and over	101
Total	Range: 18 to 84	477

Employment and Student Status

Respondents were asked about their employment and student status. Seventy-five stated that they were students (55 full-time; 20 part-time). In addition to this, 183 stated that they worked full-time; 54 worked part-time; 65 were not in paid work, describing themselves as a homemaker or retired; 14 were unemployed, including 2 who were due to start work within the next month; and 9 described their employment status as ‘Other’. Seventy-seven chose not to declare their employment or student status.

Driving Experience

Participants reported driving across a wide range of road environments, with most indicating experience in multiple settings rather than a single context. The most common was suburban/town driving, followed closely by urban/city roads and rural/ country roads, while many also regularly used motorways. A large proportion selected all four categories (rural/ country roads, suburban/town, urban/city, motorway), suggesting varied and mixed driving patterns that include commuting, local trips and longer-distance travel. Overall, the sample represents drivers who are exposed to diverse road types and conditions rather than being confined to a particular driving environment.

Car Type

Participants reported driving a very broad mix of vehicles, but most were common small and family cars typical of the UK market. The most frequently mentioned models were Ford vehicles (especially the Fiesta and Focus), Volkswagen models (particularly the Golf and Polo), Vauxhall Corsa and Astra, Toyota Yaris, Nissan Juke and Qashqai, and several Kia and Hyundai models. Respondents also included a smaller number of premium brands (e.g. Audi, BMW, Mercedes-Benz, Jaguar and Land Rover), electric or hybrid vehicles

(e.g. Nissan Leaf, Hyundai Ioniq, Volvo EX30 and Toyota Prius), and some vans and fleet vehicles such as a Ford Transit and Mercedes Sprinter. Overall, the sample covered a wide spectrum of vehicle ages, sizes and powertrains, although it was dominated by mainstream hatchbacks and compact SUVs rather than specialist or high-performance cars.

Car Ownership Model

Most participants reported driving privately owned vehicles, which overwhelmingly dominated the sample. A smaller number used company cars or work vans, typically linked to employment, while others drove vehicles through private leasing or salary-sacrifice schemes, including disability lease arrangements. A few respondents had experience with hire cars or shared family vehicles, and a very small minority reported not currently owning a car. Overall, the sample primarily reflects private car users, with comparatively limited representation of fleet, leased or temporary vehicle access.

Experience of DMS

In total, 55 respondents indicated that they had prior experience with DMS, describing a wide range of systems (in contrast, 390 respondents indicated no experience with DMS and 32 stated that they were not sure). However, most accounts clustered around two main types: insurance telematics ('black box') devices, and built-in vehicle safety and driver assistance features. Many respondents referred to black box insurance systems or smartphone-linked telematics that recorded speed, braking, acceleration, mileage, driving time and sometimes phone use, often to generate a driving score or provide feedback to insurers or employers. Others described integrated in-vehicle monitoring in newer cars and fleet vehicles, including lane-keeping assistance, adaptive cruise control, emergency braking, speed and tyre warnings, fatigue or distraction detection, hands-on-wheel alerts, and prompts to take breaks. Some systems also monitored driver behaviour for workplace or managerial review. Overall, participants' comments indicated that they commonly experienced DMS as automated, often opaque, technology that observes driving behaviour and intervenes through warnings, feedback or data reporting, with several referring to it simply as a "black box".

Experience of Driver Control and Assistance Systems

Overall, 91 respondents indicated that they had experience with DCAS (in contrast, 337 respondents indicated no experience with DCAS and 49 stated that they were not sure). Participants most commonly described systems as in-vehicle safety and convenience features that support steering, speed control and hazard awareness. Frequently mentioned functions included lane-departure warnings and lane-keeping assist, adaptive or standard cruise control and speed limiters, blind-spot monitoring, emergency or automatic braking, and collision or proximity alerts. Many also reported parking aids such as parking assist and cameras, as well as alerts about fatigue, gear changing or hands on the steering wheel. While some participants viewed these systems as helpful safeguards that can intervene in emergencies or assist with manoeuvres, others reported frustration, particularly with lane-keeping or automatic braking, which they felt could misinterpret road conditions or interfere with driver control. Overall, DCAS were experienced as active technologies that both warn and occasionally take control of the vehicle to improve safety, but with mixed perceptions of reliability and usability.

Confusion of DMS and DCAS

Responses to the DMS and DCAS experience questions suggest substantial conceptual overlap in participants' interpretations of these technologies. Many respondents appeared to conflate monitoring functions (e.g. recording driver behaviour, generating driving scores or reporting data to insurers/employers) with assistance and control features (e.g. lane-keeping assistance, adaptive cruise control and automatic emergency braking). Notably, in-vehicle safety features were frequently cited in response to both questions, and some participants described 'black box' telematics devices alongside integrated driver assistance functions as though they formed a single, unified system.

This pattern indicates that participants may not differentiate clearly between technologies that primarily observe and evaluate driver behaviour, and those that actively support or intervene in vehicle control. Instead, these systems appear to be experienced holistically as part of a broader suite of automated driving technologies. The findings therefore highlight a degree of public ambiguity, as expected prior to commencement of the project, regarding the functional boundaries between monitoring and assistance systems, which has clear implications for the design, implementation and acceptance of DMS.

4.6 Analysis Approach

Attitudes towards the driver monitoring scenarios were initially examined using descriptive statistics to characterise how participants distributed their ratings across all statements, highlighting any observable differences in the patterns of responses based on the cohort who took part. Responses were also split by age profile to examine any observable differences in response patterns between age groups.

In addition to the descriptive analyses, a number of inferential statistical tests were used to evaluate the data. Inferential statistics are used to draw conclusions, make predictions and generalise findings from a small, manageable sample to a larger, target population. They go beyond simply describing data and enable researchers to test hypotheses, identify relationships, and determine if results are significant or likely due to chance.

Acceptability data were captured using five-point Likert scales labelled from 'Completely Unacceptable' to 'Completely Acceptable'. By convention, numbers were assigned to each category for clarity (e.g. 1 = Completely Unacceptable, 5 = Completely Acceptable). However, it is important to recognise that analysis techniques must reflect the fact that respondents may not interpret the distance between categories as the same. For example, the distance between 'Completely Unacceptable' (assigned the numerical value of 1) and 'Somewhat Unacceptable' (2) may not equal the distance between 'Somewhat Acceptable' (4) and 'Completely Acceptable' (5), although the numerical values may suggest otherwise. Therefore, numerical values should be interpreted as ordered rankings during analysis. In addition, Likert data is often heavily skewed to one end of the scale, or the other, rather than following a normal distribution. As a consequence, non-parametric tests were used to analyse the Likert-scale response data.

To determine whether participants' responses to the monitoring scenarios differed, we used a Friedman ANOVA (or Friedman test). The Friedman test is a non-parametric alternative to one-way repeated-measures ANOVA when data is ordinal or does not meet normality assumptions. To explore where differences existed, the Wilcoxon signed-rank test was subsequently used. This is a non-parametric statistical test used to compare two related samples, matched pairs or repeated measurements on a single sample to determine if their population mean ranks differ. It acts as the alternative to a paired *t*-test when data is not normally distributed. To account for multiple comparisons (i.e. comparing six different scenarios), Bonferroni corrections were used. The Bonferroni correction is a statistical adjustment used to reduce the likelihood of Type I errors when performing multiple, simultaneous hypothesis tests – these are situations in which false positives are found in the data; in other words, incorrectly identifying the presence of a condition, effect or result that is not actually there. The Bonferroni correction is applied by dividing the original significance level by the number of comparisons, so in the case of six alternatives, the significance level of .05 becomes $.05 \div 6 = .0083\dots$

Finally, exploratory factor analysis (EFA) was conducted to uncover the underlying structure within the response dataset. Factor analysis is a statistical method used to identify underlying patterns within complex datasets by reducing a large set of observed variables into a smaller number of latent constructs (unobserved factors). These factors account for the shared variance among items and explain the patterns of correlations observed in the data. By summarising related variables into broader underlying dimensions, factor analysis facilitates a more parsimonious and theoretically meaningful interpretation of respondents' answers.

4.7 Results Part 1: Participant Characteristics

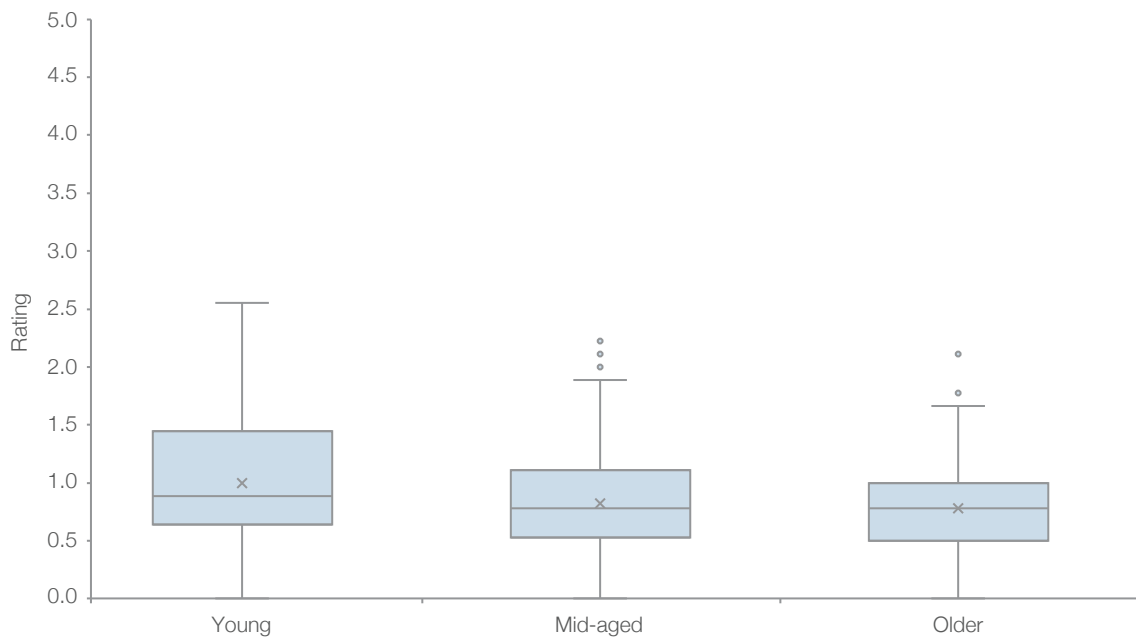
Driver Behaviour Questionnaire

As previously outlined, the DBQ is used to measure and understand self-reported, often unconscious, aberrant driving behaviours – described as violations, errors and lapses. It helps researchers and safety professionals identify risky or aggressive driving habits that can lead to traffic accidents. In the current context, the DBQ was used to highlight any observable differences between age profiles – young, mid-aged and older drivers. The distribution of DBQ score (defined as the mean value across all scales, by convention) is shown in Figure 3. Overall, scores appear relatively consistent across all age groups, with mean values towards the lower end of the scale – suggesting that drivers reported infrequent engagement in the aberrant driving behaviours outlined in the survey questions. The highest responses (up to a rating of 2.6 – indicating more frequent behaviours) were among the young drivers, although it is noted that this is still only marginally about the scale median of 2.5.

Applying a Kruskal–Wallis H test to statistically compare ratings across age groups showed a significant difference in DBQ score based on age ($\chi^2(2) = 11.71, p = .003$). Post hoc pairwise comparisons indicate that DBQ score differed significantly between young and mid-aged drivers ($p = .008$), and between young and older drivers ($p = .006$) (significance value

was adjusted by the Bonferroni correction for multiple comparisons). In other words, young drivers' DBQ scores were significantly higher than both mid-aged and older drivers, although there was no significant difference evident between mid-aged and older drivers.

Figure 3: Responses to DBQ, showing mean ratings combined across all dimensions (violations, errors, lapses), where 0 = Never and 5 = Nearly all of the time

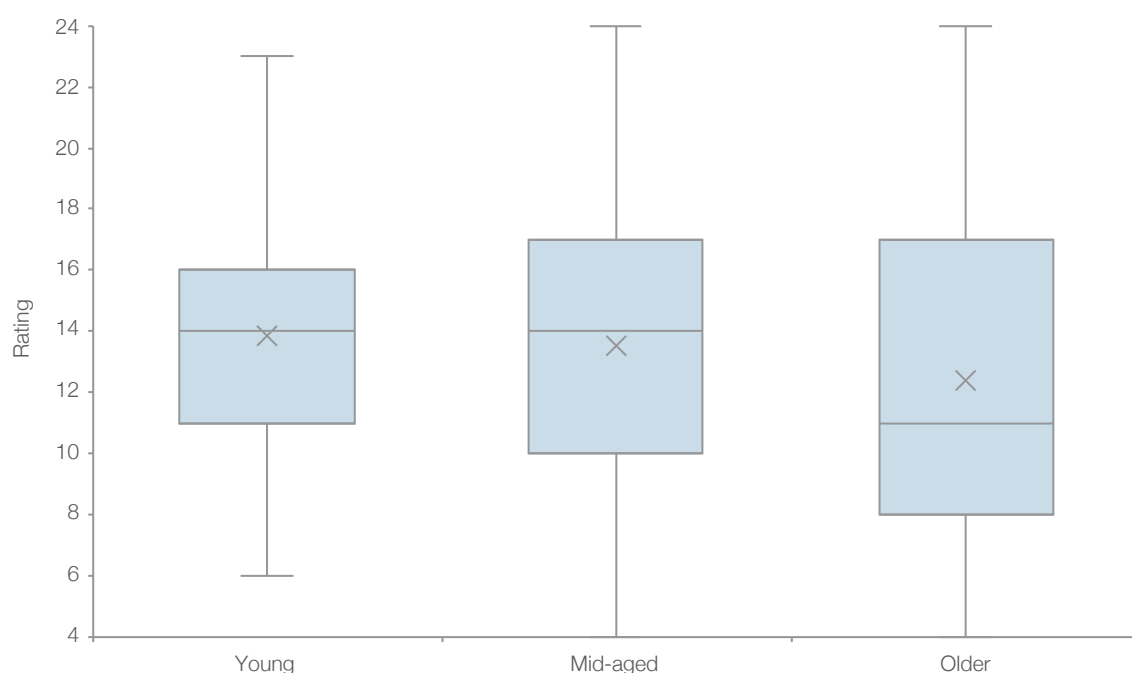


Affinity with Technology Scale

Again, as previously described, the ATI scale is used to measure an individual's tendency to actively engage in, explore and enjoy interacting with technological systems. In the current context, the ATI was used to highlight any observable differences between age profiles – young, mid-aged and older drivers. The distribution of ATI scores (defined as the cumulative value of all scales, by convention) is shown in Figure 4. Overall, ratings appear relatively similar across all age groups, with cumulative responses generally spanning across the entire range of the six-point response scale for respondents in all age groups. Group mean values (shown by crosses in Figure 4) tend to be towards the median of the scale (13.8, 13.5 and 12.4 for young, mid-aged and older drivers, respectively) – suggesting a general ambivalence towards technology. The interquartile range of responses (shown by the boxes in Figure 4 and indicating 50% of responses) extends lower for the older drivers; in addition, the median value (shown by the line within each box in Figure 4) for this group is lower (14, 14 and 11 for young, mid-aged and older drivers, respectively). These suggest lower affinity with technology among older drivers, although it is noted that responses were also received across the entire range of scale values from this cohort.

Applying a Kruskal–Wallis H test to statistically compare ratings shows no significant difference in ATI score based on age group ($\chi^2(2) = 5.92, p = .052$). Nevertheless, young drivers tended to demonstrate a higher ATI score, with older drivers indicating a comparatively lower ATI score. Mid-aged drivers' ATI score tended to sit between these extremes.

Figure 4: Responses to affinity with technology scale, showing cumulative ratings, where 1 = Completely Disagree and 6 = Completely Agree, for individual scale items, resulting in a possible range of 4 (indicating 'low affinity') to 24 (indicating 'high affinity')



4.8 Results Part 2: Responses to Monitoring Scenarios

Descriptive analyses were conducted to examine drivers' responses to statements relating to DMS as a high-level solution across the six scenarios: driver fatigue, driver distraction, driving performance, fitness to drive, driver intoxication, and data surveillance and sharing. Inferential statistics were then conducted to compare acceptability ratings across scenarios and between age groups. The results below summarise overall patterns and age-related trends evident in the graphs and any statistically significant differences in responses between age groups.

Figure 5: Responses to main driver monitoring scenarios: driver fatigue, driver distraction, driving performance, fitness to drive, driver intoxication, and data surveillance and sharing, showing distribution of acceptability ratings

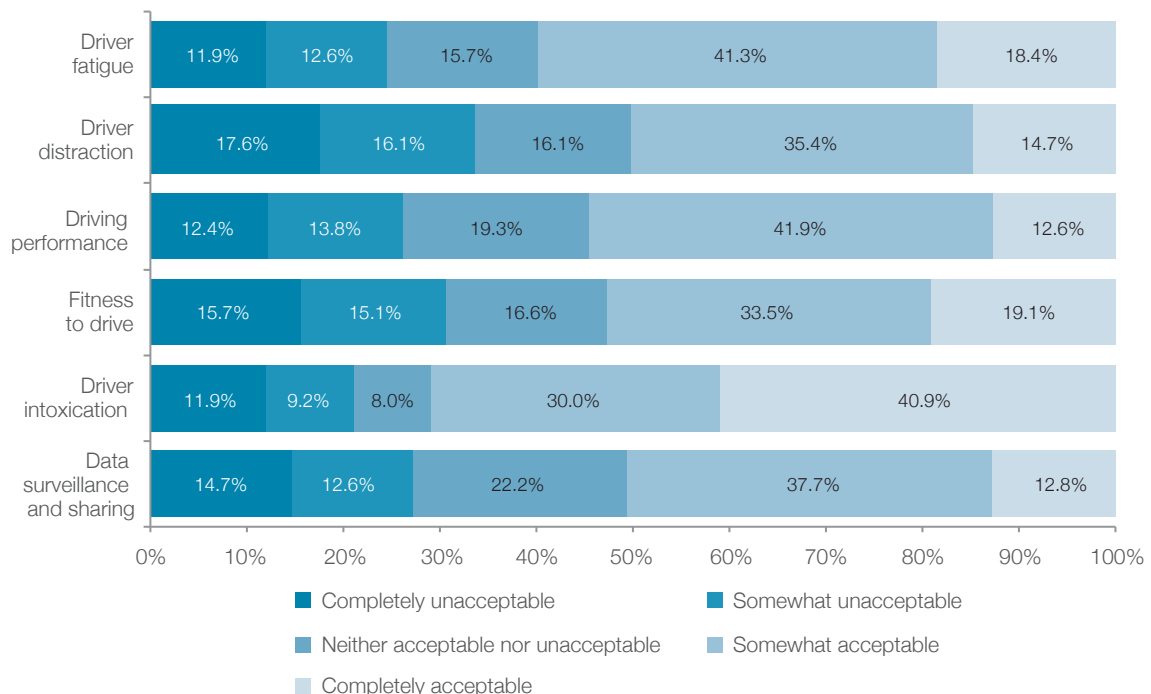


Figure 5 shows the distribution of acceptability ratings across the main driver monitoring scenarios. Initial observation of the data suggests some variability between ratings and the distribution of responses, with driver intoxication attracting the highest level of acceptability overall, with over 70% of drivers supporting this functionality. However, it is also evident in Figure 5 that between approximately 12% and 18% of drivers (depending on the scenario) considered driver monitoring to be 'Completely Unacceptable'.

A Friedman ANOVA test confirmed that there was a significant difference in acceptability ratings between scenarios ($\chi^2(5) = 176.1, p < .001$). Mean ranks are shown in Table 6. Post hoc pairwise comparisons using Wilcoxon signed-rank tests with Bonferroni corrections indicate significant differences between many of the scenarios. Presented in rank order (see Table 6), the results indicate that, overall, driver intoxication was most acceptable, followed by fatigue monitoring, fitness to drive, driving performance, and data surveillance and sharing. The least acceptable monitoring scenario among all respondents was driver distraction.

The acceptability ratings associated with each monitoring scenario were then split and compared across the three age groups (young, mid-aged, older), again revealing significant differences. Table 7 shows acceptability ratings for the main monitoring scenarios split by age group. For each age group, monitoring scenarios are listed in the order of acceptability, with the most acceptable scenario at the top of the list and the least acceptable scenario at the bottom. Among all age groups, driver intoxication monitoring attracted the highest level of acceptability. The order of acceptability differs between the other scenarios for the

different age groups, with mid-aged and older drivers apparently putting more emphasis on fatigue monitoring, whereas young drivers considered fitness to drive and performance monitoring as more acceptable. For all age groups, data surveillance and sharing, and driver distraction monitoring were seen as the least acceptable scenarios.

Table 6: Statistical comparisons of overall acceptability ratings (ns = non-significant)

	Mean Rank	Driver intoxication	Driver fatigue	Fitness to drive	Driving performance	Data surveillance and sharing	Driver distraction
Driver intoxication	4.26		Z = 7.27 p < .001	Z = 9.15 p < .001	Z = 7.20 p < .001	Z = 7.96 p < .001	Z = 9.56 p < .001
Driver fatigue	3.59			Z = 3.65 p < .001	ns	Z = 3.43 p < .001	Z = 5.35 p < .001
Fitness to drive	3.38				ns	ns	ns
Driving performance	3.37					Z = 2.81 p = .005	ns
Data surveillance and sharing	3.29						ns
Driver distraction	3.11						

Table 7: Ranked order of acceptability of monitoring scenarios, split by age group, showing statistical test results and mean rank in parentheses

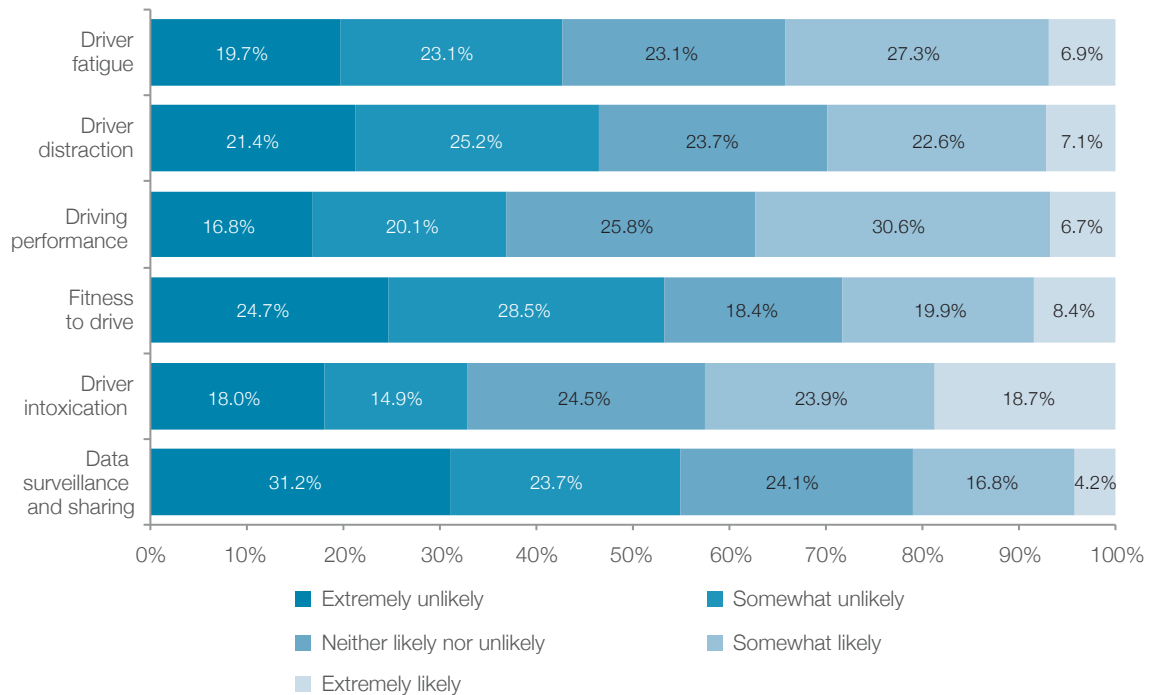
All drivers ($\chi^2(5) = 176.1, p < .001$)	Young drivers ($\chi^2(5) = 14.29, p = .014$)	Mid-aged drivers ($\chi^2(5) = 94.63, p < .001$)	Older drivers ($\chi^2(5) = 88.57, p < .001$)
Driver intoxication (4.26)	Driver intoxication (3.92)	Driver intoxication (4.24)	Driver intoxication (4.69)
Driver fatigue (3.59)	Fitness to drive (3.56)	Driver fatigue (3.55)	Driver fatigue (3.84)
Fitness to drive (3.38)	Driving performance (3.49)	Driving performance (3.41)	Fitness to drive (3.19)
Driving performance (3.37)	Driver fatigue (3.45)	Fitness to drive (3.37)	Driving performance (3.16)
Data surveillance and sharing (3.29)	Data surveillance and sharing (3.39)	Data surveillance and sharing (3.34)	Driver distraction (3.06)
Driver distraction (3.11)	Driver distraction (3.20)	Driver distraction (3.09)	Data surveillance and sharing (3.06)

Drivers were also asked to indicate the likelihood that they would choose a car in the future that provided the capability to monitor them and their driving in line with the six main driver monitoring scenarios. Likelihood ratings differed between scenarios (Figure 6). Responses to fatigue monitoring systems generally tended to cluster towards the 'likely' end of the scale, with a substantial share of drivers (34.2%) indicating that they were 'somewhat' or 'very' likely to choose a vehicle with fatigue monitoring, suggesting broad acceptance of safety

features associated with drowsiness detection. Distracted driving monitoring showed similar, although slightly lower, levels of support to fatigue monitoring (29.7%). Drivers commonly perceive distraction as a major safety risk, which may explain the stronger likelihood to choose a distraction monitoring system, despite the comparatively poor acceptability ratings associated with it. Systems designed to assess and improve driving performance (rather than prevent imminent danger) typically received more mixed reactions, with over 37% of drivers indicating that they would be likely to choose such technology within their vehicle, and a similar proportion (36.9%) stating that they would be unlikely, confirming that some drivers question the necessity or usefulness of performance optimisation monitoring. Medical fitness monitoring tended also to produce a divided distribution: while some respondents may view fitness monitoring as a valuable safety safeguard, others may perceive it as intrusive. Alcohol-detection monitoring systems generally showed the strongest support, with over 42% of drivers indicating that they would be likely to choose such technology, reflecting widespread social support for preventing alcohol-impaired driving. Systems that used personal data for suggestions (potentially beyond immediate driving-related safety threats) produced greater variability in responses, with the lowest 'likelihood' ratings overall (21%) and the highest proportion of drivers unlikely to choose such technology (54.9%) – while some respondents may appreciate personalisation and proactive assistance, others express privacy concerns.

Also evident in Figure 6 is that between approximately 17% and 31% of drivers (across the scenarios) reported being 'extremely unlikely' to choose a vehicle equipped with any of the monitoring systems under evaluation, highlighting a persistent level of resistance despite overall trends.

Figure 6: Responses to main driver monitoring scenarios: driver fatigue, driver distraction, driving performance, fitness to drive, driver intoxication, and data surveillance and sharing, showing distribution of ‘likelihood to choose’ ratings



In a similar manner to the above, ‘likelihood to choose’ results were statistically compared and are presented in ranked order (see Table 8). Notably, the ranked order of ‘likelihood to choose’ (*what drivers would select*) differed to the order of acceptability (*what drivers preferred or deemed best*), suggesting that cognitive, environmental or situational factors are overriding personal preferences. Indeed, acceptability effectively represents what drivers want, whereas likelihood to choose reflects what they might actually do under pressure, habit or limited information.

Table 8: Ranked order of ‘likelihood to choose’ a vehicle with the specified monitoring capability, split by age group, showing statistical test results and mean rank in parentheses

All drivers ($\chi^2(5) = 229.6, p < .001$)	Young drivers ($\chi^2(5) = 67.9, p < .001$)	Mid-aged drivers ($\chi^2(5) = 114.3, p < .001$)	Older drivers ($\chi^2(5) = 61.89, p < .001$)
Driver intoxication (4.15)	Driving performance (4.07)	Driver intoxication (4.11)	Driver intoxication (4.36)
Driving performance (3.78)	Driver intoxication (4.04)	Driving performance (3.78)	Driver fatigue (3.63)
Driver fatigue (3.57)	Driver fatigue (3.57)	Driver fatigue (3.55)	Driving performance (3.50)
Driver distraction (3.38)	Driver distraction (3.49)	Driver distraction (3.33)	Driver distraction (3.40)
Fitness to drive (3.22)	Fitness to drive (3.18)	Fitness to drive (3.24)	Fitness to drive (3.22)
Data surveillance and sharing (2.9)	Data surveillance and sharing (2.66)	Data surveillance and sharing (3.00)	Data surveillance and sharing (2.90)

4.9 Results Part 3: Responses to Functional Aspects of DMS Scenarios

The six driver monitoring scenarios are now explored in turn by examining responses to each of the associated statements presented in the questionnaire. These results help to understand acceptance as a measure of distinct functional roles rather than assuming DMS to be a singular technology. In addition, they enable acceptance to be explored at different levels of system authority. In each instance, descriptive analysis is presented, followed by inferential statistics (typically, the Kruskal–Wallis H test) to highlight any significant differences between age groups.

Driver Fatigue

Overall, participants expressed positive attitudes towards fatigue-related monitoring and advisory features (Figure 7). High levels of acceptability were observed for situations in which the car monitored driver fatigue, measured driving duration, advised drivers to take a break and suggested a suitable break location. Agreement was somewhat lower, though still moderate, for repeated reminders. The lowest levels of agreement were observed for the statement indicating that the vehicle would prevent drivers from resuming driving until an adequate break had been taken (Figure 8). This pattern suggests declining acceptability as system control increases.

Age-group comparisons indicated that older drivers tended to express moderately greater acceptance of fatigue monitoring and advisory functions than young drivers (65% compared to 60%, respectively). However, all groups showed reduced support for autonomy-restricting features, with mid-aged and older drivers exhibiting comparatively stronger resistance than young drivers to enforced restrictions (57% and 58%, compared to 52%, respectively). Nevertheless, Kruskal–Wallis H tests indicated no significant differences in ratings for all statements based on age group, suggesting that attitudes towards the acceptability of the functional aspects of fatigue monitoring were statistically equivalent across all drivers.

Figure 7: Distribution of responses to statement: “My car monitors me and my driving to determine if I am too tired to drive safely”, split by age profile – young, mid-aged and older

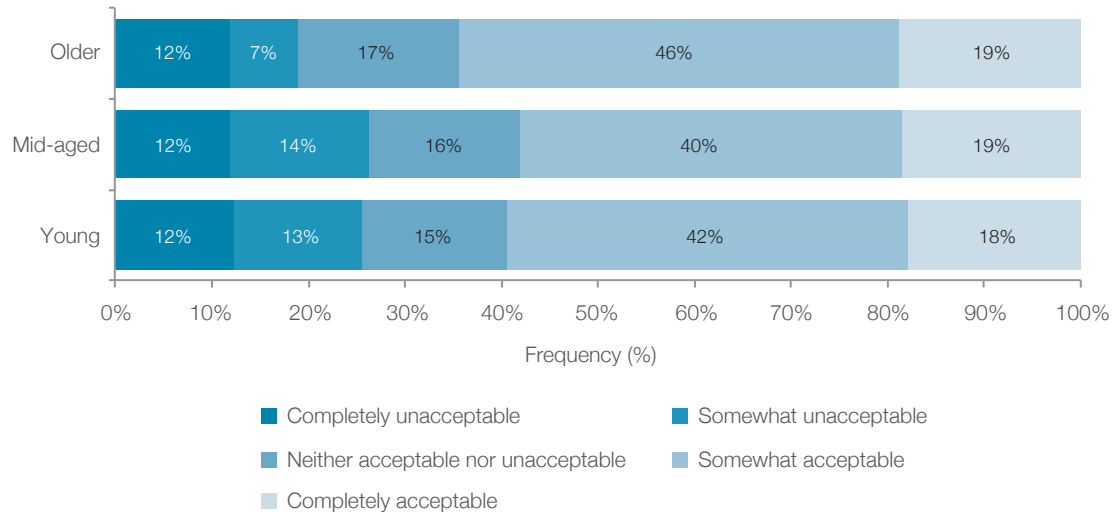
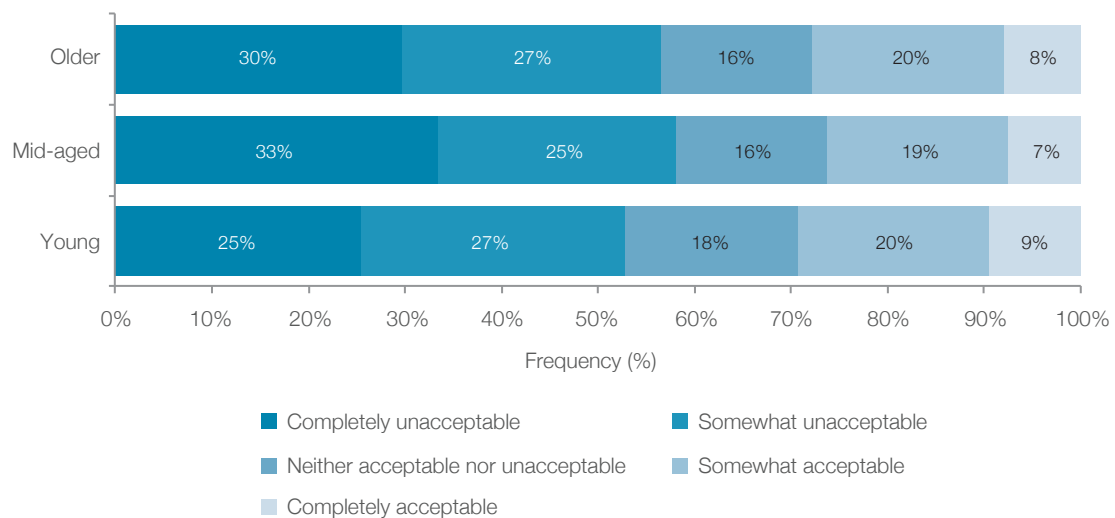


Figure 8: Distribution of responses to statement: “My car will not allow me to resume driving until I have had an adequate break”, split by age profile – young, mid-aged and older



Driver Distraction

Participants generally supported distraction monitoring functions, with up to 54% indicating their acceptance (Figure 9). Strong acceptability was observed for situations in which the vehicle monitored distraction, detected phone use, tracked gaze direction and advised drivers to refocus their attention on the road. Monitoring hands on the steering wheel was also positively received. Support decreased for more intrusive or controlling interventions, such as switching off the driver's mobile phone (if it was being used illegally while driving), taking over vehicle control or stopping at the roadside if alerts were ignored. The lowest levels of agreement were observed for notifying other road users about inattention.

Age-group comparisons suggested that young drivers were relatively more accepting of automation-based interventions (e.g. vehicle takeover) than older drivers. In contrast, older drivers were comparatively more accepting of the vehicle intervening to switch off their mobile phone. Across all age groups, advisory functions were consistently more acceptable than enforcement or public notification measures. Kruskal–Wallis H tests indicated significant differences between age groups in the distribution of acceptability ratings for several statements (shown below), with older drivers consistently reporting higher levels of acceptance than younger drivers, and mid-aged drivers generally falling between the two groups (attitudes towards the other functional aspects of driver distraction monitoring were statistically equivalent across all drivers):

1. My car monitors if I am using my phone while driving
2. My car advises me to stop using my phone while driving
3. My car switches off my phone if it detects that I am using it illegally while driving (Figure 10)
4. My car advises other road users if I am not paying attention (Figure 11)

For the statement “My car monitors if I am using my phone while driving”, older drivers rated this as significantly more acceptable than both young and mid-aged drivers. This suggests that older drivers may be more comfortable with passive monitoring technologies, possibly viewing them as supportive safety features rather than intrusive surveillance. In contrast, young and mid-aged drivers appear more cautious or resistant to the idea of being monitored.

A similar pattern was observed for “My car advises me to stop using my phone while driving”. Older drivers again rated this as significantly more acceptable than young drivers, although the difference between older and mid-aged drivers was not significant. This may indicate that advisory (rather than controlling) interventions are broadly acceptable across age groups but particularly so among older drivers. Young drivers' lower ratings may reflect greater sensitivity to perceived autonomy restrictions or annoyance from in-vehicle prompts.

The strongest age gradient emerged for the more restrictive intervention: “My car switches off my phone if it detects that I am using it illegally while driving” (Figure 10). Older drivers rated this as significantly more acceptable than both mid-aged and young drivers, and mid-aged drivers rated it as significantly more acceptable than young drivers (older = 71%; mid-aged = 57%; young = 47%). This stepwise pattern suggests that acceptability increases

progressively with increasing age as the level of system control increases. Young drivers appear least willing to accept automated enforcement measures that remove personal control, whereas older drivers may prioritise safety over autonomy.

Figure 9: Distribution of responses to statement: “My car monitors me and my driving to determine if I am too distracted to drive safely”, split by age profile – young, mid-aged and older

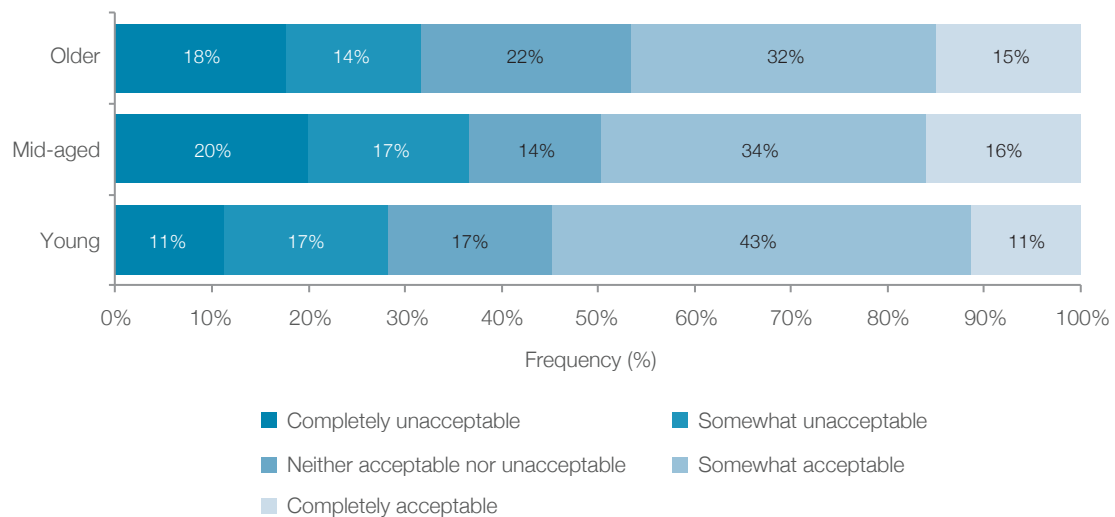


Figure 10: Distribution of responses to statement: “My car switches off my phone if it detects that I am using it illegally while driving”, split by age profile – young, mid-aged and older

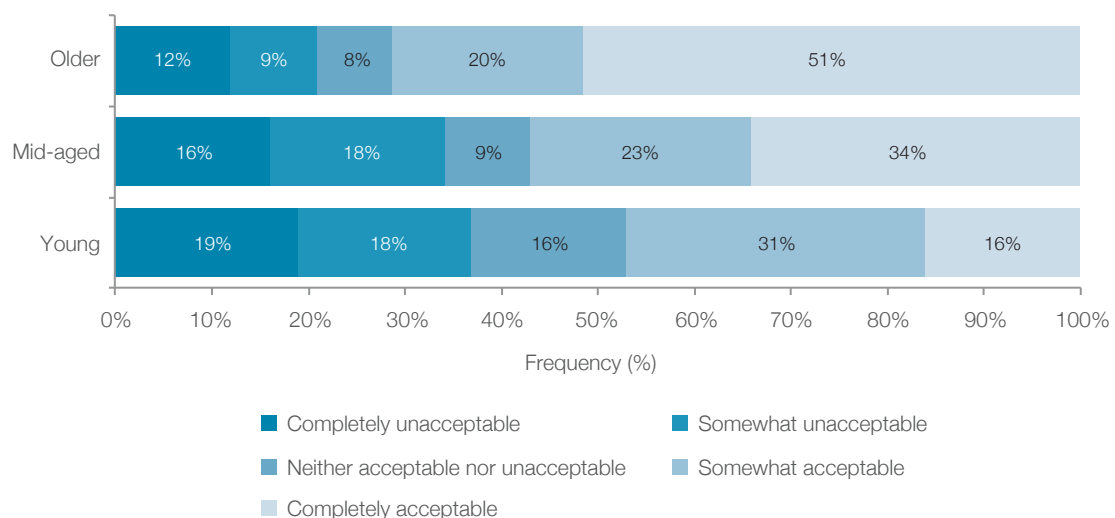
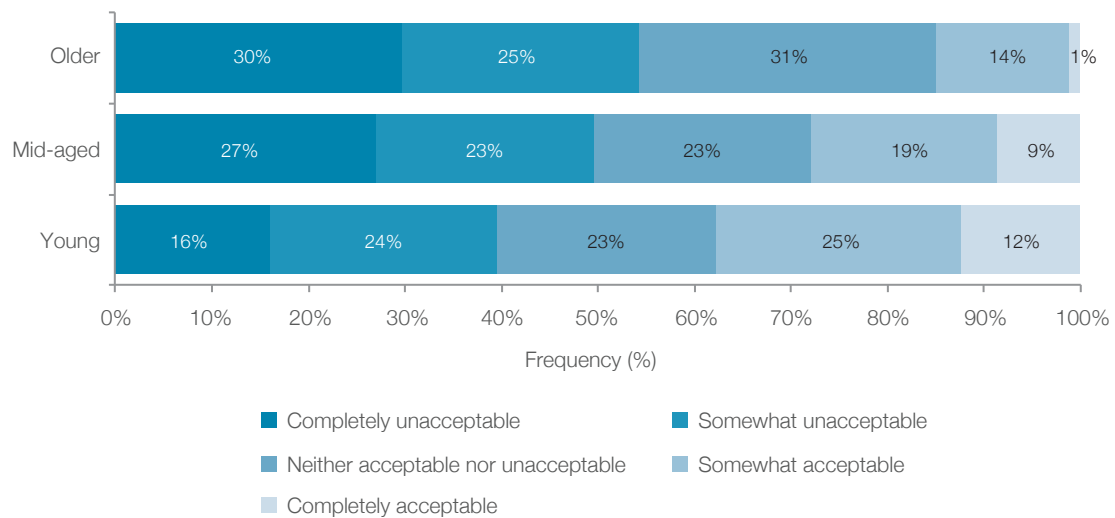


Figure 11: Distribution of responses to statement: “My car advises other road users if I am not paying attention”, split by age profile – young, mid-aged and older



Driving Performance

Participants showed moderate to high levels of agreement with statements indicating that vehicles could monitor their driving performance and provide advice or assistance to improve safety, performance or ease of driving. Assistance framed in terms of safety enhancement received stronger endorsement than assistance framed as general performance optimisation, with up to 73% of drivers indicating their support for the former (Figure 12). Statements indicating that the vehicle compared the current journey with historical driving data were also moderately endorsed. In contrast, participants expressed lower agreement with statements suggesting that vehicles made assumptions about their driver behaviour based on generalised demographic data, with up to 85% of drivers considering this to be unacceptable (Figure 13).

Age-related trends suggest that young drivers were more comfortable with AI-driven learning of driving style and behavioural analysis, whereas mid-aged and older drivers demonstrated greater scepticism towards AI-based inference and demographic profiling. Nevertheless, Kruskal–Wallis H tests indicated no significant differences in ratings for all driving performance statements based on age group, suggesting that attitudes towards the functional aspects of driver performance monitoring were statistically equivalent across all drivers.

Figure 12: Distribution of responses to statement: “My car monitors my driving performance and behaviour and provides assistance to make my driving safer”, split by age profile – young, mid-aged and older

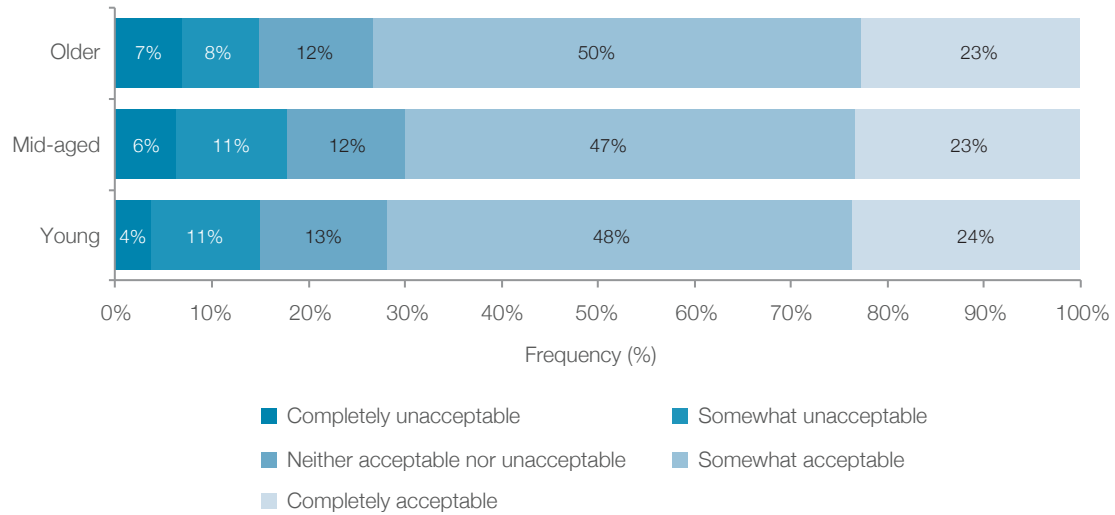
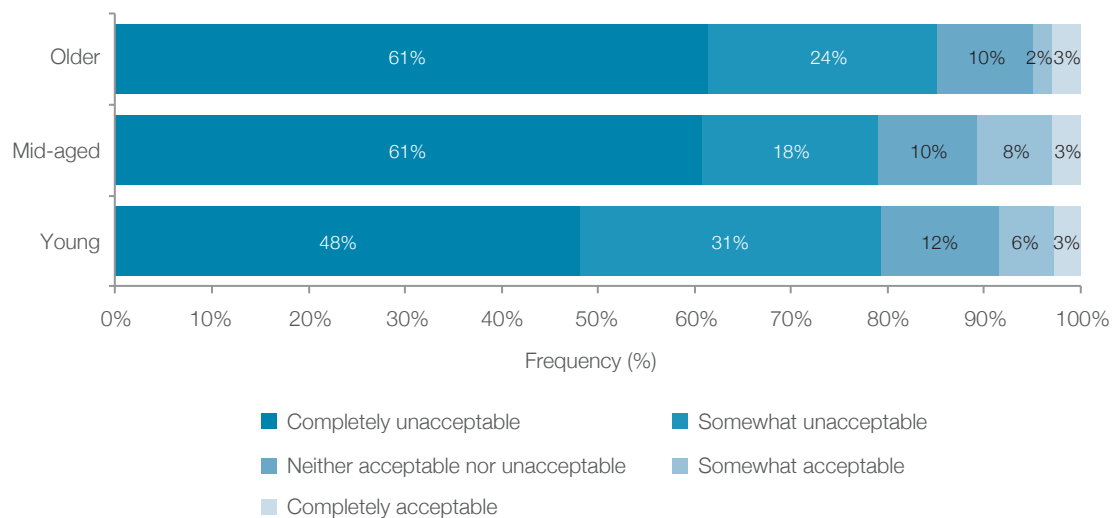


Figure 13: Distribution of responses to statement: “My car makes assumptions about my behaviour based on generalised demographic data”, split by age profile – young, mid-aged and older



Fitness to Drive

Monitoring related to medical fitness and the need for driving assistance received high levels of agreement, with up to 60% of drivers indicating their support (Figure 14). Participants showed some support for systems that monitor long-term health changes, provided these were directly linked to safety outcomes (Figure 15). Lower levels of acceptance were observed for statements relating to monitoring mood, emotions and facial expressions (e.g. to detect anger or confusion). Emotional surveillance features were among the least endorsed within this scenario, with up to 84% considering them to be unacceptable (Figure 16).

Age-related comparisons suggest that young drivers consider long-term health-related monitoring and recording of health-related data more acceptable than older and mid-aged drivers (31%, compared to 26% and 29%, respectively) (Figure 15). However, all age groups expressed reservations about continuous emotional or facial-expression monitoring, suggesting perceived intrusiveness beyond core safety functions. Kruskal-Wallis H tests indicated significant differences between age groups in the distribution of acceptability ratings for the following statement only: “My car monitors my facial expressions to determine if I am angry”. Attitudes towards the other functional aspects of fitness to drive monitoring were statistically equivalent across all drivers.

This finding indicates a reversal of the pattern observed for more behaviour-focused monitoring systems (e.g. phone-use detection). In the current situation, young drivers expressed greater acceptance of affective or emotion-based monitoring than older drivers –older drivers tended to be more supportive of systems targeting observable safety behaviours, but they were less comfortable with technology that interpreted internal emotional states. This difference may reflect generational variation in attitudes towards privacy, biometric data and emerging in-vehicle sensing technologies. Monitoring facial expressions to infer anger may be perceived by older drivers as intrusive, speculative or less directly linked to tangible driving behaviours. Emotional-state detection could be seen as crossing a boundary from behaviour monitoring into personal or psychological surveillance. Young drivers, in contrast, who have grown up with facial recognition, social media filters and affect-sensitive technologies, may perceive such monitoring as more normative or technologically acceptable.

Figure 14: Distribution of responses to statement: “My car monitors me and my driving to determine if I am medically fit to drive safely”, split by age profile – young, mid-aged and older

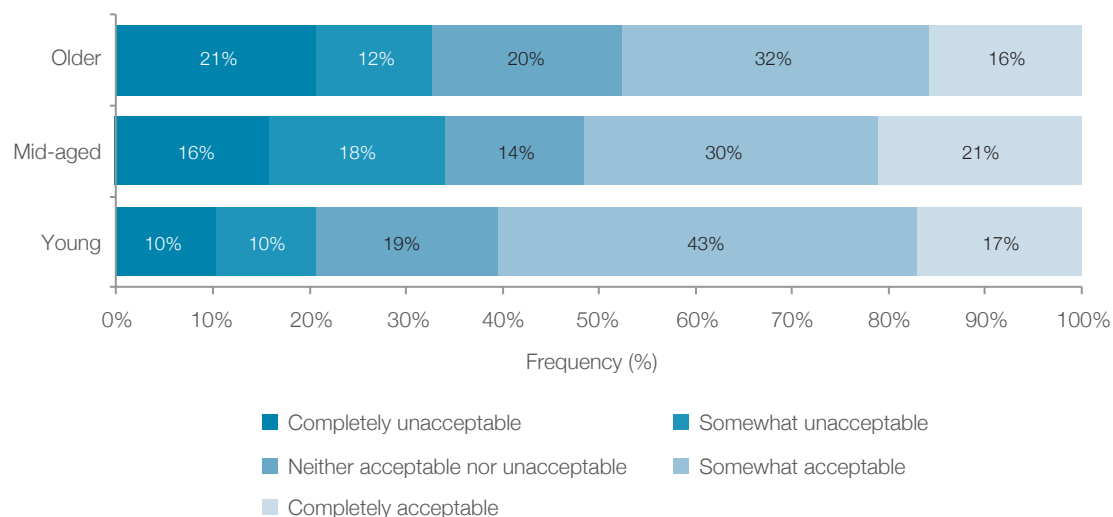


Figure 15: Distribution of responses to statement: “My car monitors and records my health-related data”, split by age profile – young, mid-aged and older

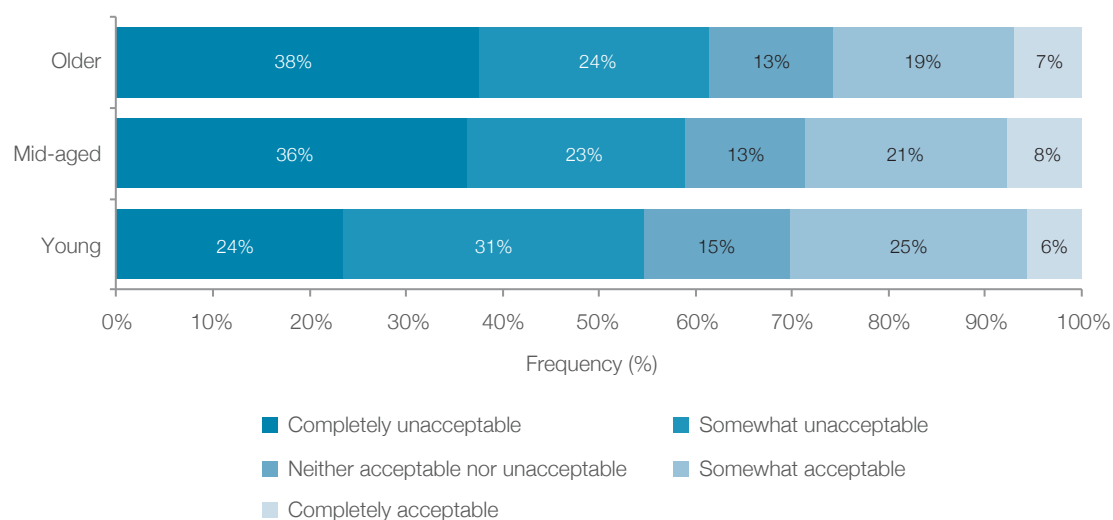
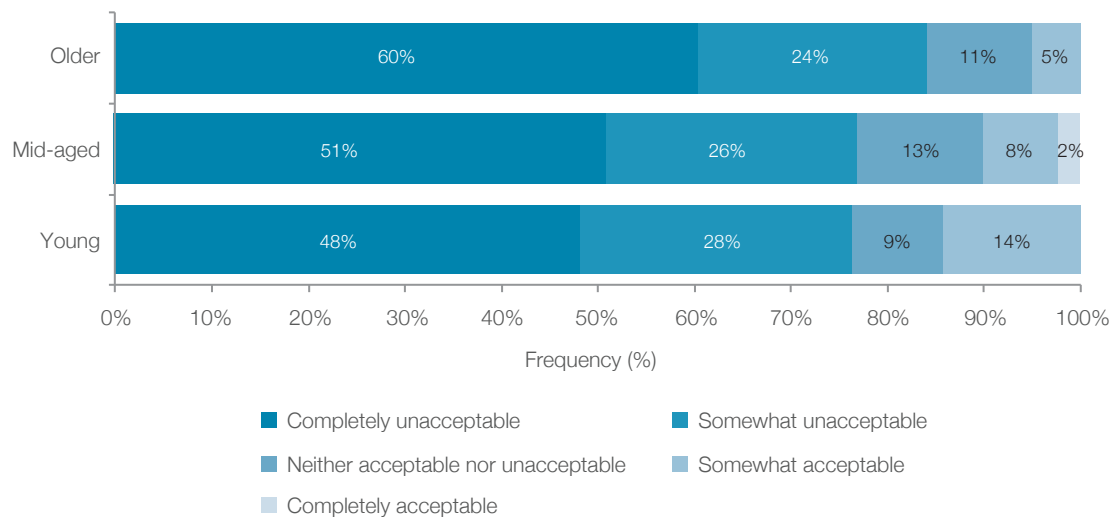


Figure 16: Distribution of responses to statement: “My car monitors my emotions”, split by age profile – young, mid-aged and older



Driver Intoxication

There was strong support for intoxication-related safety features. Participants generally agreed with functions indicating that vehicles could detect alcohol impairment and even use a breathalyser (Figure 17) or prevent driving if the driver exceeded the legal alcohol limit (Figure 18), with the latter considered acceptable by up to 86% of drivers. In contrast, strong disagreement was observed for statements suggesting that the vehicle monitored the driver's behaviour away from the car (e.g. at a pub or social gathering) and subsequently made assumptions about their fitness to drive based on their behaviour – up to 78% of drivers considered this to be unacceptable (Figure 19). This indicates a clear boundary between in-vehicle safety monitoring and off-vehicle surveillance.

Age differences appeared minimal in this scenario, although older drivers were marginally more supportive of alcohol-prevention measures, particularly the use of a breathalyser to determine if they were fit to drive. Indeed, Kruskal–Wallis H tests indicated no significant differences in ratings for all statements in this scenario based on age group, suggesting that attitudes towards the functional aspects of driver intoxication monitoring were statistically equivalent across all drivers.

Figure 17: Distribution of responses to statement: “My car uses a breathalyser to determine if I have been drinking”, split by age profile – young, mid-aged and older

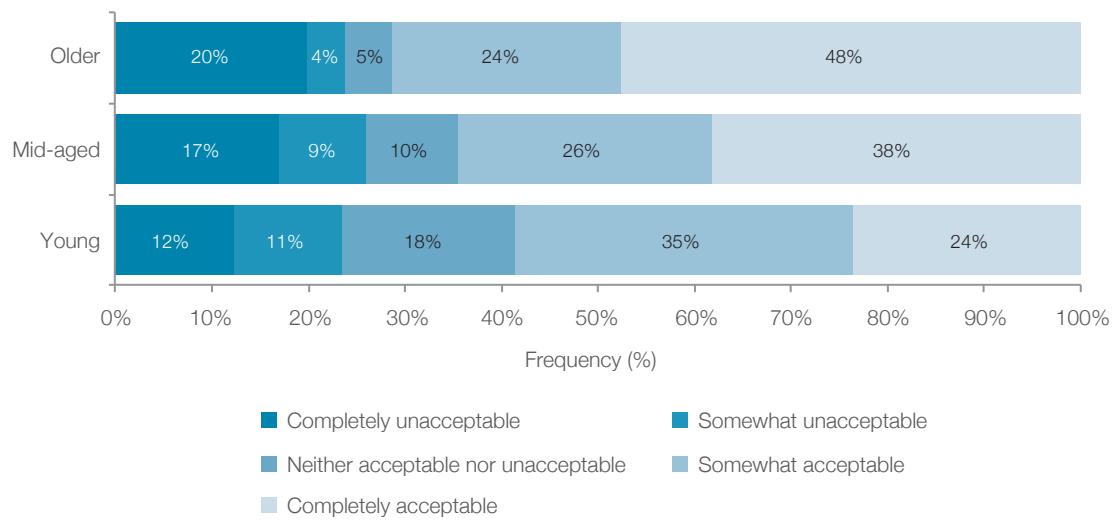


Figure 18: Distribution of responses to statement: “My car will not let me start driving if I am over the legal alcohol limit”, split by age profile – young, mid-aged and older

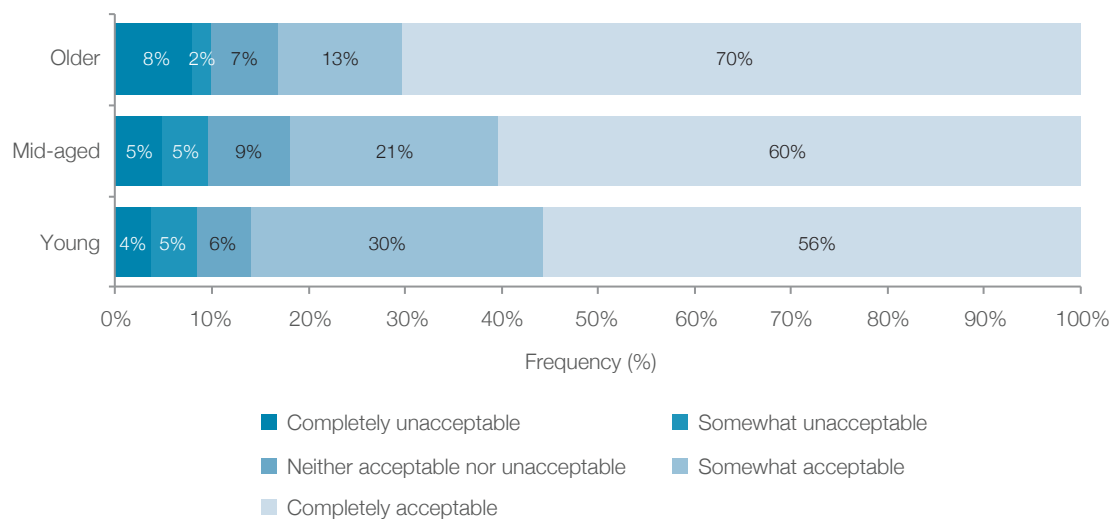
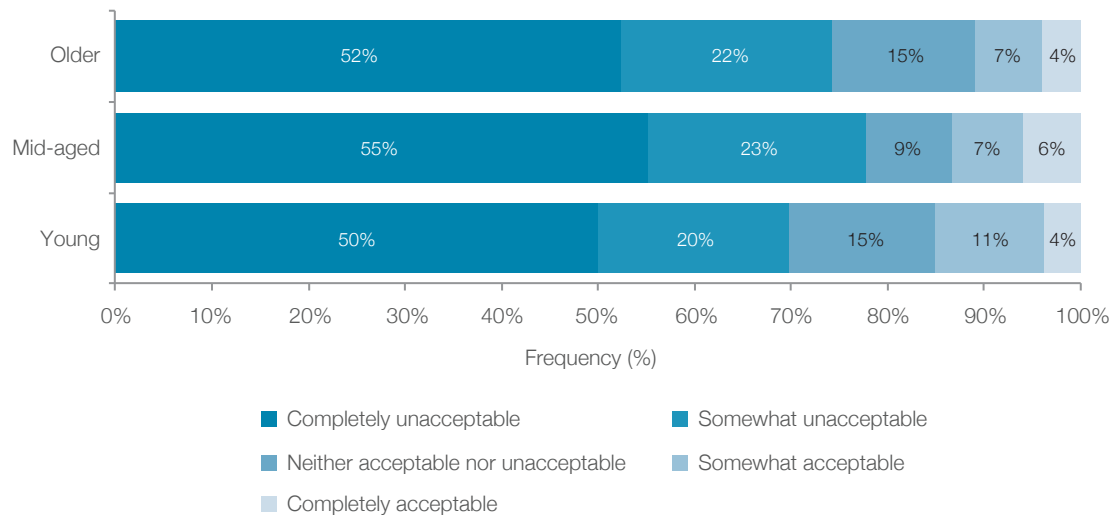


Figure 19: Distribution of responses to statement: “My car monitors my behaviour away from the car (e.g. at a pub) and then makes assumptions about my fitness to drive”, split by age profile – young, mid-aged and older



Data Surveillance and Sharing

Data governance statements produced the widest variation in responses. Participants were generally supportive of data being used to improve their driving experience and to inform the design of future vehicles, with up to 68% of drivers indicating their support for the former (Figure 20). There was also a high level of support for police access to data in the event of a road traffic collision – up to 81% of drivers (Figure 21) – and for the use of data as legal evidence. However, mixed responses were observed regarding long-term data storage, cloud-based storage and sharing driving data with insurance companies. Preferences appeared somewhat stronger for in-vehicle storage compared to cloud storage, particularly among older drivers, with the highest level of support for driving-related data to be deleted after each drive. Strong disagreement was evident for sharing driving or health data with family and friends, in particular among older drivers – 92% of whom considered this to be unacceptable (Figure 22) – and for manufacturers sharing data with third parties for competitive advantage. Continuous monitoring of location and journey details also received relatively low support.

Age-group comparisons suggest that young drivers were somewhat more accepting of cloud-based storage and AI-enabled data use, whereas older drivers expressed stronger privacy concerns and greater preference for data minimisation and local storage. Indeed, Kruskal-Wallis H tests indicated significant differences between age groups in the distribution of acceptability ratings for the following statements:

1. Data about me and my driving is stored and analysed in ‘the cloud’
2. My car shares data on my driving behaviour with the vehicle manufacturer
3. My car shares data on my driving behaviour with my family and friends

4. My car shares my health data with my healthcare provider
5. My car shares my health data with my family and friends
6. In a hire car, data on my driving behaviour and performance is shared with the hire company
7. Vehicle manufacturers share data from my car with third parties to gain a competitive advantage
8. Vehicle manufacturers use data from my car to improve my driving experience
9. My car uses face recognition to identify me as the legal owner or designated user of the car

Across the nine statements, a clear age pattern emerged: older drivers were consistently less accepting than young drivers of cloud storage, data sharing and secondary data use practices. This included storage and analysis of driving data in the cloud (14% of older drivers compared to 27% of young drivers), sharing driving behaviour with manufacturers (14% versus 31%, respectively), hire companies (23% versus 37%, respectively), or third parties and using vehicle data for competitive advantage (6% versus 12%, respectively), or even to improve the driving experience (52% versus 68%, respectively (Figure 20)). Older drivers were also less accepting of sharing both driving and health data with family, friends or healthcare providers (2% versus 15%, respectively (Figure 22)). Mid-aged drivers frequently aligned with older drivers, particularly in relation to sharing driving or health data with personal contacts. Overall, young drivers demonstrated significantly greater acceptance of connected, data-driven vehicle ecosystems.

The main exception to this pattern was face recognition for identifying the legal owner or designated user of the vehicle, which older drivers rated as more acceptable than young drivers (78% compared to 56%, respectively). This suggests that older drivers may differentiate between data use for security and access control – viewed as functional and protective – and broader data storage or sharing practices, which may raise concerns about privacy, surveillance or commercial exploitation. Taken together, the findings point to generational differences in digital trust and privacy norms, with young drivers appearing more comfortable with integrated data exchange and older drivers expressing greater caution, particularly where data flows extend beyond the immediate vehicle context.

Figure 20: Distribution of responses to statement: “Vehicle manufacturers use data from my car to improve my driving experience”, split by age profile – young, mid-aged and older

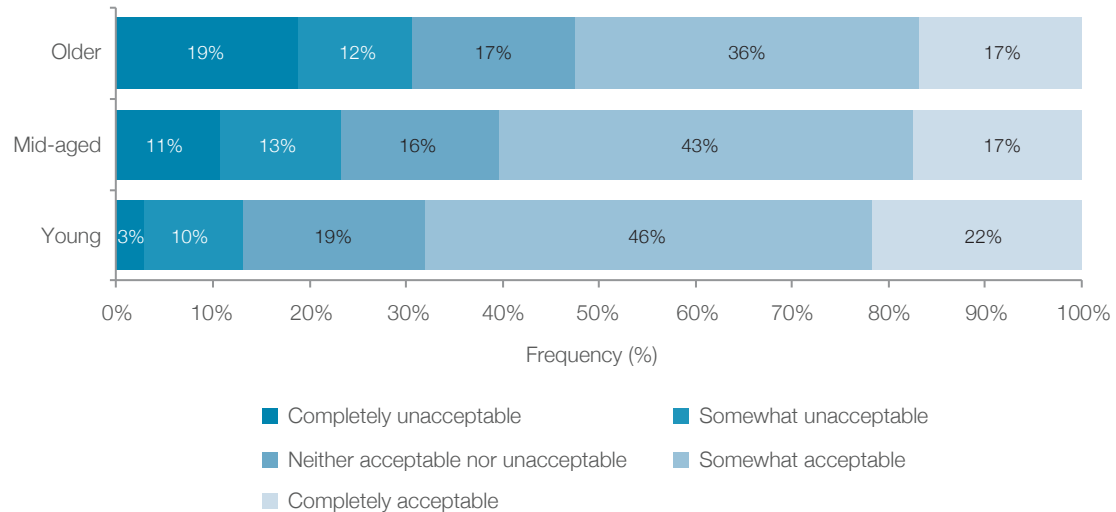


Figure 21: Distribution of responses to statement: “In the event of a road traffic collision, the police can access my data from my car”, split by age profile – young, mid-aged and older

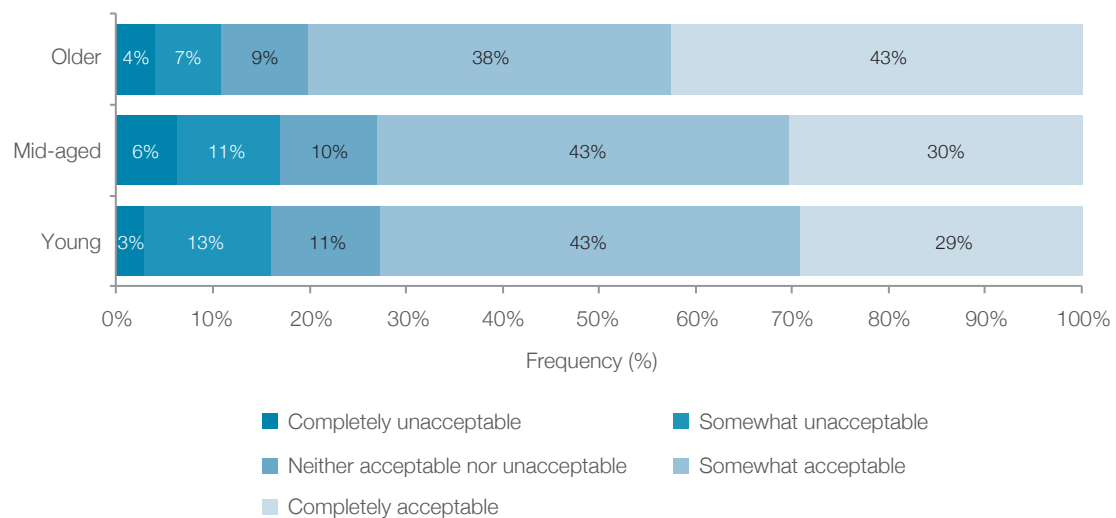
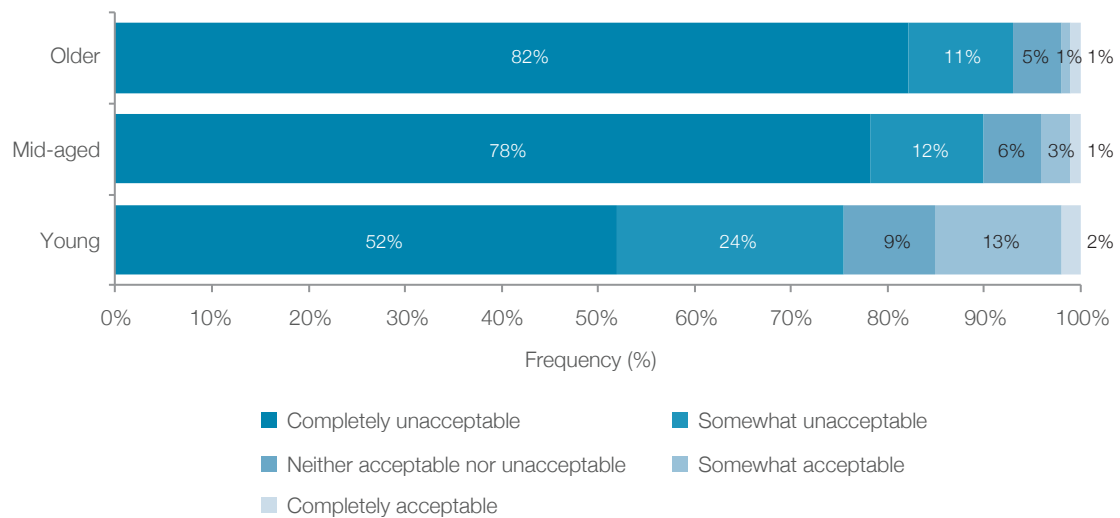


Figure 22: Distribution of responses to statement: “My car shares data on my driving behaviour with my family and friends”, split by age profile – young, mid-aged and older



Summary of Patterns in Responses Across Scenarios

Across all scenarios, participants demonstrated high acceptance of monitoring and advisory functions, particularly when clearly linked to safety benefits. Acceptance declined progressively for features involving behavioural enforcement, automated takeover, public disclosure or extensive third-party data sharing.

Age differences were consistent with generational patterns in technology acceptance: younger drivers exhibited relatively greater tolerance for AI-driven systems and automation, whereas older drivers prioritised autonomy and privacy. Nevertheless, privacy concerns and resistance to intrusive or externally shared data were evident across all age groups.

Collectively, these findings suggest that drivers support DMS features that enhance safety while preserving autonomy and limiting secondary uses of personal data.

Exploratory Factor Analysis

Although item-level analysis can yield valuable insights, examining responses at this level alone may produce a complex pattern of results and obscure meaningful relationships among variables. Factor analysis is a statistical technique that addresses this limitation by identifying the underlying structure within a dataset. Specifically, it reduces a large set of observed variables into a smaller number of latent constructs (or, unobserved factors) that account for patterns of correlation among items. By doing so, factor analysis enables a more parsimonious and theoretically meaningful interpretation of the data, revealing the underlying dimensions that explain respondents' answers.

An EFA was thus conducted to examine the underlying structure of the response data, initially using data from all 62 items. Prior to analysis, the suitability of the data for factor analysis was assessed. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy

was .96, exceeding the recommended threshold of .60, and Bartlett's test of sphericity was significant ($\chi^2(325) = 9403, p < .001$), indicating that the correlation matrix was appropriate for factor analysis.

EFA was performed using principal axis factoring with oblique (Promax) rotation – this is because correlations were observed between the factors during the suitability analysis. Examination of the eigenvalues greater than 1.0 (indicating a factor explains more variance than a single item), scree plot and interpretability of the solution supported a three-factor structure. The three factors explain the shared variance (patterns of correlation) among the survey responses.

The final three-factor solution accounted for 58.6% of the variance. This is the total cumulative variance in the data that is accounted for by the proposed model. Variance not explained by the model (i.e. the remaining 41.4%) is typically due to specific, or systematic, variance. This is variance unique to a specific item that is not shared with other items in the analysis. In the proposed model, Factor 1 explains 45.8%, Factor 2 explains 7.4% and Factor 3 explains 5.4%. Items were retained if they loaded $\geq .50$ onto their primary factor and did not exhibit cross-loadings (see Appendix C). The three factors were subsequently named based on the items they contained.

Factor 1: Adaptive Driver Assistance

This factor accounts for the highest variance in the original data. It comprised items describing systems that monitor driver behaviour and performance, and provide personalised advice or assistance aimed at improving driving safety, efficiency and comfort. The items reflect AI-enabled monitoring, learning of driver behaviour, comparison with previous journeys and the provision of tailored recommendations based on analysed driving data. This factor therefore represents perceptions of vehicle-based driver monitoring and adaptive feedback designed to support driving performance.

Factor 2: Behavioural Safety Enforcement

This factor comprised items primarily described vehicle technologies and functional aspects that relate to unsafe or illegal driving conditions and intervene to prevent them. These included monitoring for phone use, fatigue and alcohol impairment, as well as enforcement mechanisms such as warnings, disabling phone use or preventing the vehicle from starting when the driver exceeds legal alcohol limits. This factor reflects automated safety monitoring and enforcement mechanisms designed to prevent risky driving behaviour.

Factor 3: Driving Data Surveillance

This factor included items relating to the broader collection, storage and sharing of driving-related data with external parties. These items referred to monitoring behaviour beyond the vehicle, long-term storage of driving data, cloud-based analysis, and the sharing of data with organisations such as insurers, regulatory authorities, manufacturers or personal contacts. This factor therefore represents perceived surveillance and external access to driving data generated by connected vehicles.

These three factors represent the latent constructs underlying participants' responses to the survey items. In other words, they reflect the underlying dimensions through which respondents conceptualised and interpreted different forms of driver monitoring across all the scenarios presented. As such, these factors provide insight into how individuals categorise and evaluate DMS, and identify the key domains that should be considered when developing recommendations to improve the design, implementation and public acceptance of DMS.

4.9 Survey Discussion

The current study provides insights into drivers' attitudes towards different applications of DMS by examining acceptability across a range of monitoring scenarios and functional roles. When considered alongside findings from the recent *IAM RoadSmart Road Safety Report* (RoadSmart Media, 2025), a consistent picture emerges: drivers evaluate both emerging monitoring technologies and broader vehicle safety interventions through the lenses of perceived safety benefit, personal autonomy, and trust in enforcement and data use. Overall, systems that clearly support road safety while preserving driver control and limiting the sharing of personal data tended to receive the highest levels of acceptance.

Across the six principal monitoring scenarios explored in the current study, intoxication detection consistently received the strongest support, with respondents broadly endorsing the use of in-vehicle breathalysers and the prevention of driving when legal alcohol limits are exceeded. This finding aligns closely with the IAM RoadSmart report, which showed strong public backing for enforcement measures targeting impaired driving, including 82% of motorists supporting immediate licence suspension for those testing positive for drug driving offences and 83% support for alcohol interlock ('alco-lock') systems for convicted drink drivers that will not permit the car to start if they have been drinking. Both sources reflect strong social norms against drink driving, in particular, and a willingness among drivers to accept more intrusive interventions when the safety case is clear and well established.

Fatigue monitoring was also widely accepted, particularly in situations where the system provided a warning or recommendation to take a break. This is reinforced by IAM findings that 48% of drivers believe drowsiness detection technologies should be mandatory in new vehicles, suggesting that fatigue is recognised as a legitimate safety risk where assistive monitoring – and potential intervention – is appropriate.

In contrast, distraction monitoring and data surveillance scenarios attracted comparatively lower acceptability ratings in the current study. Although drivers recognised distraction as a safety risk, some interventions – particularly those involving control of personal devices, public notification or automated intervention – were perceived as intrusive. This tension reflects broader IAM findings that despite widespread concern about behaviours such as mobile phone use, a notable proportion of drivers still engage in them, with 27% of motorists reporting handheld phone use for calls while driving, highlighting a gap between risk recognition and behavioural compliance.

A consistent pattern across the functional analyses was the decline in acceptance as the level of system authority increased. Monitoring and advisory functions were generally viewed positively, whereas enforcement measures that restricted driver autonomy – such as preventing driving or automatically taking control of the vehicle – were less acceptable. This ‘gradient of authority’ is strongly supported by IAM evidence on driver assistance systems: while many safety features are endorsed in principle, actual usage remains relatively modest, with only 15–22% of drivers polled in the IAM survey describing themselves as regular users of systems such as speed limiters, lane-keeping assist or collision warnings; moreover, the most common reason cited for not using such systems is a preference for maintaining full control of the vehicle, directly reinforcing the importance of perceived autonomy and user agency in technology acceptance.

The observation that between 12% and 18% of drivers regarded DMS as ‘completely unacceptable’, and up to 31% indicated that they would be ‘extremely unlikely’ to choose a vehicle equipped with the monitoring systems under examination, carries substantive implications for the deployment and uptake of such technologies. This degree of opposition indicates the presence of a significant minority of users – potentially approaching one in three drivers – who may actively reject, disable or avoid monitoring systems. Such behaviour could materially compromise the anticipated safety benefits and limit the overall effectiveness of DMS implementation. These findings are also consistent with IAM evidence suggesting resistance to certain mandated or automated interventions. For example, while some technologies explored by IAM received majority support to be mandatory in new cars (e.g. automated emergency braking was supported by 50% of drivers), others, such as speed limiters or ‘alco-locks’, attracted lower levels of support.

Age-related differences further illustrate how drivers interpret monitoring technologies. Older drivers tended to express stronger acceptance of systems that monitor observable safety behaviours, such as mobile phone use detection or fatigue monitoring. In contrast, young drivers showed relatively greater acceptance of AI-driven behavioural analysis and emotion-based sensing. These findings are also consistent with IAM data showing higher acceptance of safety interventions among older age groups, particularly for enforcement and infrastructure measures. However, younger drivers (in the IAM survey) demonstrated higher engagement in risky behaviours (e.g. higher rates of mobile phone use and speeding) – and the same age group exhibited significantly higher mini-DBQ scores in the current survey. This may explain the relatively greater openness to advanced monitoring among young drivers, but also their resistance to strict enforcement measures that constrain their behaviour, such as disabling mobile phones. Across data governance statements, young drivers demonstrated greater tolerance for cloud-based storage and data sharing, whereas older drivers consistently expressed stronger privacy concerns and a preference for data minimisation. These patterns suggest generational differences in attitudes towards digital technologies, privacy and automation.

The comparison between acceptability and likelihood ratings also revealed an important distinction between attitudes and potential behaviour, and reflects a broader behavioural gap also identified in the IAM report. In the current study, the ranked order of features that

drivers considered most acceptable differed from those they indicated they would most likely choose when purchasing their next vehicle. This discrepancy suggests that while drivers often express support for safety features or enforcement in principle, real-world behaviour and purchasing decisions are shaped by additional, contextual factors, including convenience, cost and perceived intrusiveness. This is also evident in the relatively low routine use of many driver assistance systems reported in the IAM survey, despite their widespread availability and recognised benefits.

Finally, the EFA identified three broader dimensions through which drivers appear to conceptualise DMS: adaptive driver assistance, behavioural safety enforcement and driving data surveillance. These also align well with the IAM report's broader segmentation of driver attitudes towards vehicle technology, enforcement and policy initiatives.

This combined evidence highlights that drivers do not perceive DMS as a single, unified technology but rather as a collection of different capabilities and functionalities with distinct implications and trade-offs for safety, autonomy and privacy. Understanding these dimensions will help designers and policymakers prioritise features that align with user expectations and address concerns that may undermine trust or adoption: systems positioned within the 'assistive safety' domain are most likely to achieve widespread acceptance, whereas those associated with surveillance or coercive enforcement require stronger justification, transparency and trust-building measures.

Implications for Design

The results from the survey suggest that drivers are most supportive of monitoring technologies when they clearly contribute to road safety, preserve driver autonomy, and limit the collection or sharing of personal data. Acceptance declines when systems are perceived as intrusive, overly controlling or when personal information is shared beyond the immediate driving context.

The highest levels of acceptance were associated with monitoring features addressing clear and immediate safety risks. In particular, systems designed to detect alcohol impairment and driver fatigue were consistently rated as the most acceptable across all age groups and were also among the most likely features drivers would choose when selecting a vehicle. This suggests that while DMS design should ultimately prioritise functions that deliver the greatest safety benefits to drivers and other road users, driver acceptance remains an important consideration for successful implementation. Monitoring features that address well-recognised safety hazards may be more readily accepted because drivers can perceive a clear link between monitoring and crash prevention. Designers should therefore communicate monitoring features in terms of their safety benefits, emphasising the role of the system in supporting safe driving rather than monitoring behaviour for its own sake. This aligns with broader regulatory approaches that prioritise safety outcomes while also seeking to build public trust and acceptance of sensing technologies and automated system involvement.

The findings also highlighted the importance of preserving driver autonomy through graduated levels of system authority. Across several scenarios, acceptability declined as the level of system intervention increased. Passive monitoring and advisory feedback

were generally well supported, whereas more restrictive interventions – such as preventing the driver from continuing a journey or automatically taking control of the vehicle – were less acceptable. This pattern suggests that DMS should adopt a progressive intervention strategy in which monitoring and advisory feedback represent the primary response, with stronger interventions reserved for situations involving clearly elevated risk. Such an approach aligns with HF principles relating to perceived control and user trust, both of which are critical for the successful adoption of automated vehicle technologies.

Similarly, drivers tended to prefer advisory assistance over behavioural enforcement. Features that provided warnings, reminders or suggestions – such as advising a driver to take a break or refocus their attention – were widely accepted across all age groups. In contrast, enforcement-based actions – such as disabling a driver's mobile phone or preventing their vehicle from starting – attracted lower levels of agreement, particularly among younger drivers. These findings suggest that to maximise driver acceptance, monitoring systems should primarily be designed as supportive driver assistance tools rather than as mechanisms for policing driver behaviour. Enforcement actions may still be appropriate in situations involving illegal or high-risk behaviour, such as alcohol impairment, but they should be carefully justified and implemented in a transparent manner.

The results also highlight the importance of maintaining clear boundaries between in-vehicle safety monitoring and broader forms of personal surveillance. Drivers were generally comfortable with monitoring activities that occurred within the vehicle and were directly linked to driving safety. However, strong disagreement was observed when monitoring extended beyond the vehicle context, such as systems that inferred driver fitness to drive based on behaviour at social venues or other off-vehicle activities. This suggests that DMS design should focus strictly on driving-related behaviour and avoid monitoring drivers in contexts unrelated to vehicle operation. Respecting these contextual boundaries is likely to be important for maintaining user trust and preventing perceptions of intrusive surveillance.

Another important design consideration relates to the types of driver characteristics that are monitored. Monitoring observable driving behaviours – such as fatigue, phone use or driving performance – was generally accepted by participants. In contrast, monitoring internal states – such as emotional or psychological conditions – was viewed more cautiously. Features that attempted to detect emotions such as anger or confusion through facial-expression analysis received relatively low levels of support. This suggests that drivers perceive a distinction between behavioural monitoring that supports road safety and technologies that appear to analyse personal emotional states, which they feel may not be relevant to the quality and/or safety of their driving behaviour. Designers should therefore carefully consider the necessity and transparency of affective monitoring technologies, ensuring that any such features are clearly justified in terms of safety outcomes.

Concerns about privacy and data governance also emerged as a major theme across the findings. Drivers expressed mixed views about the storage and sharing of driving data, with many showing a preference for data to remain within the vehicle rather than being stored or analysed in the cloud. Support was generally stronger for data use that directly benefited the driver, such as improving the driving experience or informing vehicle safety design. In contrast,

lower levels of acceptance were observed for sharing driving or health data with third parties, including insurance companies, family members or external organisations. These findings suggest that DMS should follow principles of data minimisation, collecting only the information necessary for safety-related functions and providing drivers with clear information about how their data is stored, used and shared. Where possible, local data processing and storage should be prioritised to reduce concerns about external data access.

The results also reveal generational differences in attitudes towards technology and data use. Younger drivers tended to demonstrate greater acceptance of AI-enabled systems, automation and data-driven vehicle ecosystems. However, they were also more resistant to system features that removed personal control or imposed behavioural restrictions. Older drivers, by contrast, were generally more supportive of monitoring technologies designed to enhance safety but expressed stronger concerns about data privacy and external data sharing. These patterns suggest that future DMS designs may benefit from offering a degree of personalisation or customisation, allowing drivers to adjust monitoring features, data-sharing preferences or feedback styles according to their comfort levels. Designing systems that accommodate a range of user expectations may improve acceptance across diverse driver populations.

Drivers also expressed strong opposition to systems that publicly disclose or share behavioural information with others. Features that would notify other road users, family members or social contacts about the driver's behaviour were among the least supported in the survey. From a HF perspective, this suggests that DMS should avoid mechanisms that publicly broadcast driver behaviour or expose drivers to potential embarrassment or social judgement. Instead, monitoring and feedback should remain private between the driver and the vehicle system.

Lastly, the three underlying dimensions shaping driver perceptions of monitoring technologies revealed by the EFA (i.e. adaptive driver assistance, behavioural safety enforcement and driving data surveillance) also have implications for design. Systems that fall within the adaptive driver assistance category – those that monitor driving behaviour and provide personalised feedback or support – were generally viewed positively. Behavioural safety enforcement features were accepted primarily when addressing clearly unsafe or illegal behaviour, such as intoxicated driving. In contrast, technologies associated with broader data surveillance, including extensive data storage or sharing with external organisations, were viewed less favourably. These findings suggest that DMS design should emphasise supportive assistance and safety-focused monitoring, while minimising features that may be perceived as surveillance or data exploitation.

Considered together, the results indicate that drivers are broadly supportive of monitoring technologies when they enhance road safety, preserve personal autonomy and respect privacy boundaries. Designing DMS in a way that emphasises transparency, proportional intervention and responsible data governance will therefore be critical for ensuring user acceptance and effective integration into future vehicle systems.

4.10 Survey Conclusions

The survey demonstrates that drivers generally support DMS when they are clearly linked to safety improvements and operate primarily as advisory or assistive tools. However, acceptance declines as systems become more controlling, or involve extensive collection and sharing of personal data. Drivers appear to draw clear boundaries between supportive in-vehicle safety monitoring and technologies perceived as intrusive surveillance or external data exploitation, although a significant minority of respondents (between 12% and 18%) consider DMS to be completely unacceptable and up to 31% of respondents indicated that they would be unlikely to choose a vehicle with the monitoring capabilities explored in the survey.

The findings suggest that the successful implementation and adoption of DMS will therefore depend not only on technological capability but also on careful consideration of system authority, transparency and data governance. For achieving widescale public acceptance of DMS, it is likely to be critical to design systems that prioritise safety benefits while maintaining driver autonomy and clear control over personal data. The findings from the online survey have been translated into guidelines and recommendations to improve the design, implementation and public acceptance of DMS, which are presented in the next chapter.

5. DMS Guidelines and Recommendations



The final aim of this research was to develop evidence-based guidelines and recommendations from the survey findings in order to support greater public acceptance and uptake of DMS.

In doing so, it is important to acknowledge that many current DMS implementations are still perceived primarily as compliance-oriented technologies, rather than as driver-centred safety systems. Interview data indicated that stakeholders frequently view DMS as a requirement imposed by regulation or by Euro NCAP assessment criteria, with limited industry incentive to go beyond minimum performance thresholds. As a result, the quality, capability and reliability of DMS – and particularly their interaction with ADAS or other vehicle control functions – can vary considerably between manufacturers.

A clear distinction should therefore be made between DMS as a sensing and monitoring technology, and the broader set of ADAS or automated interventions that may act on DMS-derived outputs. Many of the concerns raised by stakeholders were not directed at driver monitoring itself, but at downstream intervention systems that may be perceived as intrusive, inconsistent or insufficiently aligned with driver intent and situational awareness.

Given these issues, it is understandable that drivers may choose to disengage from, or disable, systems they perceive as unreliable or disproportionate; this research does not seek to mandate acceptance of such interventions.

Instead, the recommendations presented here focus specifically on the design, implementation and acceptance of DMS as a monitoring and feedback tool. Established HF research demonstrates that safety technologies are most effective when they are trusted, transparent and compatible with natural human behaviour. Accordingly, securing user acceptance of DMS is not an ancillary consideration but a core requirement for realising its safety benefit.

More broadly, public acceptance of DMS is also essential at a societal level. Widespread and sustained adoption will be necessary if DMS-equipped systems are to contribute meaningfully to reductions in road traffic injuries and fatalities across all road user groups.

5.1 What are Guidelines and Recommendations?

It is important to distinguish between guidelines and recommendations, as these terms are related but not interchangeable. Guidelines generally refer to high-level design principles grounded in empirical evidence on human attitudes, cognition and performance. They provide broad direction for decision-making across different contexts (Salvendy, 2012; Shneiderman, 2010). Recommendations, in contrast, are more specific and operational in nature, translating these general principles into actionable design guidance tailored to a particular system or implementation context.

For example, a guideline might state: “Ensure transparency in data use and system decisions.” A corresponding recommendation would specify how this principle should be implemented in practice, such as: “Clearly communicate what data is collected, why it is collected, how long it is stored and who it can be accessed by.”

In light of this distinction, the following section presents a set of guidelines and design recommendations derived from the survey findings. These have been developed with the aim of improving public acceptance and supporting the long-term adoption of DMS, thereby helping to ensure that their intended safety benefits are fully realised. A summary of the guidelines and associated recommendations is provided below, with full details set out in Table 9.

5.2 DMS Design Guidelines

1. Prioritise Safety-Critical Monitoring

DMS should prioritise monitoring functions that address immediate and well-recognised safety risks, such as driver intoxication, fatigue and distraction. Features that clearly contribute to accident prevention are more readily accepted by drivers and are more likely to influence vehicle purchase decisions.

2. Use Graduated and Predictable Levels of System Authority

Drivers are more accepting of monitoring technologies when the system behaves in a consistent and predictable way. System interventions should therefore be proportionate, predictable and clearly justified and follow a progressive escalation model of intervention: Passive monitoring → Advisory feedback (warnings or suggestions) → Escalated alerts → Automated intervention (but only when risk thresholds are exceeded). This approach preserves driver autonomy while enabling appropriate responses to critical safety conditions.

3. Prioritise Advisory Assistance Over Behavioural Enforcement

Systems should be designed primarily as supportive driver assistance tools that provide feedback and recommendations. Behavioural enforcement actions (e.g. disabling functions or preventing driving) should be limited to situations involving illegal or high-risk behaviours, such as alcohol impairment.

4. Maintain Clear Boundaries Around Monitoring Scope

DMS should concentrate on observable behaviours that are directly linked to driving within the vehicle environment. Monitoring activities beyond this context, or attempting to infer behaviour from external actions or internal emotional states, risks undermining user trust and may be perceived as unnecessarily intrusive. Accordingly, systems should prioritise the assessment of measurable driving behaviours, while the use of technologies that analyse facial expressions or emotions should only be implemented where there is a clear and demonstrable safety justification.

5. Ensure Transparency in Data Use and System Decisions

Drivers should be provided with clear information about what data is collected, how it is used and who can access it. Transparent communication supports user trust and helps drivers develop accurate mental models of system operation.

6. Apply Data Minimisation and Privacy Protection Principles

DMS should collect and store only the data that is strictly necessary to support safety-related functions, with local processing and storage within the vehicle prioritised wherever possible to minimise concerns about external access and misuse. To preserve driver privacy and trust, systems should avoid features that disclose driving behaviour to third parties, including family members or social contacts, ensuring that feedback remains confidential and limited to communication between the driver and the vehicle system.

7. Design for Generational Differences in Technology Attitudes

DMS design should account for differences in attitudes across driver groups. Younger drivers may be more accepting of AI-driven technologies but less tolerant of restrictions on control, while older drivers may prioritise privacy and data protection. Systems should therefore support configurable settings and personalisation.

8. Frame Monitoring Around Safety Rather Than Surveillance or Optimisation

Monitoring functions should have a clear and transparent safety rationale. Systems perceived as directly improving road safety are more acceptable than those perceived as evaluating or surveilling driver behaviour.

9. Maintain Strong Functional Justification for Biometric Identification

The use of biometric or health-related data should be limited and clearly justified. Drivers accept biometric monitoring when its purpose is clear, bounded and protective.

10. Align DMS Design with the Core User Perceptions

DMS should primarily function as adaptive driver assistance systems that provide personalised feedback and support safe driving behaviour, rather than acting as surveillance tools.

Table 9: Guidelines and recommendations emerging from the research

Design Principle	Key Survey Finding	Design Guidelines & Recommendations	Human Factors Rationale
1. Prioritise Safety-Critical Monitoring	Monitoring for intoxication and fatigue had the highest acceptability and likelihood of adoption across all age groups.	• Prioritise DMS features addressing clear and immediate safety risks, particularly: • Alcohol impairment detection • Fatigue detection • Distraction detection. • Clearly communicate the safety purpose of monitoring features in system feedback and user interfaces. • Frame interventions in terms of risk reduction and driver protection, rather than behavioural surveillance.	Drivers are more accepting of monitoring technologies when their benefits are obvious and safety-critical, aligning with established principles of perceived usefulness and risk-benefit trade-offs in technology acceptance.

Design Principle	Key Survey Finding	Design Guidelines & Recommendations	Human Factors Rationale
2. Use Graduated and Predictable Levels of System Authority	Trust and acceptance were closely tied to the perceived role of DMS (assistant versus surveillance). Acceptance decreased as system authority increased (monitoring → advising → enforcing → restricting control).	• Ensure system behaviour is consistent and predictable. • Provide clear feedback when the system intervenes. • Avoid sudden or unexplained interventions, particularly autonomy-restricting actions unless the risk threshold is high. • Implement graduated intervention strategies: 1. Monitoring (passive sensing) 2. Advisory feedback (warnings, recommendations) 3. Escalated alerts (persistent warnings) 4. Automated intervention (restricted control, only when risk is severe). Examples: • Fatigue detection → suggestion to take a break • Repeated fatigue → stronger warning • Extreme fatigue → limited system intervention.	Gradual escalation preserves driver autonomy and perceived control, supporting trust and acceptance in automated systems, while predictable system behaviour enables appropriate trust calibration and accurate mental models of automation.
3. Prioritise Advisory Assistance Over Behavioural Enforcement	Advisory features were consistently more acceptable than automated enforcement mechanisms.	• Design DMS primarily as supportive driver assistance tools, not punitive systems. • Provide clear, actionable guidance (e.g. <i>"Consider taking a break in 10 minutes"</i>). • Reserve enforcement actions (e.g. disabling functions or preventing driving) for: • legally mandated safety violations • severe risk conditions (e.g. intoxication).	Drivers are more receptive to collaborative systems than systems perceived as controlling or punitive.

Design Principle	Key Survey Finding	Design Guidelines & Recommendations	Human Factors Rationale
4. Maintain Clear Boundaries Around Monitoring Scope	Drivers strongly rejected monitoring that extends beyond the driving context, such as surveillance of behaviour in social settings like pubs, and also showed low support for emotional-state monitoring systems, including those that infer states such as anger from facial expressions.	• Restrict monitoring to events directly related to driving activity. • Avoid collecting data about driver behaviour outside the vehicle environment. • Explicitly communicate system boundaries to drivers. • Focus monitoring on observable safety-relevant behaviours rather than internal emotional states. • If emotional sensing is used: • Ensure clear safety justification • Provide transparent explanations of how it works. • Allow users to disable or customise the feature.	Respecting contextual boundaries reduces privacy concerns and perceived surveillance, which strongly influence acceptance of monitoring technologies. Emotion monitoring can be perceived as psychological surveillance, raising concerns about privacy, misinterpretation and trust.
5. Ensure Transparency in Data Use and System Decisions	Data storage, cloud analysis and third-party sharing were among the least acceptable features.	• Provide clear explanations of: • what data is collected • why it is collected • how long it is stored • who can access it. • Integrate driver-accessible data interfaces showing recorded information and permissions. • Implement clear consent mechanisms for data sharing.	Transparency supports trust calibration, enabling users to understand and appropriately rely on automated systems.

Design Principle	Key Survey Finding	Design Guidelines & Recommendations	Human Factors Rationale
6. Apply Data Minimisation and Privacy Protection Principles	Drivers preferred local storage and data deletion after each drive. Informing other road users or personal contacts (family and friends) about driver behaviour received very low acceptance.	• Default to in-vehicle data processing and storage whenever possible. • Limit long-term storage unless necessary for safety or legal purposes. • Offer settings allowing drivers to: • delete data • opt out of non-essential data collection • manage data-sharing permissions. • Avoid features that publicly broadcast driver behaviour (e.g. notifying other road users of inattention). • Avoid automatic sharing of behaviour data with family, friends or social networks.	Data minimisation reduces privacy concerns and perceived surveillance, increasing system acceptance. Public disclosure can produce embarrassment, stigma and perceived loss of control, undermining user trust.
7. Design for Generational Differences in Technology Attitudes	Younger drivers were more accepting of AI and automation, but more resistant to autonomy restrictions. Older drivers were more accepting of safety monitoring, but more concerned about privacy and data sharing.	• Provide customisable system behaviour: • Adjustable alert styles • Customisable monitoring features • User-selectable privacy settings. • Interface design should also consider age-related differences: • Clear visual feedback • Simple explanations of AI functions • Optional system tutorials.	Adaptive systems accommodate individual differences in technology acceptance and trust.

Design Principle	Key Survey Finding	Design Guidelines & Recommendations	Human Factors Rationale
8. Frame Monitoring Around Safety Rather Than Surveillance or Optimisation	Monitoring framed as safety enhancement was more acceptable than performance optimisation.	• Present feedback as improving safety and driving comfort, not evaluating driver competence. • Avoid language implying judgement or evaluation (e.g. "poor driving behaviour"). • Provide constructive guidance rather than performance scoring.	Reducing evaluative framing lowers defensive reactions and resistance.
9. Maintain Strong Functional Justification for Biometric Identification	Face recognition for identifying the legal driver was relatively acceptable, particularly among older drivers.	• Use biometric technologies primarily for security and access control. • Clearly communicate the functional benefit (e.g. theft prevention, personalised settings).	Drivers accept biometric monitoring when its purpose is clear, bounded and protective
10. Align DMS Design with the Core User Perceptions	The factor analysis revealed three underlying dimensions influencing acceptance: 1. Adaptive driver assistance 2. Behavioural safety enforcement 3. Driving data surveillance	Successful DMS should emphasise adaptive assistance, cautiously implement safety enforcement and minimise data surveillance.	Drivers <i>accept</i> systems that: • provide personalised feedback • support safe driving behaviour. Drivers <i>tolerate</i> enforcement mechanisms when: • risks are severe • the legal or safety justification is clear. Drivers <i>resist</i> systems that: • collect extensive personal data • share information externally.

6. Overall Conclusions



The literature review established the theoretical foundation for the research, defining DMS as technologies designed to evaluate a driver's ability to operate a vehicle safely through the collection and analysis of driver-related data. Building on this foundation, stakeholder interviews provided an industry perspective on technological development, regulatory influences and practical implementation challenges. These interviews suggested that current DMS implementations may fall short of HF best practice due to compliance-driven development, limited personalisation, poor alignment with drivers' mental models and intrusive interaction design.

The focus groups explored drivers' understanding of DMS and revealed that this is shaped by the complex, uncertain and context-dependent nature of driving. Drivers' physiological and psychological states, self-assessments, goals, and surrounding conditions are continually changing, influencing how monitoring technologies are interpreted and may be accepted in practice.

Findings from the online survey suggested that drivers may be more accepting of driver monitoring than is often assumed. While a minority expressed strong resistance to all forms of monitoring, participants generally supported monitoring systems when they function as advisory or assistive technologies and when the safety rationale is transparent and proportionate. Acceptance declined, however, as systems became more controlling, or involved extensive

collection, storage or sharing of personal data. Drivers appeared to draw clear boundaries between supportive in-vehicle safety monitoring and technologies perceived as intrusive surveillance or mechanisms for external data exploitation. Further analysis identified three underlying ways in which respondents conceptualised driver monitoring: adaptive driver assistance, behavioural safety enforcement and driving data surveillance.

The findings have important implications for the future deployment of conditional and higher levels of vehicle automation. As automated driving systems increasingly rely on assessing a driver's readiness and ability to retake control, understanding public acceptance of DMS becomes critical. The findings suggest that acceptance is not determined solely by the presence of monitoring itself, but also by how transparently, proportionately and respectfully monitoring is implemented. This highlights the importance of designing DMS that drivers perceive as legitimate safety tools, rather than mechanisms of surveillance or behavioural control.

The research also suggests that regulation alone may not be sufficient to ensure successful driver monitoring implementation. Although regulatory frameworks are intended to improve vehicle safety, they may encourage a compliance-focused or 'tick-box' approach in which systems satisfy engineering specifications while failing to meet broader HF requirements. In contrast, DMS designed around HF principles – including transparency, contextual sensitivity, appropriate system authority and respect for driver autonomy – are more likely to achieve both driver acceptance and effective safety outcomes.

Based on these findings, a set of ten design recommendations was proposed to support the development of driver-centred DMS. Collectively, these recommendations emphasise that effective driver monitoring should remain clearly safety-oriented, proportionate to the driving context, and transparent in both operation and data use. Moreover, systems that support drivers without unnecessarily intruding on autonomy or privacy are likely to achieve greater public acceptance and more successful long-term adoption.

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Appendix A – Stakeholder Interview Questions and Script

Preamble: Thank you for agreeing to be interviewed. We are interested in understanding your views on driver monitoring systems (DMS). We are talking to you as an expert or stakeholder in the automotive industry and are interested in your personal views. Anything you tell us will remain anonymous and will be treated as confidential. It will not be possible to directly associate any of your responses with you or your organisation.

We may use parts of what you tell us in presentations, publications, and reports but we will not share your responses in any way that could identify you. We will audio-record this interview so we can produce a written transcript of what is said. Once this is done, we will delete the recording.

If at any point, you'd like to stop the interview or ask further questions, please let me know. Do you have any questions before we begin?

Participant Information

- a. What is your current job role?
- b. What experience do you have in, or associated with, the automotive industry?
- c. Please briefly explain any professional interest in driving monitoring systems.

Definition, Terminology and Scope

1. What do you understand by the term driver monitoring system (DMS)?

Prompts/further questions:

- What (else) could or should DMS monitor (e.g. visual attention, drive state/ physiological/ intoxication, visual behaviour, driving performance, other data)?
- How should it be measured? Are DMS limited to camera-based systems only?
- Who should DMS monitor (driver, passenger, people outside vehicle)?
- How does or how should the system determine what constitutes 'appropriate' behaviour? Should this be based on absolutes or on historical/personal data?

Strategy and Vision

2. Do you see DMS as a regulatory requirement or a value-added safety feature?

Prompts/further questions:

- What drives the decision to include DMS in a vehicle?
- In your opinion, how important should DMS be in an automotive company's overall vehicle safety strategy/roadmap?
- How should the benefits of DMS be communicated to drivers?

Regulation and Compliance

3. Do you think that DMS should be mandatory and regulated?

Prompts/further questions:

- How are evolving regulations shaping the development and implementation of DMS systems?
- Should DMS systems feature in all cars?
- Do you think the introduction of DMS will make driving safer?
- How do we avoid ending up with badly implemented or ineffective DMS (i.e. the technology meets the regulations but doesn't provide any real 'value' to drivers)?

Consumer Perception and Privacy

4. How do you balance privacy concerns with the safety benefits of driver monitoring systems?

Prompts/further questions:

- (How) should the driver be informed about the types of behaviours monitored and the potential consequences of inappropriate behaviour?
- Is driver consent always required for the monitoring and intervention process?
- What are the implications for privacy/ethics etc?
- How do you avoid drivers delegating their own responsibility for safe driving and using DMS as a fall-back?
- Should drivers be able to override the system in non-critical situations, and how should this be managed safely?
- Should DMS use real-time data only (closed loop) and/or be based on historical/trend/personal data? Where should these data reside?
- Pre-regs DMS are not closed loop—what should or could data collected by these systems be used for? (What are OEMs actually doing with these data?)
- What has been the public response to DMS features so far?
- What other concerns might consumers have (e.g. trust, acceptance) and how should these be addressed?

Future Developments

5. How do you see DMS evolving with AI and autonomous driving?

Prompts/further questions:

- Do you think DMS will still be needed in fully autonomous vehicles?
- What other benefits might DMS offer in fully autonomous vehicles?
- How can these benefits be extended to other passengers (e.g. in ridesharing situations)?
- Should DMS extend beyond the vehicle (e.g. detects driver is too tired/intoxicated to drive and therefore won't even let them enter or start the vehicle)?
- How could future DMS personalise the in-vehicle experience for the driver and other occupants? What are the benefits/implications of this (e.g. reduce workload versus added complexity)?

Appendix B – Focus Group Script and Storyboards

Preamble: “Thank you for agreeing to take part in the focus group. We are interested in exploring your understanding of different driving-related situations. Five different scenarios will be presented to you as comic book style storyboards. We would like you to think about and discuss aloud *what* you think is happening, *how* you think it is happening, and *why* you think it is happening. Specific prompts or questions will help guide you. We will record the focus group so we can produce a written transcript of what is said. Anything you tell us will remain anonymous and will be treated as confidential. The focus group should last approximately 1½ hours. At the end of the session, you will receive a £20 shopping voucher as a gift for taking part. Do you have any questions before we begin?”

Instructions to focus group facilitator:

- Ask questions in bold and use supplementary probes if/as required.
- Use the same questions for each scenario.
- Complete scenarios in the same numerical order for each focus group (1, 2, 3, 4, 5).
- Scenario 1 is driver fatigue; 2 driver distraction; 3 cognitive decline; 4 driver intoxication; and 5 data surveillance and sharing. This is for your information only. Please do not use or offer these descriptors when introducing each new scenario to participants. Go with whatever they suggest, unless it is widely off the mark, in which case, redirect them, as necessary.

Probe Questions:

1. **What do you think is happening in this situation?** [context]
2. **What specifically do you think the car is trying to achieve in this scenario?** [goal]
 - a. Ask participants to consider short-term versus long-term goals/implications
3. **What information or data do you think is being captured?** [cue/knowledge]
 - a. Ask participants to consider the type of data (e.g. driver behaviour versus car performance data) and how accurate this might be and/or what else it might mean
4. **How do you think this information or data is being captured?** [information]
 - a. Ask participants to consider what technology could be used and if there are any practical, ethical, legal and/or societal issues

5. **What do you think happens to this data?**
 - a. Ask participants to consider how and where the data will be analysed and stored, and what else it might be used for (including issues of consent)
6. **How accurate and reliable do you think the system will be?** [errors]
 - a. Ask participants to consider whether they think the system will always interpret the data correctly and make the correct decision/ recommendation
7. **What do you think are the potential outcomes in the scenario? (What do you think happens next?)** [action]
 - a. Ask participants to consider how the system knows if the driver has responded appropriately, and what 'responding appropriately' means in this context
 - b. Ask participants to consider what should happen next, if the driver doesn't respond
 - c. Ask participants to consider if the system should adapt over time, and if so, how?
 - d. Ask participants to consider if the system is fair, inclusive and respectful, and if not, why not?
 - e. Ask participants to consider if drivers should be given the option to 'opt in' or 'opt out'?

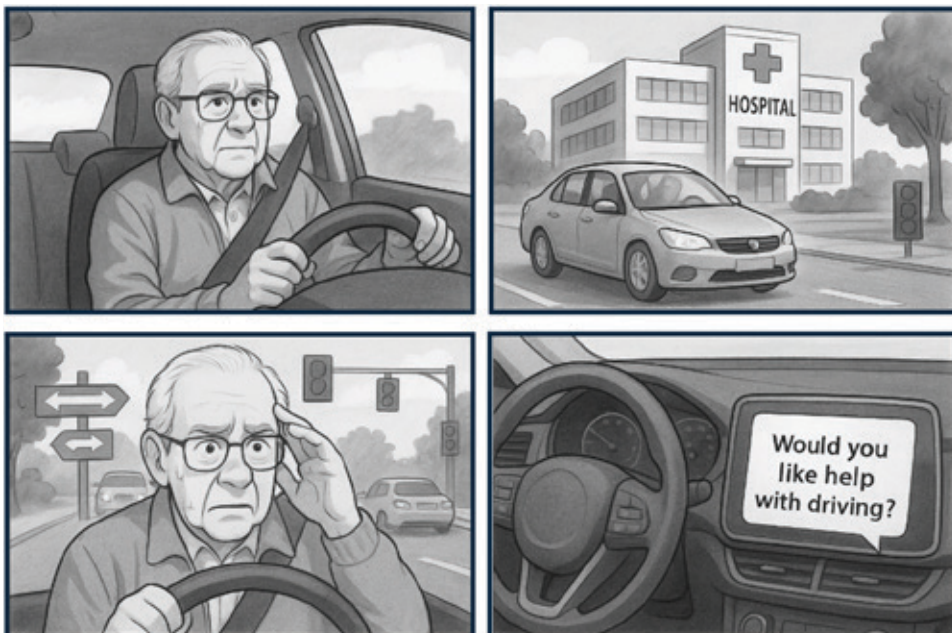
Scenario 1: Driver Fatigue



Scenario 2: Driver Distraction



Scenario 3: Cognitive Decline



Scenario 4: Driver Intoxication



Scenario 5: Data Surveillance and Sharing



Appendix C – Online Survey

Information

We are interested in exploring your attitudes towards systems and technology that monitor you and your driving. The work is being conducted by the University of Nottingham and is funded by the RAC Foundation.

The survey contains 4 sections. In each, you will be presented with a number of statements and asked to rate each of those statements using the scales provided.

Please answer honestly – your responses will be amalgamated with those from other respondents, and it will not be possible to identify you directly from your responses. Anonymised data will be stored securely at the University of Nottingham for 7 years and will be used for research purposes only in reports, academic articles and conference presentations, which may be publicly available.

The survey will take approximately 10-15 minutes to complete and you will receive £3 following completion of the survey in line with Prolific terms and conditions.

If you have any questions about the survey, please contact Dr David R. Large at the University of Nottingham – David.R.Large@Nottingham.ac.uk

Consent

You do not have to take part in the survey, and you may withdraw at any point, without penalty. By continuing, you are confirming that you...

- Have read and understood the above information
- Understand that your participation is voluntary and that you are free to withdraw at any time
- Understand that the survey intends to capture your personal attitudes towards systems and technology that monitor your behaviour and performance while you are driving or in your car, and it will not be possible to associate your responses directly with you
- Understand that anonymised data will be stored for 7 years and will be used in reports, academic articles and conference presentations, which may be publicly available
- Understand that you will be paid £3 in line with the Prolific policies and procedures
- Agree to participate in the survey

Section 1 – Driver Behaviour Questionnaire

The following statements refer to different driving behaviours. Drivers may do these things at different times and to different degrees. Please indicate how often you carry out each of the driving behaviours, using the scale provided. Please answer honestly – your responses are confidential and will only be used for research purposes

Never	Hardly ever	Occasionally	Quite Often	Frequently	Nearly all the time
☐	☐	☐	☐	☐	☐

1. Driving especially close or “flashing” the car in front as a signal for that driver to go faster or get out of your way
2. Deliberately disregarding the speed limits late at night or very early in the morning
3. Getting involved in unofficial “races” with other car drivers
4. Turning right on to a main road into the path of an oncoming vehicle that you had not seen, or whose speed you had misjudged
5. Failing to notice, because you are lost in thought or distracted, someone waiting at a zebra crossing, or that a pelican crossing light has just turned red
6. Misjudging the speed of a moving vehicle when overtaking
7. Forgetting where you left your car in a multi-storey car park
8. Getting into the wrong lane at a roundabout or when approaching a road junction
9. Failing to read road signs correctly, when exiting from a roundabout on the wrong road

Section 2 – Affinity with Technology Scale

Please indicate the degree to which you agree/disagree with each of the following 4 statements, using the following scale

Completely Disagree	Largely Disagree	Slightly Disagree	Slightly Agree	Largely Agree	Completely Agree
☐	☐	☐	☐	☐	☐

1. I like to occupy myself in great detail with technical systems
2. I like testing the functions of new technical systems
3. It is enough for me that a technical system works; I don't care how or why
4. It is enough for me to know the basic functions of a technical system

Section 3 – Attitudes towards Driver Monitoring Systems

(Note: order of statements was randomised in the online version)

Please indicate the level of acceptability you associate with each of the following statements, using the following scale

Completely Unacceptable	Somewhat Unacceptable	Neither acceptable nor unacceptable	Somewhat Acceptable	Completely Acceptable
☐	☐	☐	☐	☐

1. My car monitors me and my driving to determine if I am too tired to drive safely
2. My car helps me to recognise when I am tired
3. My car advises me to take a break if I am tired
4. My car keeps reminding me to take a break if I am tired
5. My car measures how long I have been driving
6. My car suggests a suitable location if I am tired and need a break
7. My car will not allow me to resume driving until I have had an adequate break
8. My car monitors me and my driving to determine if I am too distracted to drive safely
9. My car monitors where I am looking
10. My car advises me to look back at the road if I am distracted
11. My car detects when I have taken my hands off the steering wheel
12. My car monitors if I am using my phone while driving
13. My car advises me to stop using my phone while driving
14. My car switches off my phone if it detects that I am using it illegally while driving
15. My car takes over control of driving if I do not look back at the road when alerted
16. My car stops at the roadside if I do not look back at the road after repeated alerts
17. My car advises other road users if I am not paying attention
18. My car monitors me and my driving to determine if I am medically fit to drive safely
19. My car monitors and records my health-related data
20. My car informs me if I need help with my driving
21. My car monitors long term changes to my health
22. My car monitors my general mood and wellbeing
23. My car monitors my emotions
24. My car monitors my facial expressions to determine if I am angry
25. My car monitors my facial expressions to determine if I am confused
26. My car monitors me and my driving to determine if I could drive better
27. My car monitors my driving performance and behaviour and provides advice to make my driving better
28. My car monitors my driving performance and behaviour and provides advice to make driving easier
29. My car monitors my driving performance and behaviour and provides advice to make my driving safer
30. My car monitors my driving performance and behaviour and provides assistance to make my driving better

31. My car monitors my driving performance and behaviour and provides assistance to make driving easier
32. My car monitors my driving performance and behaviour and provides assistance to make my driving safer
33. My car compares my current driving to previous journeys based on historical data
34. My car makes assumptions about my behaviour based on generalised demographic data
35. My car uses AI to learn my driving behaviour and style
36. My car monitors me and my driving to determine if I have been drinking and am unsafe to drive
37. My car uses a breathalyser to determine if I have been drinking
38. My car will not let me start driving if I am over the legal alcohol limit
39. My car monitors my behaviour away from the car (e.g. at a pub) and then makes assumptions about my fitness to drive
40. My car helps me to decide when I should or should not be driving
41. My car monitors me and my driving and provides information and suggestions that I might be interested in
42. My car provides information and suggestions based on my phone's browsing history and/or social media use
43. Data on my driving is stored for a long time so it can be analysed for trends in behaviour
44. Data about me and my driving is stored and analysed in 'the cloud'
45. Data about me and my driving is stored and analysed within my car
46. Data on my driving is deleted after each drive
47. My car shares data on my driving behaviour with the vehicle manufacturer
48. My car shares data on my driving behaviour with my insurance company
49. My car shares data on my driving behaviour with the DVLA
50. My car shares data on my driving behaviour with the police
51. My car shares data on my driving behaviour with my family and friends
52. My car shares my health data with my healthcare provider
53. My car shares my health data with my family and friends
54. In a company car, data on my driving behaviour and performance is shared with my employer
55. In a hire car, data on my driving behaviour and performance is shared with the hire company
56. In the event of a road traffic collision, the police can access my data from my car
57. Data on my driving can be used as evidence in a court
58. Vehicle manufacturers share data from my car with third parties to gain a competitive advantage
59. Vehicle manufacturers use data from my car to improve my driving experience
60. Vehicle manufacturers use data from my car to inform the design of future cars
61. My car uses face recognition to identify me as the legal owner or designated user of the car
62. My car monitors my location and journey details at all times

Now, please answer the following questions using the scale provided

Extremely Unlikely	Somewhat Unlikely	Neither Likely nor Unlikely	Somewhat Likely	Extremely Likely
☐	☐	☐	☐	☐

1. How likely or unlikely are you to choose a car in the future that monitors you and your driving to determine if you are too tired to drive safely?
2. How likely or unlikely are you to choose a car in the future that monitors you and your driving to determine if you are too distracted to drive safely?
3. How likely or unlikely are you to choose a car in the future that monitors you and your driving to determine if you are medically unfit to drive safely?
4. How likely or unlikely are you to choose a car in the future that monitors you and your driving to determine if you could drive better?
5. How likely or unlikely are you to choose a car in the future that monitors you and your driving to determine if you have been drinking and are therefore unsafe to drive?
6. How likely or unlikely are you to choose a car in the future that provides information and suggestions based on your personal data?

Section 4 – Participant Demographics

1. Age:
2. Gender: ☐ Male ☐ Female ☐ Non-Binary ☐ Other ☐ Prefer not to say
3. Do you have a valid UK driver's licence (or equivalent)?
☐ Yes – Full licence ☐ Yes – Provisional Licence ☐ No
4. Approximate number of years driving experience:
5. Average number of days you drive each week:
6. Approximate number of miles you have driven in the last 12 months:
☐ 0 – 5000 miles
☐ 5001 – 10,000 miles
☐ 10,001 – 15,000 miles
☐ 15,001 – 20,000 miles
☐ More than 20,000 miles
7. Most common type/s of driving environment? (Select all that apply)
☐ Rural
☐ Urban
☐ Motorway
☐ Other (please specify:)

8. Make and model of vehicle/s that you commonly drive?
9. Which of the following terms describe the car/s you commonly drive? (Select all that apply)
- ☐ Company car
 - ☐ Hire car
 - ☐ Private lease
 - ☐ Privately owned
 - ☐ Other (please specify:)
10. Do you have any experience of driver monitoring systems?
- ☐ Yes ☐ No ☐ Don't know If 'Yes', please add details below
-
11. Do you have any experience of driver control assistance systems?
- ☐ Yes ☐ No ☐ Don't know If 'Yes', please add details below
-

The following attention check questions (ACQs) were also added to the survey to identify inattentive respondents, filter out careless data and ensure data quality. The ACQs help detect survey fraud, such as straight-lining (selecting the same answer for all questions) or automated 'bot' activity, particularly in long surveys. ACQs ultimately improve the accuracy and validity of survey results.

How many hours are there in a day?

- ☐ 1
- ☐ 12
- ☐ 24
- ☐ 36

Which of the following is a fruit?

- ☐ Bed
- ☐ Apple
- ☐ Rabbit
- ☐ All of the above

Exploratory Factor Analysis – Factor Loadings

Item Description	Factor		
	1	2	3
My car monitors my driving performance and behaviour and provides assistance to make driving easier	0.954		
My car monitors my driving performance and behaviour and provides assistance to make my driving better	0.953		
My car monitors my driving performance and behaviour and provides advice to make my driving better	0.895		
My car monitors my driving performance and behaviour and provides advice to make my driving safer	0.879		
My car monitors my driving performance and behaviour and provides advice to make driving easier	0.869		
My car monitors me and my driving and provides information and suggestions that I might be interested in	0.821		
My car monitors me and my driving to determine if I could drive better	0.783		
My car uses AI to learn my driving behaviour and style	0.721		
My car advises me to look back at the road if I am distracted	0.578		
My car compares my current driving to previous journeys based on historical data	0.578		
Data about me and my driving is stored and analysed within my car	0.531		
My car will not let me start driving if I am over the legal alcohol limit		0.812	
My car switches off my phone if it detects that I am using it illegally while driving		0.771	
My car monitors if I am using my phone while driving		0.747	
My car monitors me and my driving to determine if I have been drinking and am unsafe to drive		0.727	
My car advises me to stop using my phone while driving		0.726	
My car uses a breathalyser to determine if I have been drinking		0.683	
My car monitors me and my driving to determine if I am too tired to drive safely		0.504	
My car shares data on my driving behaviour with my family and friends			0.808
My car shares data on my driving behaviour with my insurance company			0.675
My car monitors my behaviour away from the car (e.g. at a pub) and then makes assumptions about my fitness to drive			0.645
Data about me and my driving is stored and analysed in 'the cloud'			0.604
My car shares data on my driving behaviour with the vehicle manufacturer			0.603
My car shares data on my driving behaviour with my insurance company			0.597
Data on my driving is stored for a long time so it can be analysed for trends in behaviour			0.576
My car shares data on my driving behaviour with the DVLA			0.572

The table shows which items contribute to (or load onto) each of the 3 factors. In other words, which items participants intrinsically grouped together. The numerical values, which can range from -1.0 to 1.0, show the strength and direction of the relationship between each specific observed item and the underlying factor. A value closer to 1.0 or -1.0 is considered high and indicates the responses to that item strongly influence the overall factor. As a rule of thumb, a loading above 0.3 or 0.4 is generally considered significant. Determining which factors are important – and therefore how many to extract during the analysis – means that some items do not exist in the proposed model. This is common and is because they do not share enough common variance with other items, resulting in low correlations.



The Royal Automobile Club Foundation for Motoring Ltd is a transport policy and research organisation which explores the economic, mobility, safety and environmental issues relating to roads and their users. The Foundation publishes independent and authoritative research with which it promotes informed debate and advocates policy in the interest of the responsible motorist.

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