Reducing Cognitive Overload in Highly Automated Vehicles through Adaptive HMI Strategies

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Abstract:

Highly automated vehicles are increasingly integrating advanced driver assistance and autonomous capabilities, shifting the role of the human from active operator to passive supervisor. While this transition improves convenience and safety, it can also introduce cognitive overload when drivers are required to monitor complex interfaces, respond to system handovers, or interpret multiple streams of vehicle information. This paper explores adaptive Human–Machine Interface (HMI) strategies designed to reduce cognitive burden and enhance situational awareness in highly automated driving environments. The proposed approach emphasizes dynamic interface customization based on driver state, driving context, and system automation level. By leveraging real-time monitoring techniques such as eye tracking, behavioral analysis, and workload estimation, the HMI can selectively filter, prioritize, and present information in a simplified and context-aware manner. Additionally, multimodal interaction methods including visual, auditory, and haptic feedback are employed to ensure critical alerts are communicated effectively without overwhelming the user. The findings suggest that adaptive HMI systems can significantly improve user comprehension, reduce reaction time during transitions of control, and enhance overall trust in automated driving systems. However, challenges remain in ensuring system reliability, minimizing distraction caused by adaptation itself, and maintaining consistency across different driving scenarios. Overall, adaptive HMI strategies represent a promising direction for improving human experience and safety in next-generation highly automated vehicles.

Key words:

Highly Automated Vehicles, Cognitive Overload, Adaptive Human–Machine Interface (HMI), Driver State Monitoring, Situation Awareness,

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Autonomous Driving, Multimodal Interaction, Human Factors, Workload Estimation, Autonomous Vehicle Systems.

1.0 Introduction

The rapid development of highly automated vehicles has transformed the role of the human driver from an active controller to a passive supervisor of automated systems. As vehicles increasingly handle perception, decision-making, and control functions, drivers are expected to monitor system performance, remain attentive, and intervene when necessary.[1] However, this shift introduces new human–machine interaction challenges, particularly cognitive overload, where excessive or poorly structured information can exceed the user's mental processing capacity. This condition may lead to delayed reactions, reduced situation awareness, and decreased trust in automation.[3]

In highly automated driving environments, drivers are often required to interpret complex interface displays, respond to system alerts, and manage transitions between different levels of automation. When these interactions are not properly designed, they can contribute to confusion and increased mental workload, especially during critical driving situations. [2]Therefore, maintaining an optimal balance between information delivery and user comprehension becomes essential for ensuring safety and usability.

Adaptive Human–Machine Interface (HMI) strategies have emerged as a promising solution to address these challenges. Unlike traditional static interfaces, adaptive HMIs dynamically adjust the presentation of information based on real-time driver state, environmental conditions, and system requirements. By tailoring information flow and using intelligent feedback mechanisms, these systems aim to reduce unnecessary cognitive demands while ensuring that essential information remains accessible.

This paper explores the concept of reducing cognitive overload in highly automated vehicles through adaptive HMI strategies. It highlights the importance of human-centered design principles and discusses how intelligent interface adaptation can improve driving performance, enhance situational awareness, and support safer human–vehicle interaction in future autonomous mobility systems.

2.1 Driver Cognitive Load Assessment

Driver Cognitive Load Assessment in the context of reducing cognitive overload in highly automated vehicles refers to the systematic measurement and interpretation of

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a driver's mental workload during interaction with advanced automation systems.[5] In highly automated driving environments, drivers are not continuously engaged in manual control but are required to monitor system status, interpret alerts, and respond appropriately during takeover situations. To ensure that the Human–Machine Interface (HMI) adapts effectively, real-time cognitive load assessment is essential.

This is achieved by analyzing multiple physiological and behavioral indicators such as eye gaze patterns, pupil dilation, blink frequency, steering micro-corrections, reaction time delays, and heart rate variability.[7] These parameters provide insights into the driver's attention level, fatigue state, and mental effort required to process incoming information. Advanced systems may also integrate machine learning models to fuse these signals and estimate cognitive workload more accurately under varying driving conditions.

By continuously evaluating driver state, the system can identify moments of high mental demand and trigger adaptive interface responses, such as simplifying displayed information or prioritizing critical alerts. This enables the HMI to maintain an optimal balance between automation support and human awareness, thereby reducing cognitive overload and improving overall driving safety.

2.2 Information Prioritization Mechanism

Information Prioritization Mechanism in highly automated vehicles refers to the structured process of classifying, filtering, & presenting vehicle-generated information based on its relevance and urgency to the driver's current cognitive state and driving context.[4] Since automated driving systems continuously generate multiple alerts, notifications, and status updates, presenting all information simultaneously can significantly increase cognitive demand and contribute to overload.[7] To address this, the mechanism assigns priority levels—typically critical, important, and non-essential—to incoming data such as collision warnings, system handover requests, navigation updates, and infotainment messages.[3]

Critical information, such as imminent safety threats or takeover requests, is delivered immediately using high-salience multimodal cues, while lower-priority information is delayed, simplified, or temporarily suppressed during high workload conditions. The prioritization process is dynamically controlled by integrating real-time inputs from driver monitoring systems and vehicle sensors, ensuring that only contextually

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relevant information is presented at any given moment.[8] This adaptive filtering approach reduces unnecessary visual and cognitive distractions, allowing the driver to focus on essential driving-related cues. Ultimately, the mechanism enhances situational awareness, supports faster decision-making during transitions between automation levels, & plays a key role in minimizing cognitive overload in highly automated driving environments.

2.3 Adaptive Interface Design

Adaptive Interface Design in highly automated vehicles refers to the development of intelligent Human–Machine Interfaces (HMIs) that dynamically modify how information is presented to the driver based on real-time cognitive state, driving context, and system automation level. Unlike static interfaces that display fixed information regardless of user condition, adaptive interfaces continuously adjust layout complexity, information density, and modality to prevent excessive mental workload. This is achieved by integrating data from driver monitoring systems, vehicle sensors, and environmental inputs to determine when the driver is under high cognitive demand or when the driving situation requires increased attention. Based on this assessment, the interface can simplify visual displays, highlight only safety-critical alerts, or shift certain information to auditory or haptic channels to reduce visual strain. Additionally, adaptive design may include scaling of font size, prioritization of dashboard elements, and suppression of non-essential notifications during critical driving phases such as takeover requests or complex traffic scenarios. Machine learning algorithms can further enhance this process by learning driver behavior patterns and predicting when cognitive overload is likely to occur. [8] Overall, adaptive interface design ensures that information delivery remains context-sensitive, reducing unnecessary cognitive effort while maintaining awareness of essential driving conditions and improving overall human–vehicle interaction efficiency.[11]

The figure titled “Adaptive Interface Design in Automated Vehicles”illustrates how an intelligent in-vehicle human–machine interface dynamically adjusts its display and information presentation based on the driver’s cognitive load. The central idea is that the vehicle continuously monitors the driver and surrounding context in order to

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optimize the amount and type of information shown, thereby improving safety, usability, and situational awareness.

At the top of the diagram are three key input sources that feed into the adaptive system: Driver Monitoring, Driving Context, and Environmental Data.[6] Driver monitoring refers to the system's ability to assess the driver's state, such as attention level, engagement, fatigue, or distraction, typically using cameras, sensors, or behavioral indicators. Driving context includes situational factors such as traffic density, road type (highway, urban, rural), speed, navigation complexity, and current driving mode (manual or automated). Environmental data encompasses external conditions like weather, lighting, road hazards, and the presence of pedestrians or other vehicles. Together, these inputs provide a comprehensive understanding of both the driver's internal state and the external driving environment.

These inputs feed into a decision-making process that determines whether the driver is in a Low Cognitive Load State or a High Cognitive Load State. Cognitive load refers to the mental effort required to process information and perform driving-related tasks. In a low cognitive load state, the driver is relatively relaxed, with sufficient attention resources available. In contrast, a high cognitive load state occurs when the driver is under stress, facing complex driving conditions, or required to respond quickly to critical situations.

The system's core mechanism is represented by Dynamic [12]Adjustment,shown as a bidirectional process between the two states. This indicates that the interface is not static; instead, it continuously adapts in real time as the driver's cognitive load changes. The goal is to present only the most relevant information in a manner that minimizes distraction and cognitive overload.

On the left side of the figure, under the Low Cognitive Load State, the vehicle's interface displays a Full Display along with Non-Critical Information. This includes richer visual content such as navigation maps, entertainment options, system status details, and other supplementary data. Because the driver has sufficient cognitive capacity, the system can afford to present more detailed information without overwhelming them. The outcome of this mode is Reduced Cognitive Overload, meaning the driver can comfortably process available information while maintaining awareness of the driving environment.

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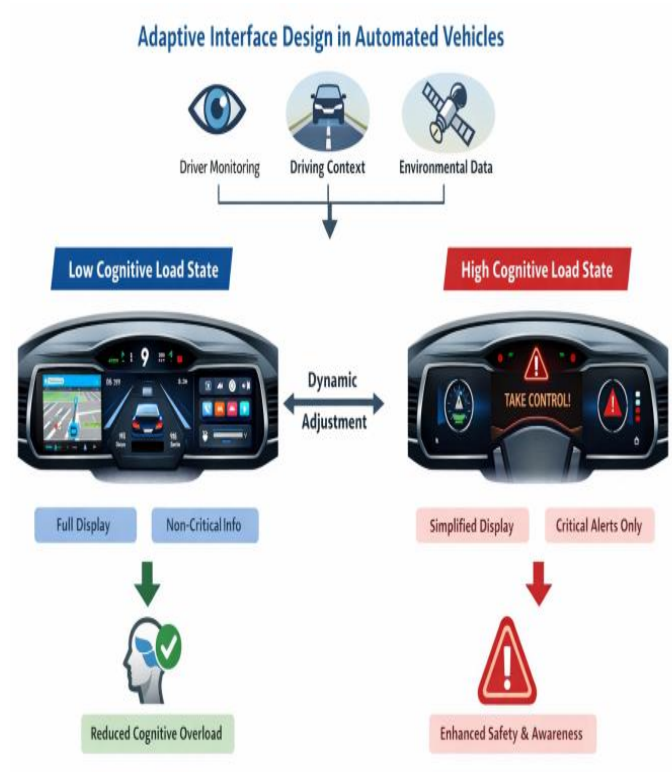
On the right side, under the High Cognitive Load State, the interface shifts to a Simplified Display showing Critical Alerts Only.[13] In this mode, non-essential information is suppressed to reduce distraction. The system prioritizes urgent notifications such as collision warnings, lane departure alerts, or immediate take-over requests. A prominent visual cue such as "TAKE CONTROL" indicates heightened urgency. This streamlined presentation supports rapid decision-making in stressful or complex driving conditions. The intended outcome here is Enhanced Safety and Awareness, ensuring the driver focuses only on the most important information needed for immediate action.

Overall, the figure demonstrates a closed-loop adaptive interface system in automated vehicles that enhances human–machine interaction. By continuously assessing driver state and environmental conditions, the system intelligently adjusts the interface complexity. This ensures that when cognitive demand is low, the driver benefits from richer information, and when cognitive demand is high, the system simplifies the display to prioritize safety-critical information. The result is a balanced approach that reduces cognitive overload while improving situational awareness and drivingsafety.



3.1 Workload-Aware Interface Adaptation

Systems monitor driver state using multimodal sensors (eye tracking, physiological sensors, steering inputs) to estimate workload and attention. [8] This is often modeled using theories such as Cognitive Load Theory.

Real-time workload estimation allows the HMI to adjust information density, modality, and timing.

Reducing visual complexity during high workload phases improves driver comprehension and takeover response [5]

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Interfaces that delay non-urgent notifications during high cognitive load phases reduce distraction without reducing trust.

3.2 Adaptive Information Presentation

Adaptive HMIs prioritize information dynamically based on driving context (traffic complexity, automation reliability, driver state).

Context-aware filtering reduces unnecessary alerts by up to 30–50% in simulator studies.

Hierarchical information layering (primary alerts vs. secondary details) improves scanning efficiency and lowers visual demand.

Predictive displays that show future vehicle intent (e.g., lane changes, trajectory planning) improve situation awareness and reduce decision time.

3.3 Takeover Performance Enhancement

Adaptive interfaces play a key role in improving responses to takeover requests (TORs), which is critical in automated driving systems based on SAE Levels of Driving Automation.

Multimodal alerts (visual + auditory + haptic) reduce reaction times by 20–40% compared to single-mode warnings.

Adaptive warning timing based on urgency and driver readiness improves steering stability and reduces braking variability.

Personalized alert timing reduces surprise effects and lowers accident risk during transitions.

4.0 Maintaining Situation Awareness

Interfaces that provide low-intensity continuous feedback (ambient cues, peripheral displays) reduce out-of-the-loop effects.[14] Adaptive summarization of environmental changes (e.g., upcoming hazards, vehicle decisions) helps maintain mental models without overwhelming the driver.

4.1 Trust Calibration and Transparency

Transparent display of system confidence and sensor limitations leads to more appropriate driver reliance.

Adaptive trust cues (e.g., confidence indicators, uncertainty visualization) improve takeover preparedness.

4.2 Personalization and Learning

Machine learning models tailor interface behavior to individual users.

Personalization improves comfort and reduces mental workload by adapting alert thresholds, interface density, and interaction

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style.[15] Systems that learn driver behavior over time improve engagement and acceptance.

Across multiple studies, adaptive HMI strategies significantly reduce cognitive workload, improve takeover safety, enhance situational awareness, and promote appropriate trust in highly automated vehicles.

5.0 Conclusion

Research on reducing cognitive overload in highly automated vehicles through adaptive HMI strategies shows that well-designed adaptive interfaces can significantly improve safety, usability, and user experience in Highly Automated Vehicles. By tailoring information presentation, timing, and modality to the driver's current state and the driving context, adaptive Human–Machine Interface systems help maintain driver engagement and reduce mental workload during automated driving.

A key conclusion is that context-aware adaptation such as prioritizing safety-critical alerts, filtering non-essential information, and using multimodal cues—reduces cognitive burden while preserving situation awareness. This leads to faster and safer takeover performance, particularly in time-critical scenarios where drivers must quickly regain control.

Overall, the evidence indicates that adaptive, context-aware, and user-centered HMI designs are essential for safe and effective deployment of automated driving systems particularly as vehicles operate at higher levels of autonomy.[16] Developing these interfaces will be critical to ensuring smooth human–machine collaboration and safe transitions of control in future mobility systems.

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