Putting the Focus on Drivers: Exploring Public Understanding of Driver Monitoring Systems

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SUMMARY

Driver monitoring systems (DMS) are increasingly embedded in modern vehicles and safety assessment frameworks, yet little is known about how drivers themselves understand these systems and how their beliefs shape usage, trust and acceptance. Ten focus groups (n = 30 UK drivers, aged 20–79) were conducted in which pictorial storyboards depicting five generic driver monitoring scenarios (fatigue, distraction, cognitive decline, intoxication and data privacy) were shown to participants, who were then asked to discuss *what* they thought was happening, *how* they thought it was happening, and *why* they thought it was happening. Findings suggest that drivers perceived DMS as socio-technical systems shaped by behaviour, context, interface design and data governance, with acceptance driven more by trust, autonomy and expectations than detection accuracy. Drivers highlighted fluctuating states and subjective self-assessment, indicating binary "fit/unfit" judgements poorly reflect real-world driving. Transparent, advisory and explainable systems were favoured, while opaque inferences, intrusive monitoring and unclear data use reduced trust. Findings will be used to inform the design of a large-scale survey to measure acceptance.

KEYWORDS

Driver monitoring systems, public understanding, focus group study, AI-generated storyboards

Background

Driver monitoring systems (DMS) are commonly considered with respect to novel technological innovations and are therefore typically associated with modern camera-based systems that measure driver attention to support emerging levels of vehicle automation and new driver control and assistance systems (DCAS). Indeed, DMS now feature in safety assessment programmes, such as EuroNCAP, which mandates that all new cars must include systems that warn about drowsiness and distraction in their Safe Driving Driver Engagement Protocol (see: EuroNCAP, 2024). As a consequence, DMS have attracted substantial research attention across domains, including human factors, computer vision and artificial intelligence (e.g. Öztürk et al., 2026).

Nevertheless, rudimentary DMS (such as seatbelt sensors) have existed since the early 1970s. Moreover, the idea of 'monitoring drivers and their driving behaviour' extends far beyond the use of regulated, closed-loop camera-based systems, with modern automobiles collecting reams of data about drivers and their driving behaviour (Are, 2023). DMS are therefore likely to differ significantly in the type and amount of data they collect and the level of support they offer. For example, simple fatigue detection systems have traditionally displayed a 'coffee cup' icon on the dashboard as a gentle reminder to the driver that they should take a break – typically appearing after their journey time has exceeded a predefined duration. In contrast, current state-of-the-art DMS use driver-facing cameras and complex AI-algorithms to monitor and analyse eye movements, head position and gaze behaviour to determine if the driver is drowsy or distracted, and subsequently may only permit drivers to use certain driving systems when they can demonstrate that they are fully attentive to the road and continue to remain so (see: www.ford.co.uk, n.d.).

There is also increasing interest in user-centred, ‘smart’ vehicle interiors that profess to monitor drivers’ mood and wellbeing, and even promises of systems that can detect the early signs of neurodegenerative illnesses, such as Alzheimer’s disease or Parkinson’s disease (Baraniuk, 2021). Naturally, the greater the perceived capability of monitoring technology, the greater the depth and quantity of driver-related data which needs to be acquired and analysed: this raises important ethical, moral and legal questions about what data *could* and, more importantly, *should* be captured about drivers and their car. It has also created an extremely complex and confusing DMS landscape for drivers, who may not be fully aware of what data are being collected; how these data are being captured; where they are being stored and analysed; how they are being interpreted; and what information, support or intervention may be forthcoming. Drivers may therefore inadvertently (or even intentionally) rely upon a DMS to support them in a manner for which for was neither intended nor designed, chose to disregard or override its advice at inopportune moments, or carelessly agree to the sharing and repurposing of sensitive personal data with third parties.

The current lack of understanding and transparency has important implications for trust, system acceptance and appropriate reliance, but to evaluate this further, we must first understand precisely what drivers believe is happening. To capture drivers’ tacit knowledge and current understanding of DMS, we conducted a focus group study, with the ultimate aim of informing the design of a large-scale survey to measure acceptance.

Method

To explore drivers’ understanding of DMS, we needed to explain various monitoring concepts while avoiding biasing participants’ responses. Using terms such as “fatigue monitoring” or referencing specific technologies, such as a driver-facing camera, might influence participants when asked to consider what was happening. As a consequence, no specific systems, brands or technologies were mentioned. Instead, generic visual storyboards were created to show unfolding driving situations, including the context, aberrant driver behaviour and the resulting advice or intervention; this also allowed us to explore future use-cases, such as prohibiting access to the vehicle if the driver was deemed to be intoxicated – a scenario for which no commercial system currently exists.

Inspired by related research (see: Harvey et al., 2026), generative AI (ChatGPT) was used to produce these visual prompts. The storyboards avoided showing specific monitoring terminology and used third-person language (where required), to reduce superiority bias – people overestimating their driving abilities – and social desirability bias, whereby participants report attitudes or behaviours they believe others will view favourably. Five storyboards were subsequently created, depicting; driver fatigue, driver distraction, cognitive decline, driver intoxication and data privacy violation (see: Figure 1). Each storyboard was shown in turn to participants. The scenarios were presented in the order in which they are introduced above, and this remained the same during each focus group to support narrative and cognitive flow. In other words, the use-cases were selected to represent increasingly futuristic and potentially controversial applications. The earlier storyboards – depicting contemporary applications – therefore set context for the later ones, and by considering current, less contentious applications first, we aimed to avoid any emotional carryover from the more contentious examples. The scenarios were designed to convey clear and distinct concepts. However, if participants misinterpreted aspects of 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 extreme cases, participants were encouraged to reconsider the scenario.

For each storyboard, participants were asked a series of questions, inspired by the critical decision method (CDM) interview probes (Klein et al., 1989). Essentially, these were used to uncover *what* participants thought was happening, *how* they thought it was happening, and *why* they thought it is happening. Focus groups were either conducted in person or online using MS Teams, with MS Teams used to record and transcribe the dialogue in all situations. Each focus group lasted approximately 1½ hours, and each participant received a £20 online shopping vouchers for taking part. The study design was approved by the University of Nottingham Faculty of Engineering ethics committee.

Figure 1: Storyboards used during focus groups, showing (clockwise from top left): driver fatigue, driver distraction, driver intoxication, data privacy violation and cognitive decline

Participants

Thirty participants were recruited to take part using purposive sampling (in particular, to target older and younger drivers). Participants were distributed across 10 focus groups based on their age profile, effectively differentiating older and younger age cohorts. The mean age across all participants was 42.4, with ages ranging from 20 to 79. 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. Participants indicated limited prior experience with DMS or driver control and assistance systems (DCAS); only six described specific technologies. Two had a vehicle "black box" that rated fatigue, speed, time of day and smoothness after journeys. One reported a lane-departure warning sensor, and another had only heard of ADAS fatigue-detection systems tracking steering, blinking, and head movement. One participant, who stated their profession as a delivery driver, said they used vans equipped with trackers, cameras and sensors monitoring speed and braking.

Analysis and Results

Dialogue was automatically transcribed by 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 being 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 & Clark, 2006). Using this approach, three human factors 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 rubric. The final themes are below. Each of these themes had several subthemes and coding elements (Table 1).

Table 1: Main themes and first-level subthemes describing drivers' understanding of DMS

Main Theme	Subtheme	Further Details
Driver physiological and affective state	• Physical and Medical Condition • Cognitive and Psychological State • Perceived Capability and Readiness to Drive	Transient physical, cognitive and affective states influencing driving capability and self-assessment
Contextual Factors Shaping Understanding	• Contextual & Situational Factors associated with the Journey • Driver State and Personal Circumstances • Vehicle & System Factors	Situational, personal, environmental and vehicle-related moderators of driver behaviour and system perception
Attitudes Toward DMS Concepts and Scenarios	• Understanding, Purpose, and Functional Framing of DMS • Control, Autonomy and Governance of Use • Risks, Consequences, and Ethical-Societal Concerns	Trust, perceived control, autonomy and moral alignment with DMS intervention concepts
Driver Monitoring and Inferred States	• Driving Behaviour and Vehicle Control Performance • Attention, Interaction and Task Engagement • Physiological and Affective Driver State • Contextual, Identity and Data Ecosystem Factors	Physiological, behavioural and contextual signals used to infer driver capability and intent

Main Theme	Subtheme	Further Details
Human–machine interface and intervention design	• Feedback Philosophy and System Role • Feedback Design, Delivery and System Intelligence • Perceived Effectiveness, Usefulness and Need • User Experience, Trust and Perceived Risks	Design of information, alerts and interventions that affect trust, workload and emotional response
Driver Response to Monitoring, Feedback and Intervention	• Driver Engagement and Attitudes Toward Assistance • Driver Interpretation and Judgement of System Alerts • Behavioural Adaptation and Performance Outcomes • Learning, Skill Development and Capability Building	Adaptive and learning-related responses to system feedback
Data governance, interpretation and secondary use	• Data Governance and Control • Benefits and Value of Data Use • Risks, Ethics and Fairness • Contexts of Data Application	Perceived risks and benefits of data collection, ownership and downstream use
System-Level Trust, Fairness and Reliability	• Perceptions of the System • Ethics, Agency and Responsibility • Value and Practical Trade-Offs • Social and Contextual Influences	Overall evaluations of system competence, equity and role allocation
Human-Centred Expectations and Boundaries for Driver Monitoring Systems	• Adaptive and Responsive System Functions • Safety Enforcement and Intervention • Feedback and Behaviour Change • Transparency and Acceptable Limits	Drivers' expectations regarding adaptive support, authority and transparency
Driver Engagement, Use and Adaptation to Driver Monitoring Systems (DMS)	• Acceptance, Adoption and Willingness to Use • Trust, Reliability and Accuracy • Interaction and Compliance • Perceived System Experience	Drivers are not passive users; they experiment, resist, rely, ignore and negotiate their relationship with the system over time
Perceptions of Other Drivers' Acceptance and Use of DMS	• Driver Demographics and Characteristics • Perceptions and Attitudes Toward Monitoring • Driver Acceptance and Compliance • Perceived Effects of DMS on Drivers	DMS acceptance is shaped not just by individual usability, but by identity, norms, stigma, fairness and perceived legitimacy

Discussion

The aim of the focus group study was to uncover drivers' tacit knowledge and current understanding of DMS to inform the design of an online survey to measure acceptance. 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 appear to depend less on detection accuracy than on compatibility with drivers' expectations, values and lived experiences.

Participants highlighted that driver physiological and affective state plays a central role in perceived driving capability and openness to DMS. Transient conditions such as fatigue, emotional distress, confusion, somatic discomfort and sensory or attentional degradation were commonly described as influencing both actual driving performance and drivers' self-assessment of fitness to drive. Importantly, participants emphasised uncertainty and fluctuation in these states, with several describing a subjective sense of "not feeling right" rather than any clearly defined impairment. These findings suggest that binary system judgements of "fit" versus "unfit" to drive are poorly aligned with drivers' lived experiences. From a human factors perspective, DMS feedback and logic should therefore accommodate ambiguity, support self-awareness and reflect the graded and dynamic nature of driver state.

Closely related to driver state were participants' cognitive appraisals and self-assessments, including their interpretations of both their own capabilities and the role of the DMS. Drivers' mental models of system capability, limitations and authority strongly shaped their understanding and anticipated acceptance and compliance. Misalignment between a driver's self-assessment and system feedback was viewed as particularly problematic, especially where system boundaries were unclear. These findings underline the importance of providing feedback that makes system limits visible and calibrates system authority relative with the driver's own judgement.

Participants also described a wide range of contextual factors that moderate both driving behaviour and their understanding of and potential acceptance of DMS. These included situational factors preceding a journey, driver goals and preferences, current psychophysiological state, journey characteristics, broader life stress factors, vehicle condition and environmental conditions. Acceptance was seen as highly context dependent, with the appropriateness of monitoring, advice or intervention varying across situations. This highlights the need for context-sensitive DMS logic and timing of feedback.

Observable driver behaviour and driving performance were generally accepted as relevant inputs for a DMS, but only insofar as monitoring and subsequent advice or intervention were perceived as fair, meaningful and actionable. Participants were resistant to behavioural monitoring that felt punitive or judgemental, particularly when removed from contextual explanation. This suggests that acceptance would likely depend not merely on what behaviours are monitored, but on how those behaviours are interpreted and acted upon by the system.

Attitudes toward DMS concepts and intervention scenarios revealed tensions around trust, autonomy, responsibility and moral alignment. Concerns about intrusion, data privacy and loss of autonomy coexisted with conditional optimism about the technology's potential safety benefits. Participants expressed a clear preference for systems that act as advisory supports rather than authoritative decision-makers, and for system adoption to be voluntary rather than mandatory. Transparency and keeping the human-in-the-loop were repeatedly emphasised as prerequisites for acceptance.

With respect to driver monitoring and inferred states, participants made a clear distinction between directly measured data (e.g. speed, steering input) and higher-level inferences (e.g. emotion, intent, fitness to drive). Acceptance is consequently expected to be lower where inferences were perceived as opaque, disproportionate or poorly justified. Explainability and perceived relevance therefore emerge as key determinants of trust. From a human factors perspective, systems must carefully manage how inferred states are communicated and acted upon.

Participants' responses to human–machine interface (HMI), feedback and intervention design suggest an emotional and social dimension to system interaction. Feedback tone, modality, timing and persistence all influenced whether feedback was perceived as supportive or insulting. Escalation strategies and automation takeover were particularly sensitive areas, with poorly timed or overly forceful interventions seen as potentially counterproductive or even harmful. These findings reinforce the need for respectful, proportionate and context-aware feedback design.

Concerns surrounding data governance, interpretation and secondary use were pervasive and are expected to be strongly linked to acceptance. Participants expressed apprehension about data sharing, algorithmic interpretation, insurance and legal consequences, commercial exploitation, workplace surveillance and discrimination. While some recognised safety and emergency-response benefits, acceptance is likely to be contingent on clear purpose limitation, transparency and user-controlled consent.

At a system level, participants interpreted DMS in terms of trust, fairness, reliability and role allocation. Perceptions of accuracy, robustness, inclusivity and appropriate distribution of responsibility between the driver and the system are therefore likely to impact on acceptance. Systems that appear to claim final authority without visibly handling uncertainty were viewed sceptically. These findings indicate that trust is not binary but must be calibrated and resilient, suggesting the need to go beyond simple yes/no ratings for trust and acceptance.

Participants also reflected on behavioural adaptation and compliance, noting that DMS could potentially support learning, skill development and safe recovery if feedback was framed constructively. However, systems perceived as judgemental or punitive risked disengagement, misuse or resistance. This highlights the importance of designing DMS as learning-oriented supports rather than evaluative tools.

Finally, expectations regarding desired system roles, anticipated personal use and social norms frequently featured in discussions; these are also likely to affect acceptance. Participants articulated preferences for advisory over enforcing systems, concerns about over-reliance and loss of skill, and conditional willingness to comply based on experience and familiarity. 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. These findings highlight that acceptance is likely to be dynamic, socially situated and influenced by first-hand experience.

Development of Survey

A further 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 seminal Technology Acceptance Model (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 achieve this, we translated the qualitative focus-group insights into measurable survey constructs, retaining as much of the language used by 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, for example, *"My car monitors me and my driving to determine if I am too tired to drive safely"*. Survey respondents were then asked to indicate the level of acceptability they associated with each of the statements, with their response captured on a 5-point Likert scale 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. Given the diversity of statements, this also enabled us to analyse acceptance at different levels of system authority.

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 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 provides a 'threshold of acceptability', which represents 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. Work on the survey is ongoing, and findings will be reported in subsequent papers.

Conclusion

The focus groups uncovered valuable insights about drivers' 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 surrounding conditions continually fluctuate. Participants viewed rigid, authoritative or opaque systems as poorly aligned with lived driving experiences, particularly where system judgements conflicted with personal judgement or ignored uncertainty and context. In contrast, DMS that 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, are likely to invite the highest level of trust and acceptance. From a human factors' 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 also translated into questionnaire prompts to evaluate driver acceptance of DMS in a large-scale online survey, focussing on distinct functional roles – revealed by the focus group study – rather than measuring acceptance of DMS as a single technology.

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