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Integrating Human-Centred Design Approach Into the Safety Assurance of CCAM Systems: A Framework for STAC

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ABSTRACT

The development of Connected, Cooperative, and Automated Mobility (CCAM) systems has focused on technical safety, but safety alone does not ensure adoption. Users need systems that align with their needs, preferences, and expectations. The European project CERTAIN addresses this by integrating Safety, Trust, Acceptance, and Comfort (STAC) into a user-centred design (UCD) framework across the CCAM lifecycle. This work applies UCD to Human–Machine Interfaces (HMI), defining STAC-related KPIs, scenarios, and use cases across automation levels (L2–L4), including mixed-level configurations and L4 delivery pods. A systematic literature review and stakeholder interviews refine STAC KPIs capturing human perceptions, behaviours, and needs. The UCD process operationalizes STAC dimensions iteratively in design and evaluation, emphasizing inclusivity, accessibility, and diverse cultural contexts. Three HMI use cases—complete journeys, unscheduled handovers, and software updates—test STAC KPIs in context, combining subjective (perceived safety, trust, comfort, acceptance) and objective (behavioural adaptation, trust calibration) measures. Grounded in human factors, this framework guides the design of HMIs that are not only technically safe but also perceived as safe, trustworthy, acceptable, and comfortable, supporting adoption and societal alignment of CCAM systems.

Keywords: Human–machine interaction, Safety, Trust, Acceptance, CCAM, Human factors, STAC

INTRODUCTION

Connected, Cooperative and Automated Mobility (CCAM) promises to transform European transport systems by enhancing road safety, efficiency, sustainability, and accessibility. Automated driving systems have been shown to have the potential to reduce traffic accidents by mitigating human error, which is implicated in the vast majority of road collisions. They are therefore aligned with the European Union's Vision Zero ambition of eliminating serious injuries and fatalities from road transport.

Despite advances in automation technology, technical safety performance alone is insufficient to guarantee successful deployment and societal benefit. Research on advanced driver assistance systems and automated vehicles consistently shows that human perceptions including perceived safety, trust, and acceptance are critical determinants of whether users are willing to adopt and rely on these technologies. For example, perceived safety and trust have

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been demonstrated to influence intentions to use automated systems, with higher trust associated with lower perceived risk and greater acceptance.

Moreover, perceived risk and trust are not fixed traits but are shaped by user experience, transparency of system behaviour, and system communication with users.

In this context, the Horizon Europe project CERTAIN adopts a resilient and continuous safety assurance methodology for CCAM that explicitly prioritises four interrelated human-centric dimensions: Safety, Trustworthiness, Acceptance, and Comfort (STAC), across the lifecycle of CCAM systems. This approach recognises that users' perceptions and experiences with automation are central to real-world safety outcomes, as they affect user interaction, reliance, and ultimately the effectiveness of automated functions.

However, operationalising these human-centric aspects remains challenging due to the lack of agreed definitions, measurable KPIs, and validated evaluation methods across STAC dimensions. This paper addresses that gap by presenting a methodology for defining STAC dimensions and their associated KPIs within CERTAIN. We describe how collaborative exercises with human factors experts and structured triangulation of objective, physiological, and subjective measures were used to derive robust KPI sets. The resulting framework aims to support CCAM system designers and evaluators in developing systems that are not only technically safe, but also trusted, accepted, and comfortable for users — thereby enhancing the likelihood of meaningful deployment and contribution to European road safety and mobility goals.

Definition of STAC

STAC is used in this work as an overarching framework to structure the assessment of automated driving systems from a human-centred perspective. Before detailing each dimension individually, this section clarifies what is meant by STAC in the context of the project CERTAIN and how its dimensions are conceptually defined and delimited. Given the diversity of automated driving use cases, STAC is not treated as a fixed or purely theoretical construct, but as a flexible framework whose dimensions must be interpreted and operationalised in relation to specific system characteristics, operational contexts, and human–system interactions. The following subsections therefore define each STAC dimension, outline its scope, and explain how it is translated into measurable constructs and indicators relevant for subsequent evaluation activities.

SAFETY

Safety in automated driving systems refers to the system's ability to operate without causing harm while maintaining acceptable levels of risk across its intended operational conditions. In line with the system-oriented safety vision promoted by the NHTSA (2017), safety goes beyond collision avoidance to encompass the reliable detection and mitigation of hazards, appropriate system responses to unexpected situations, and the protection of both vehicle occupants and other road users. Safety is therefore not limited to technical performance alone but also depends on how consistently and robustly the system behaves across different traffic scenarios, environmental conditions, and operational contexts. Safety manifests through both technical performance—including reaction time, event detection, and failure management—and operational integrity, which reflects how safely the system behaves in mixed traffic and under various weather or road conditions. The framework makes a crucial distinction between perceived safety and objective safety: while objective safety relies on aggregated statistics such as accident rates, perceived safety (PS) captures how secure individuals actually feel in the automated environment (Syropoulos et al., 2024).

ACCEPTANCE

Acceptance represents the user's willingness and intention to adopt and regularly use an automated system, reflecting the critical transition from technological capability to real-world integration into daily driving routines. Rooted in established technology adoption frameworks, acceptance is shaped by multiple interrelated determinants that collectively influence whether users embrace automated driving (Davis, 1989). Perceived usefulness—the belief that the system genuinely enhances driving performance and provides meaningful benefits—stands alongside perceived ease of use, which reflects how intuitive and effortless the system is to interact with (Davis, 1989; Mir, 2025). These foundational elements intertwine with satisfaction, trust, and perceived safety to create a comprehensive evaluation of system value (Van der Laan et al., 1997; Choi & Ji, 2015).

COMFORT

Comfort encompasses the user's comprehensive physical and psychological state of well-being while experiencing automated driving systems, representing a holistic measure of how pleasant and stress-free the journey feels (Nilsson, J., et al, 2017). This multidimensional construct divides into physical and psychological components that together determine overall user satisfaction. Physical comfort addresses tangible bodily experiences including vehicle motion characteristics, acceleration and jerk profiles, seating posture, noise and vibration levels, climate control, interior design aesthetics, and critically, the prevention or minimization of motion sickness—a challenge that intensifies as passengers shift from active driving to passive observation. Psychological comfort captures the mental and emotional dimensions of the experience: feelings of relaxation, absence of stress or anxiety, sense of safety, and trust in the system's capabilities.

METHODOLOGY

The identification of KPIs followed a structured and iterative methodology grounded in the STAC framework. The process began with a collaborative workshop using the platform Miro during which project partners were invited to define each STAC dimension: Safety, Trustworthiness, Acceptance, and Comfort, using a post-it–based brainstorming exercise. Participants then identified relevant KPIs for each dimension based on existing literature and experience, currently available indicators, and areas requiring further exploration. This initial set of KPIs was subsequently consolidated and reviewed during two dedicated meetings involving human factors experts, allowing for critical discussion and refinement.

Human Factors Constructs

To support systematic analysis and facilitate interpretation, human factors constructs were introduced to organize the KPIs into coherent groups. Five Human factors constructs were retained and defined: Situation Awareness, Acceptability, Automation Surprise, Cognitive Load and Mode Awareness. For each HF construct, the relationships with the STAC dimensions were explicitly defined by distinguishing between direct and indirect links. For example, Cognitive Load was identified as being directly related (**++**) to Safety, while also being indirectly (**+**) associated with Acceptance, Trustworthiness, and Comfort.

Table 1: The link between the STAC and the HF constructs.

STAC / HF constructs	Safety	Trustworthiness	Acceptance	Comfort
Situation Awareness	++	+	+	+
Cognitive load	++	+	+	+
Acceptability	+	++	++	+
Mode Awareness	++	+	+	+
Automation Surprise	++	++	++	++

Situation Awareness

Situation Awareness is defined as "*the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future*" (Endsley, 1995). This model distinguishes three interrelated levels of SA:

- Level 1 – Perception
- Level 2 – Comprehension
- Level 3 – Projection

In automated and AI-driven mobility systems, users rely heavily on the Human–Machine Interface to build and maintain adequate Situation Awareness across all three levels. Consequently, user needs cannot be limited to information provision alone, but must be understood in relation to how information supports perception, comprehension and projection. Situation

Awareness (SA) is evaluated through multiple KPIs. SA accuracy measures the driver's understanding of the driving environment, assessed through correct responses to situational questions. Situational trust reflects the level of confidence the driver places in the automated vehicle's performance and reactions during specific driving events. Explanation satisfaction captures how clear, detailed, and helpful the provided explanations are perceived by the driver. Finally, mental workload evaluates the cognitive effort required to process the explanations while maintaining attention to the driving task (Avetisyan et al., 2022).

Mode Awareness

Mode awareness refers to the driver's ability to correctly perceive, understand, and anticipate the current and future operational state of an automated vehicle, including its level of automation, system capabilities, and authority boundaries. In the context of automated driving, automation is designed to reduce human error, which accounts for approximately 75% to 94% of road traffic accidents (Medina et al., 2004; Singh, 2015). Automated vehicles support drivers across different levels of automation, from full manual control to high automation, making accurate awareness of the active mode essential for safe interaction (Hoeger et al., 2011; SAE International, 2016). Although automation can reduce driver workload, it may negatively impact situation awareness when the driver becomes a passive monitor, limiting their ability to detect changes in system state and environmental conditions (Bainbridge, 1983; Endsley, 1996; De Winter et al., 2014). A lack of mode awareness can result in mode confusion, a phenomenon for which multiple definitions exist. KPIs used to assess mode awareness include the mode confusion rate, defined as the percentage of events in which the driver's predicted mode differs from the actual system mode (Eom & Lee, 2022); recognition accuracy, measuring how accurately drivers identify the active mode with or without consulting the HMI (Eom & Lee, 2022); reaction time, capturing the delay in responding to system requests or critical events (Miller et al., 2014); and subjective measures collected through 5-point Likert scales assessing trust, safety, convenience, workload, and overall satisfaction (Eom & Lee, 2022; Miller et al., 2014).

Cognitive Load

Cognitive Load refers to the amount of mental resources required to process information, make decisions, and execute actions in a given task (Vasta & Biondi, 2025). In the context of partially automated driving (Level 2 systems), cognitive load can be influenced by the shift from active manual control to a supervisory role. While automation may reduce continuous operational demands, supervising the system can itself generate high cognitive effort, particularly when drivers engage in non-driving-related tasks (NDRTs) or encounter unfamiliar system behavior (Vasta & Biondi, 2025). Meta-analytic evidence suggests no significant overall difference in cognitive load between manual and partially automated driving, indicating that both modes can impose comparable mental demands (Vasta & Biondi, 2025). To evaluate cognitive load, researchers often rely on KPIs, which serve as measurable proxies for mental effort. Examples include visual behavior metrics, such as Total Eyes-Off-Road Time (TEORT), gaze distribution, or glance frequency toward critical versus non-driving areas; NDRT engagement, capturing the likelihood and duration of secondary task involvement; and workload measures, including performance on secondary tasks (e.g., Detection Response Task, DRT) and physiological indicators like heart rate variability or pupil dilation (Vasta & Biondi, 2025). These KPIs illustrate common approaches, but they do not represent an exhaustive set, other behavioral, subjective, and neurophysiological measures can also be employed depending on the research objectives and experimental context.

Acceptability

Acceptability refers to a prospective evaluation of a technology, reflecting how potential users anticipate its usefulness, ease of use, and overall value before they have direct experience with the system (Distler, 2018; Riener et al., 2022). It captures expectations and attitudes formed during the early stages of technology introduction. In contrast, acceptance relates to users' judgments, attitudes, and behavioral responses after interacting with the technology, once experience has informed their perceptions and use patterns (Riener et al., 2022). The literature often describes this progression as a transition from initial expectations to actual use and, ultimately, to longer-term integration into everyday practices, a process commonly referred to as technology appropriation (Distler, 2018). Different models with different KPIs explain technology adoption through constructs including perceived usefulness, perceived ease of use, social influence, and facilitating conditions (Davis, 1989; Venkatesh et al., 2003).

Automation Surprise

Automation Surprise refers to situations in which an automated system behaves in a way that differs from the human operator's expectations. Researchers have examined expectation mismatches in semi- and highly automated driving, highlighting the role of attention, intervention timing, and system feedback (Hurts & de Boer, 2015; Dong et al., 2024; Kim et al., 2025). Automation surprise is now often operationalized as a measurable interaction outcome, including mode confusion, delayed interventions, or failures to detect system transitions.

Automation surprise is operationalized via different KPIs :The frequency and Severity Scores: Fraction of events where automation surprise occurs, and severity scales ranging from no consequences to major safety-critical outcomes (Hurts & de Boer, 2015). Behavioral Metrics: Visual attention allocation, such as eyes-off-road time or fixation on non-driving-related areas during unexpected system behaviors (Dong et al., 2024). Intervention Metrics: Response times to critical system prompts or required driver interventions following an automation surprise (Kim et al., 2025; Tivesten et al., 2019). Subjective Measures: Self-reported feelings of confusion, uncertainty, or surprise during system operation (Rushby, 2002; Rankin et al., 2016).

CONCLUSION

The STAC framework is composed of four major dimensions, each encompassing multiple human factors (HF) constructs. Ensuring the robustness of the STAC requires that the HF constructs associated with each dimension are thoroughly assessed using appropriate KPIs. For instance, to evaluate whether a system can be considered trustworthy, it is essential to verify that the driver exhibits adequate situation awareness, maintains accurate mode awareness, experiences a balanced cognitive load and perceives the system as acceptable. By systematically measuring these constructs through validated KPIs, researchers and practitioners can obtain a comprehensive understanding of the system's human-centered performance and safety. The framework provides the methodological foundation necessary to design, evaluate, and improve CCAM systems that users will not only find technically capable but will genuinely trust, accept, and integrate into their daily lives. As automated mobility transitions from controlled testing environments to complex real-world deployments, the STAC framework offers essential guidance for ensuring that these transformative technologies deliver on their promise of safer, more efficient, and more accessible transportation while maintaining the human-centered focus necessary for widespread societal adoption and lasting positive impact. This approach ensures that subsequent evaluations are both evidence-based and closely aligned with actual user requirements, enhancing the relevance and applicability of the STAC framework in real-world automated driving scenarios.

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