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Human-Autonomy Teams: The Case of Remote Operators and Automated Driving Systems

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Autonomous functions, systems, and operations are expected to play a significant role in a number of industries, including energy, process, and transportation. In these, human operator teams frequently monitor, supervise, and intervene in the system's operations, acting as a safety barrier in the event of emergencies. As the Level of Automation of these systems increases, the need to study the Human-Autonomy Team's (HAT's) performance becomes fundamental. Recent developments in Automated Driving Systems (ADS) deployed for passenger transport services highlight the need to revisit assumptions about the role of remote operators performing driving assistance and emergency management tasks. While human factors research has explored the implications of human-system interactions in ADS contexts for drivers, the focus on HAT dynamics is still incipient, particularly in remote operations. This work draws from remote control operations in nuclear, oil & gas, and maritime industries, aiming to model fundamental aspects of HATs in remote ADS operations. Thus, instead of only considering human-system interaction schemes, team performance models such as the Information, Decision, and Action in Crew (IDAC) context can be applied to study the developing HAT dynamics. This work explores the applicability of Performance Shaping Factors (PSFs) used in Human Reliability Analysis (HRA) models, identifying potential factors influencing the performance of both human and automated agents in remote ADS operations, focusing on the relationship, tasks, and challenges remote operators face when interacting with vehicles equipped with advanced ADS.

Keywords: automated driving systems, remote driving assistance, performance shaping factors.

1. Introduction

Autonomous systems are integrated into complex socio-technical systems operation across multiple industries (Akdağ et al., 2022; Gadmer et al., 2021; Timotic & Netjasov, 2022). Efforts to enhance systems' abilities to self-diagnose, regulate, and operate autonomously are driven by the goal of increasing efficiency and safety, as well as enabling new capabilities. This shift is also envisioned as a path to remove human operators from hazardous on-site locations. However, operators remain integral to supporting system safety and, for many systems, are expected to continue intervening remotely during operation. Therefore, developing methods that adequately represent the impact of human-system interactions on system safety are needed to ensure adequate system, procedure, and operation design (di Nardo et al., 2015). Recent research into human-system interaction has increasingly emphasized collaborative and team-oriented dynamics, such as task division and allocation strategies, operators' trust in automation, attention management, and the challenges associated with the explainability of the autonomous systems' decisions (Lyons et al., 2021). As systems achieve higher Levels of Automation, questions remain regarding the methods used to assess human-machine team performance (Mehak et al., 2024).

Driving automation is categorized into six levels based on the division of Dynamic Driving Tasks (DDTs) between a human driver and the system (SAE International, 2021). At level 4 (L4), the Automated Driving System (ADS) is designed to execute all DDTs independently, without requiring human driver intervention, provided the system operates within its predefined operational design domain (ODD). While current L4 ADS developments primarily focus on driverless passenger transport, it is anticipated that remote human assistance will remain necessary for supporting vehicle and passenger operations in the near term (Kettwich et al., 2021). Remote monitoring, supervision, guidance, and intervention introduce many challenges from both technical and organizational perspectives (Mutzenich et al., 2021b). These tasks depend entirely on the information relayed through the control room's human-system interface (HSI) subjected to network latency, connectivity reliability, and cybersecurity vulnerabilities (Kuru, 2021). Thus, evaluating the feasibility of remote operator interventions – and determining which tasks are appropriate – requires comprehensive modeling and analysis of the factors influencing the overall safety and performance of the system.

This work explores the role, tasks, and challenges of remote operators supervising L4 ADS fleets from a team-based perspective introduced in (Correa-Jullian et al., 2024b). Drawing from the Information, Decision, and Action in a Crew context (IDAC) cognitive model, the human-system interaction schemes and influencing factors are discussed, as well as their input to system modeling, data collection, risk assessments, and system design.

2. Human Reliability Analysis and Human-Autonomy Teams

Human Reliability Analysis (HRA) has been an instrumental tool in risk management across sectors such as energy and process industries, offering both qualitative and quantitative insights to improve system, procedure, and operation design (Zarei et al., 2021). Operator teams play pivotal roles in complex system operations, and thus, team dynamics can significantly impact system safety. Research highlights that inadequate communication and coordination among team members are primary contributors to accidents and unsafe behaviors, rather than insufficient technical knowledge of systems and operational procedures (Ham et al., 2021; Kim et al., 2020). Frameworks such as IDAC use Performance Shaping or Influencing Factors (PSF/PIF) to express the impact of various elements on the probability of a Human Failure Event (HFE) (Chang & Mosleh, 2007). These factors span the Information, Decision, and Action stages (Fig. 1), including task complexity, attention, procedure quality, and system design. HRA methods support the identification of critical contributors to high-risk scenario development (Wang et al., 2023). To better account for the impact of team dynamics, the Team-Centered IDAC (Tc-IDAC) extended IDAC to examine how collective task allocation and error management affect team performance (Azarkhil et al., 2025a, 2025b).

The introduction of automation often aims to shift the human operator's role from active controller to supervisor, primarily tasked to intervene in emergency situations. The concept of Human-Autonomy Teams (HATs) offers a framework for analyzing these interactions from a collaborative perspective. A HAT is defined as a team comprising at least one *autonomous machine agent* – expressing degrees of agency, interdependence, and proactivity – working alongside human team members to achieve a shared goal (Mosier et al., 2017; O'Neill et al., 2023). Hence, HRA methods and tools, traditionally focused on human team dynamics, can be adapted to assess all agents within a HAT – human and autonomy – identifying and evaluating the factors influencing their performance with a comparable level of granularity. As a step towards developing an HRA-based HAT model, this work evaluates the applicability of existing PSFs and proposes new factors to describe the HAT's performance.

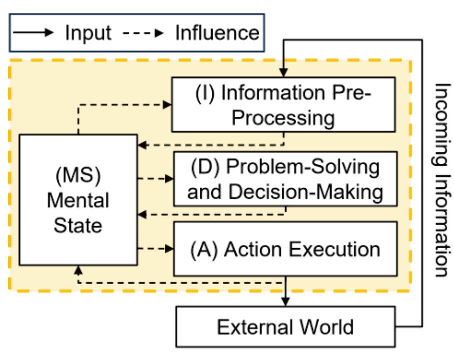

Fig 1: IDAC operator cognitive flow model.

3. Remote Operations for Automated Driving Systems

The design of L4 ADS fleet operations can vary depending on the company managing the fleet, local legislation, and other factors, such as connectivity quality. This work adopts the system described in (Correa-Jullian et al., 2024a, 2024b), in which the fleet is supported by remote operators, who are trained and/or certified personnel responsible for overseeing passenger transport fleet operations from a control room (at a Fleet Operations Center). Their tasks may include providing preemptive or system-requested driving assistance, such as object classification and tactical driving commands, based on alarms and data transmitted by the ADS, with the additional pressures of wireless communication reliability and impaired perception conditions (Bogdoll et al., 2022). The challenges these remote operators face differ substantially from on-board drivers, primarily due to their physical disconnection from the vehicle.

To perform remote assistance tasks, operators must rely on video, audio, location, and other sensor data to assess the situation and issue waypoints or other commands to the vehicle (Mutzenich et al., 2021a). While high-automation driving systems are designed to execute fallback actions and achieve Minimal Risk Conditions, network latency remains a critical factor. In the event of automation failure or edge cases – especially those involving passengers – the remote operator may need to intervene to provide alternatives to the ADS's fail-safe strategies (Goodall, 2020; Mutzenich et al., 2021b). The limitations of communication infrastructure further add to the difficulty of maintaining and regaining situational awareness during emergency situations, particularly under limited perception conditions (Tener & Lanir, 2022). Fig. 2 illustrates the communication flow between the remote operator, the ADS-equipped vehicle, and the driving environment ('World'), as well as the potential introduction of an ADS advisory to assist the remote operator. The interaction dynamics between remote operators and the ADS can have significant impacts on system, traffic, and passenger safety (Mutzenich et al., 2021b; Tener & Lanir, 2022). Although remote operators are intended to provide tactical support in non-safety critical situations, real-world traffic scenarios may not allow for clear-cut distinctions or sufficient time to determine the potential risk levels. This implies additional design considerations for HSI, component redundancy, safety alarm systems, and extensive human factors integral to remote operators' functions.

4. Performance Shaping Factors

Developing a team performance model informed by HRA literature requires analyzing and adapting/extending existing PSF nomenclature to represent both the remote operator and the automated system. While the decision-making processes of autonomous agents differ fundamentally from humans, their observable behaviors can still be influenced by internal and external factors, e.g., scenario and design elements. Effective error detection, indication, and correction within the team require shared mental models of system performance, as well as mutual performance monitoring, backup behavior, and team adaptability (Mosier et al., 2017).

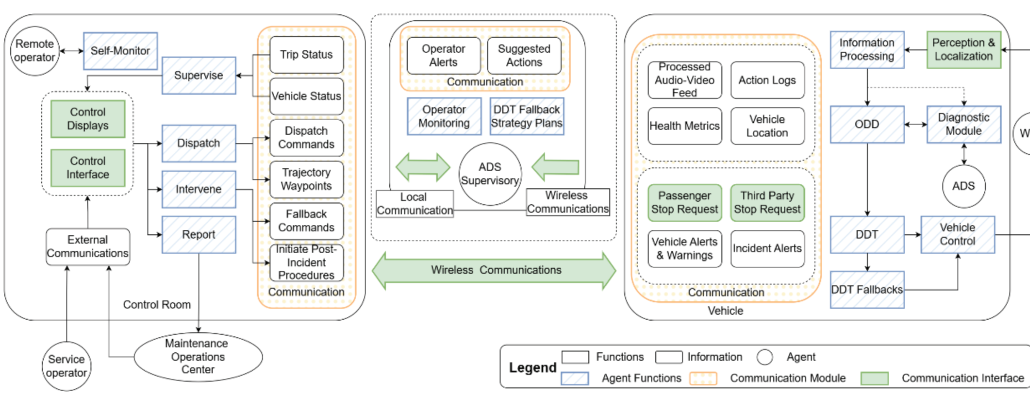

Fig.2: Overview of remote operator-ADS fleet interactions.

Building on the hierarchy developed in (Groth & Mosleh, 2012), this section illustrates how PSF concepts can be applied to the remote operator-ADS HAT. PSF models, such as the ones developed in (Azarkhil et al., 2025b), can provide greater transparency into system-level decision-making by interpreting these dynamics through team interactions.

4.1 *Organization and system-based factors*

The organization-based and system-based factors are controlled by the organization operating and designing the system, respectively. Three potentially overlapping entities can fulfill these functions: the fleet operator, the ADS developer, and the vehicle OEM. Each organization's overarching *safety culture* is reflected in its internal risk management policies and how responsibilities are managed. While these roles may be consolidated within a single organization, it is likely that as operations scale, fleet operators acquire the vehicles from external ADS developer-OEM partnerships. For example, control room operations will likely be determined by the fleet operator and the ADS developer, the ADS design will depend on the ADS developer and/or the vehicle OEM. Organizational elements, such as *workplace adequacy* and *task allocation*, significantly influence the remote operator's performance. One critical consideration is determining the operator-to-vehicle ratio based on performance goals and task complexity (Wu et al., 2024). Similarly, research has focused on defining the limits of human capabilities and latency conditions to enable effective remote assistance across operational (e.g., accelerating), tactical (e.g., obstacle avoidance), and strategic (e.g., navigational planning) levels (Correa-Jullian et al., 2024). As with other complex engineering systems, ADS fleet operations will likely rely on the availability and quality of decision-support *procedures*. Thus, remote operator *training programs* and certification processes may become essential, depending on the *task allocation and scheduling* – potentially consisting of detecting and responding to ODD breaches, managing DDT fallback scenarios, post-incident management, and handling communications with passengers, first responders and law enforcement (Automated Vehicle Safety Consortium, 2024). While many behavioral and functional elements of ADS vehicles are fixed at design time (e.g., robustness of the design, verification, validation, and testing performance), some operational software and hardware elements may be periodically updated. These updates rely on the availability and quality of *corrective action programs* – i.e., how operational experience is incorporated as feedback into system improvement processes (Zhao et al., 2020). Such updates may alter *task allocation and scheduling* requirements, as well as the availability and quality of *procedures, tools,* or *information* necessary for effective task execution by both human operators and automated systems.

4.2 *Agent-based factors*

This category encompasses internal factors influencing an agent's performance on an individual level, including *attention, experience,* and *risk tolerance*. While defined for operators in control room environments, many of these factors can be analogously applied to the underlying ADS design and problem-solving capabilities. Situational awareness and *attention* management have been extensively studied in control room operations (Kim et al., 2020). Attention – defined as an operator's strategy to distribute available cognitive resources – can be conceptually mapped to the ADS's *resource allocation* strategies, as shaped by its electrical/electronic architecture design (Askaripoor et al., 2023). *Physical and psychological abilities* pertain to an operator's internal available resources to perform their tasks, including the level of alertness, fatigue, impairment, or physical attributes. Analogously, these factors correspond to the ADS's *resource availability*, addressing how operational conditions impact system degradation (e.g., sensor or software reliability and calibration) and computational resource limitations such as energy, memory, and processing capacity (Zhang et al., 2023). Factors such as *experience, knowledge, perceived familiarity, bias*, *skill,* and *risk tolerance* integrate individual characteristics with cumulative organization and situation-based factors, such as training and prior interactions with the system. For the ADS, these factors are significantly shaped by design choices, verification and validation processes, and software maintenance of the ADS. Consequently, the factor *system maturity* is proposed to account for (1) data exposure (e.g., dynamic environmental conditions, HD map accuracy, and driving behavior model sophistication), (2) testing performance (e.g., real-world scenarios, closed tracks, simulation), and (3) the extent of the certified ODD. Bias within the ADS may arise from the quality of the training data quality (data-based bias), decision-making algorithm sophistication (algorithm-based bias), or sensor limitations under varying conditions (sensor-based bias). Similarly, skill in the ADS context can be analyzed through its perception (e.g., hazard detection, localization), decision-making (e.g., path and maneuvers planning, risk assessment), and control capabilities (vehicle control precision and responsiveness) (Di & Shi, 2021). Software architecture design can directly impact *risk tolerance*, from selecting safety margins or confidence thresholds to trigger automated fallbacks, or sensor fusion schemes impacting object and event detection and reaction tasks (Lodhi et al., 2023). This is particularly critical for rule-based decision making, traffic law compliance, and prioritizing safety based on contextual cues. While individual variations are not expected within the vehicle fleet, organizational policies for hardware and software will influence performance consistency (Correa-Jullian et al., 2024a).

4.3 *Situation-based Factors*

These factors represent the influence of scenario development on an agent's performance. Broadly, these can be categorized into factors related to observable scenario characteristics and those addressing the agent's perception of the scenario. Observable scenario's characteristics include elements such as the *external environment*, the presence of *conditioning events*, and *task complexity*. In this context, the *external environment* refers to driving conditions (e.g., weather, road geometry, traffic density) and interactions with other road users (e.g., vehicles, cyclists, pedestrians). Remote operators must also account for factors within the control room, including limited perception and communication, capabilities, as well as passenger activity (e.g., stop requests). *Conditioning events* encompass latent failures and alert-triggering events, such as ODD breaches, vehicle malfunctions and connectivity failures, which may require DDT fallback responses and/or appropriate intervention by the remote operator. *Task complexity* refers to the overall difficulty in diagnosing scenarios and executing tasks based on the knowledge, procedure, and precision required, as well as the ambiguity of the situation and task switching – the latter highly dependent on the selected operator-to-vehicle ratio. For the ADS, *task complexity* extends to the computational demands, such as tasks performed within the ODD or in response to an ODD breach and contextual factors (e.g., road geometry, traffic density, weather conditions) increasing maneuvering difficulty.

Factors addressing the agent's perception of scenario development include latency, interface design, and communication issues which can significantly affect operator performance by increasing *task, information,* and *time load*. These are particularly acute during incident management or when supporting the ADS in ambiguous scenarios (Automated Vehicle Safety Consortium, 2023). Additional perception-based factors affecting the remote operator include *stress* and *perceived urgency, severity,* and *decision responsibility*. For the ADS, these factors may be more accurately expressed through the aforementioned *risk tolerance* factor, defined by the risk metrics and safety margins guiding its decision-making process. Similarly, the proposed *resource availability* captures the ADS's perceived *information* and *time* loads, where capacity limitations of conflict-resolving algorithms in data processing, localization, and planning tasks may lead to unreasonable latency and unsafe action execution.

4.4 *Team Factors*

Adopting a team perspective in automation-heavy systems can enhance problem-solving resource availability, enabling a layered approach to safety and greater adaptability across diverse scenarios (Azarkhil et al., 2025a, 2025b). To fully leverage the complementary capabilities of HATs, system designers and operators must address key factors influencing team dynamics, including social and functional *cohesion* and *role awareness*, *communication*, and *leadership* within the team (Ham et al., 2021). Individual team-behaviors, such as *team cohesion* and *role awareness,* are likely more applicable to human operators, shaped by their training, experience, and perception of the ADS's capabilities. The degree of an operator's *trust* in the system will also be determined by the calibration of alarms and time-based triggers for interventions – considering the time required for a successful operator's intervention and robust system performance in scenarios where unsuccessful interventions pose unacceptable risks. Indeed, *role awareness* – the attitude towards the team's roles, responsibilities, and goals – may be critical under emergency situations. In this regard, conflict management between multiple operators and ADS fleet vehicles raises additional concerns in relation to the role of *leadership* and decision hierarchies (Correa-Jullian et al., 2024). This factor is particularly important in procedure-intensive, control room-based operations. Although frequently considered a system-based factor, fleet management contexts may warrant the explicit consideration of *HSI design* and *availability* as *team communication* factors (Azarkhil et al., 2025a, 2025b). However, only aspects of communication quality and effectiveness would fall under this category, as message format, mode, and content are determined by design (Xing et al., 2021). All these elements significantly impact *team coordination* and the likelihood of achieving overarching safety and mission goals (Fig.3) (Azarkhil et al., 2025b). This factor reflects task interdependence between the ADS and the remote operator, observed through indicators such engagement rate, responsiveness, and task quality. It involves the division of responsibilities and teamwork in planning, scheduling, and action implementation (Ham et al., 2021; Lyons et al., 2021).

5. Discussion

As driverless passenger services scale, operational data can help refine the roles and responsibilities of human operators involved in ADS operations. Comprehensive risk assessments that incorporate both system and operator performance are essential to support safe operations and inform data-driven safety policies. HRA methods and team performance models, accounting for the influence of PSFs across organizational, individual, team, system, and scenario levels, can support safety metric and risk-based criteria development to guide operator intervention, building robust operational risks management mechanisms stemming from causal human-system interaction models. Insights from real-world operations—such as error patterns, operator response times, and ADS system performance under various conditions—can inform updates to training programs, interface designs, and decision-support tools, supporting system improvement alongside continuously evolving operational environments. In this regard, tools such as system dynamics-inspired causal effect diagrams, system-theoretic process analysis and concurrent task analysis pose powerful avenues to model and simulate complex socio-technical system behaviors (Correa-Jullian et al., 2024a; di Nardo et al., 2015).

Adopting a team-based perspective for operator-ADS relationships introduces a wide breadth of tools, literature, and technical language that enhance system interpretability. This approach highlights the impact of ADS design on the overall system's safety and the value of remote operator interventions, as opposed to characterizing operators only as technology users (Walliser et al., 2019). While research efforts have focused on driver reaction times in shared autonomy settings, it is crucial to extend these studies to remote operators, studying potential involvement in operational, tactical, and strategic decision support. By treating the ADS and the operator as a cohesive HAT, the system can be designed to actively manage and compensate for mutual errors, exchange information and commands effectively, and mitigate common team-level challenges such as miscommunication or misinterpretation. As with other HRA approaches, validation remains a challenge, considering the limited data collection initiatives focused on remote supervision operations. However, pursuing a team-based and data-supported approach can become key for ADS operation design to maintain high levels safety and mission success. As the paradigm of control room operations for ADS evolves, it will be fundamental to share insights across other industries aiming to define the supervisory risk tasks of human operators (Veitch & Andreas Alsos, 2022).

6. Conclusions

While remote operators may play a role in managing risks of ADS fleet operations, increased research and data collection efforts are needed to determine system requirements to support their tasks – including connectivity, task, procedure, and workplace design. This work introduces a HAT perspective on remote operator's interactions with L4 ADS and explores the applicability of HRA-based PSFs, building towards the development of a risk-informed team performance model tailored to ADS operations

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