Proactive Remote Operation of Automated Vehicles: Supporting Human Controllability

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from Reaction to Anticipation

The Book Chapter

Content presented in this set of slides is based on the following book chapter:

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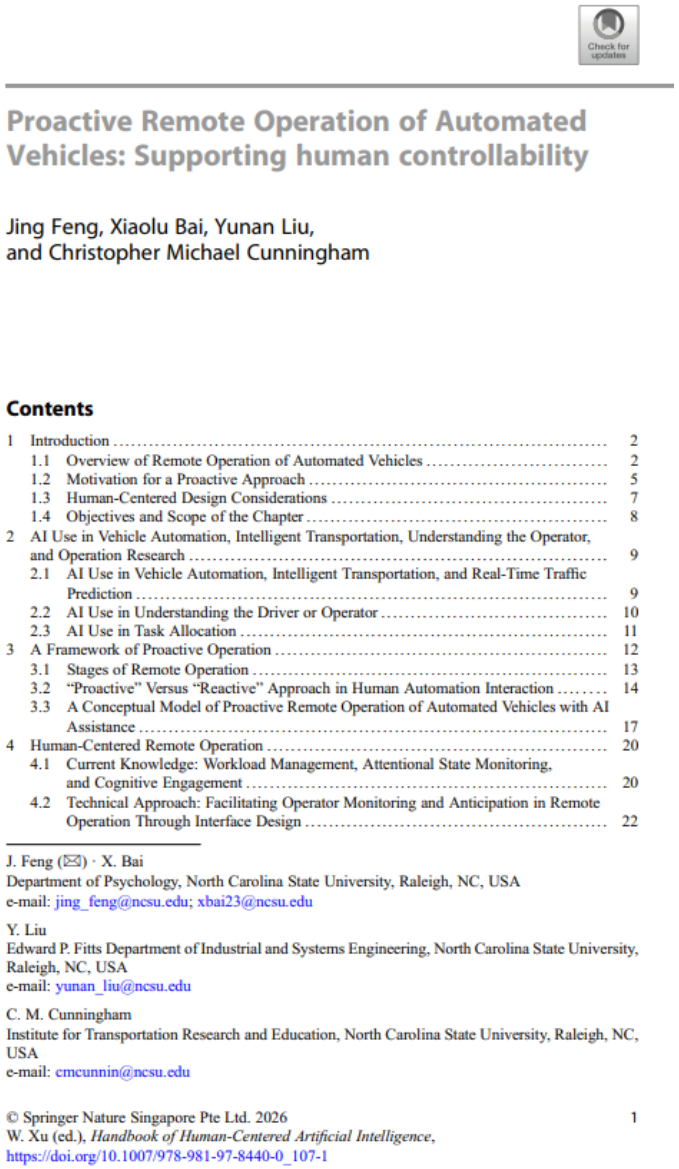
[Link to the Handbook]

This chapter presents a human-centered framework for integrating remote operators, AI, and operations research to ensure safety and efficient in the next generation of transportation.



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Remote Operation for Mobility is Growing

A significant part of the future of mobility will be remote operation.

$38 Billion

Expected market size for remote operation of automated vehicles by 2030[1].

4.9 Trillion

Total traveled miles projected by 2030[2].

The transition from in-vehicle drivers to remote operators is a critical component of L4 automation, with companies already testing robotaxis in US cities.

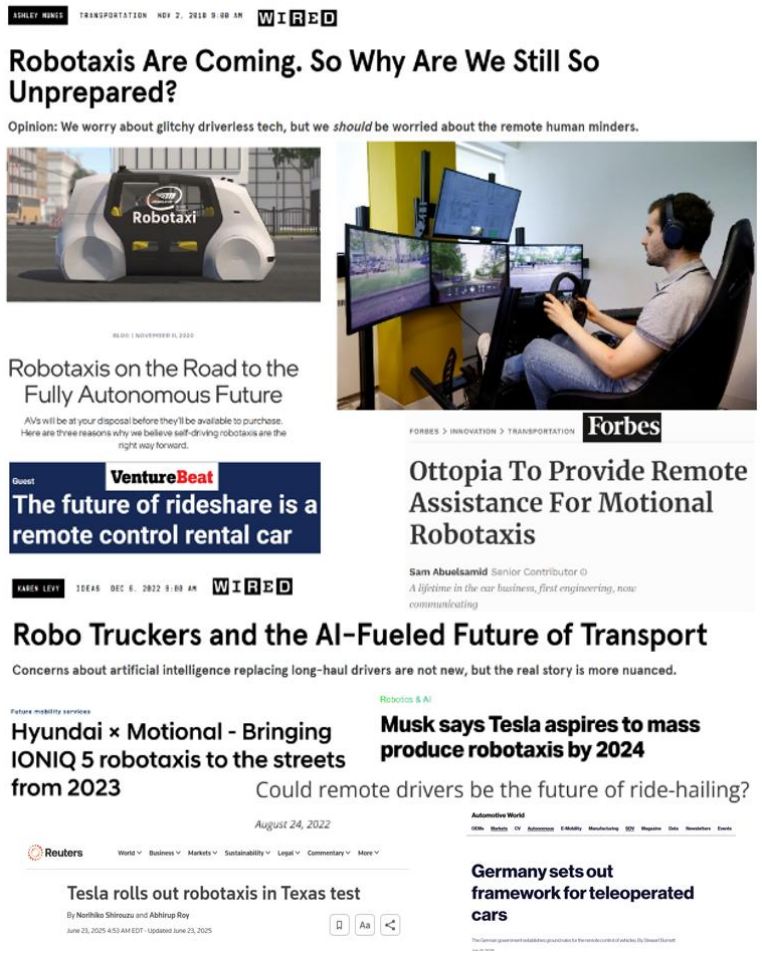


Figure 1 Rapid growth of transportation with automation and reliance on remote operation

[1] Abhay, S., Lalit, K., & Sonia, M. (2021). Global robotaxi market: By application, component used, propulsion, level of automation, and region. *Allied Market Research*, 1–266.
[2] Ambadipudi, A., Heineke, K., Kampshoff, P., & Shao, E. (2017). Gauging the disruptive power of robo-taxis in autonomous driving. *McKinsey Center for Future Mobility*, 1– 10.

Three Stages of Remote Operation

	Stage 1 Remote driver	Stage 2 Remote monitor	Stage 3 Remote commander
			
Scenario	1 operator – 1 vehicle Operator performs the driving task	1 operator – 1 or n vehicles Operator monitors vehicles and can intervene	Operator provides high-level commands Anyone including riders can make inputs Small number of admin-operators
Human Factors Questions	• How to create the driving environment for a remote operator? • How to warn an operator about poor connectivity? • How to support riders' trust of the operator?	• How many vehicles can an operator monitor and what are the cognitive and task factors? • How to support remote monitoring, anticipation, and intervention? • How to train remote operators in supervisory control?	• How to design App interface to enable everyday user to send commands and stay informed of the trip? • What are the tasks for the admin-operator and how to display information from a large volume of vehicles?

Figure 2 Three stages of remote operation of automated vehicles

The Current 'Reactive' Approach: A System Under Stress

A reactive system tasks a human operator to intervene only after automation fails and requests assistance. The operator is a fallback, not a partner.

Human Factors

- **Extreme Cognitive Load:** Operators must build situation awareness under intense time pressure.
- **High Stress & Impaired Performance:** Operators describe the job as "overwhelming", "stressful", and "a huge effort"[4].
- **The "Out-of-the-Loop" Problem:** Prolonged monitoring with low engagement leads to vigilance decrement and delayed responses.

Traffic Engineering

- **Traffic Disruption:** Delayed interventions lead to traffic blockages and increase the risk of collisions.
- **Unpredictable Maneuvers:** Sudden, erratic vehicle movements disrupt the flow of surrounding traffic.

Vehicle Technology

- **The Automation Paradox[3]:** The better the automation, the more humans struggle when it fails.
- **Missed Learning Opportunities:** The system only flags total failures, missing crucial data from near-misses and edge cases where a human would have proactively intervened.

[3] Bainbridge, L. (1983). Ironies of automation. *Automatica, 19*(6), 775–779.
[4] Tener, F., & Lanir, J. (2022). Driving from a distance: Challenges and guidelines for autonomous vehicle teleoperation interfaces. *CHI 22*, New Orleans, LA, USA.

Needed Shift to A 'Proactive' Approach: Empowering Operators to Anticipate

A proactive approach ensures operators remain engaged and aware, enabling them to preemptively address situations and enhance overall system safety and traffic management.

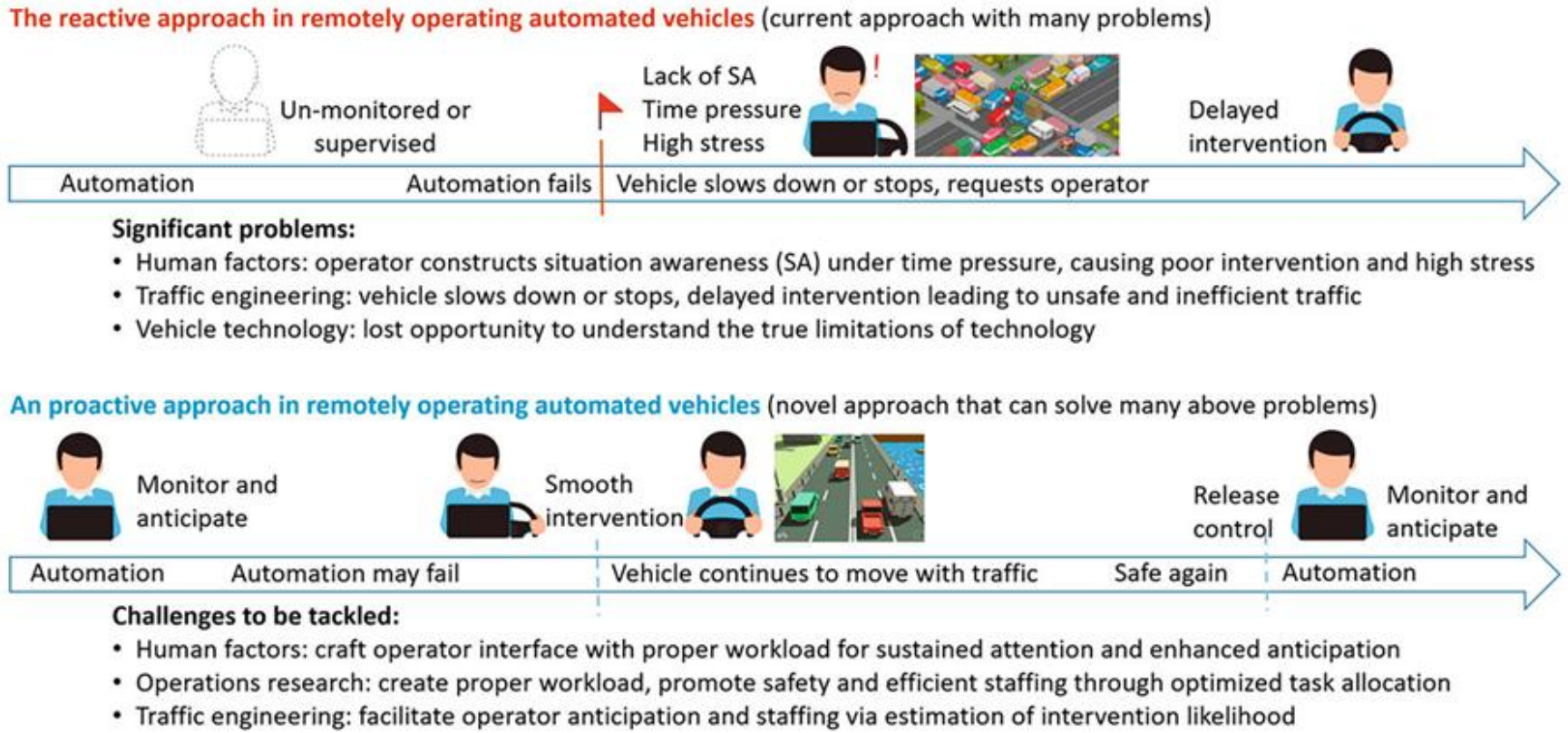


Figure 3 A contrast between the current reactive approach and the novel proactive approach

A Human-Centered Framework for Proactive Operation

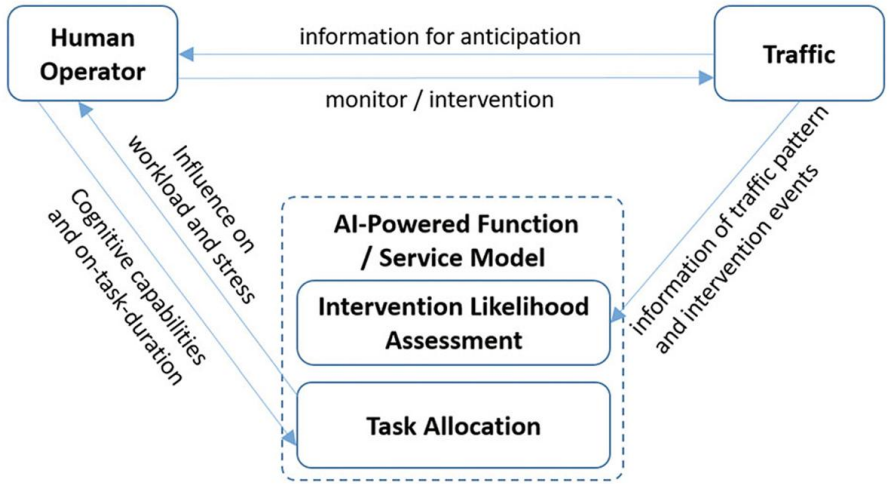


Figure 4 General system components of proactive remote operation

This is a joint cognitive system where AI and remote operators work in tandem. It is built on a continuous feedback loop between three key elements:

- **The Human Operator:** provides monitoring and intervention, but their cognitive capabilities and workload are key inputs to the system.
- **The AI-Powered Service Model:** contains two modules: Intervention Likelihood Assessment, and Task Allocation.
- **The Traffic Environment:** provides real-time data to the AI model and receives the output of the operator's actions.

Core Principle: This system aims to ensure human controllability and meaningful oversight.

A Proposed System for Proactive Remote Operation

- A vehicle's journey is segmented into short episodes.
- The **Intervention Likelihood Assessment Module** analyzes data to classify each episode as high likelihood or low likelihood.
- The **Task Allocation Module** assigns episodes based on the risk level.
- **Scenario 1 (low likelihood, proactive intervention):** An operator monitoring multiple low-risk episodes notices a potential issue and intervenes proactively.
- **Scenario 4 (low likelihood, reactive):** An unmonitored vehicle fails, forcing a stressful reactive intervention. The exact scenario to minimize.
- **Scenario 5 (high likelihood, proactive intervention):** The episode is assigned to a dedicated operator who is primed to anticipate and intervene.

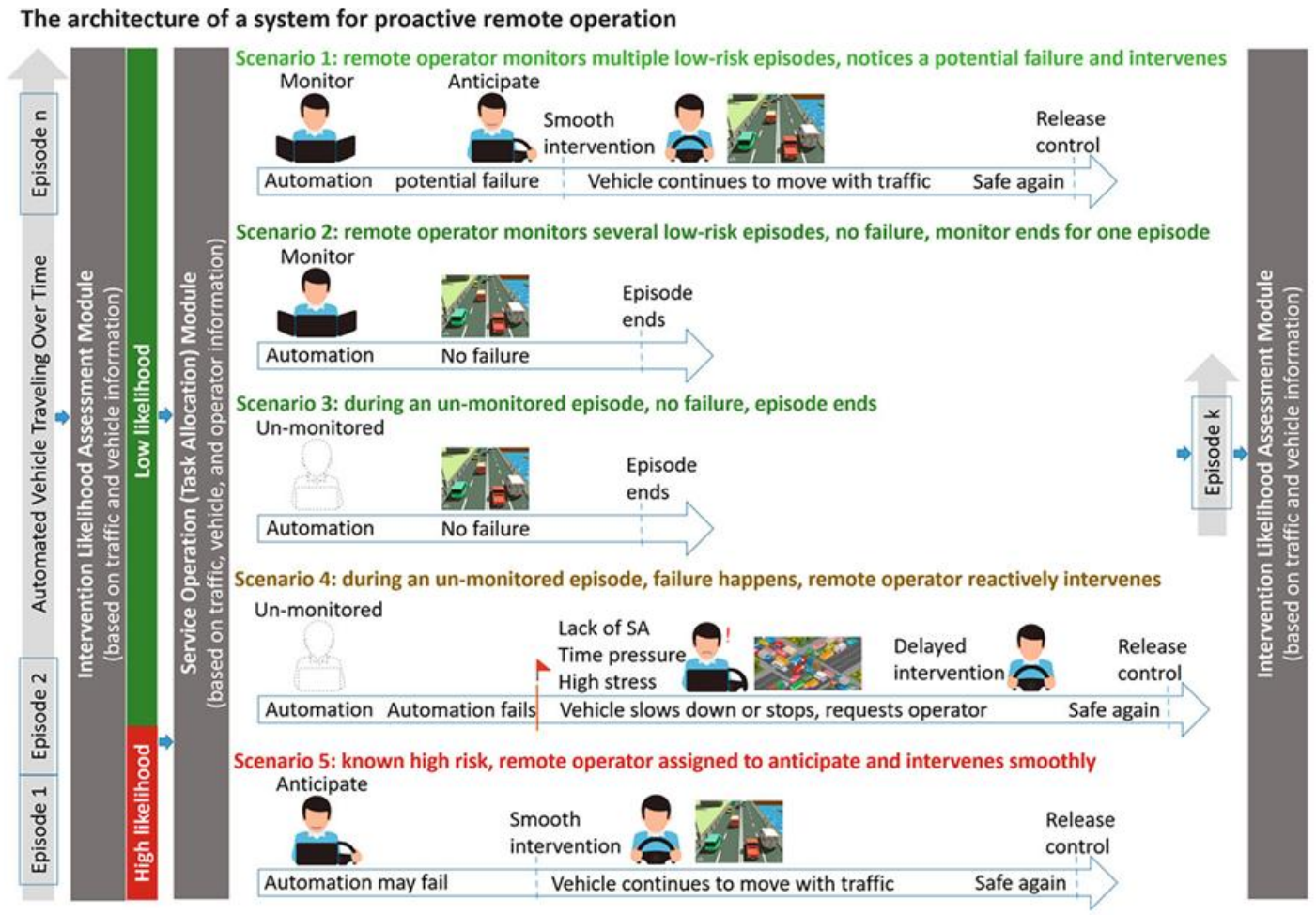


Figure 5 The architecture of a system for proactive remote operation of automated vehicles in mixed traffic

Pillar 1: Human-Centered Interfaces Designed for Anticipation and Engagement

The Challenge

Operators have cognitive limitations. They can only attend to a small number of visual objects simultaneously[5], and performance suffers from both cognitive overload and underload[6,7].

The Goal

The interface must be designed to facilitate two key factors:

- **Effective Monitoring:** Present information for multiple vehicles without overwhelming the operator.
- **Informed Anticipation:** Provide contextual cues and predictive alerts that guide attention to where it is needed most.

The system must actively manage operator workload to maintain a state of engagement and vigilance, where they are alert and mentally invested.

[5] Feng, J., Pratt, J., & Spence, I. (2012). Attention and visuospatial working memory share the same processing resources. *Frontiers in Psychology, 3*, 103.
[6] Matthews, G., & Campbell, S. E. (2009). Sustained performance under overload: Personality and individual differences in stress and coping. *Theoretical Issues in Ergonomics Science, 10*(5), 417–442.
[7] Geden, M., Staicu, A., & Feng, J. (2018). The impact of perceptual load and time on mind wandering while driving. *Transportation Research Part F: Traffic Psychology and Behaviour, 57*, 75– 83.

A Potential Interface for Multi-Vehicle Monitoring and Anticipation

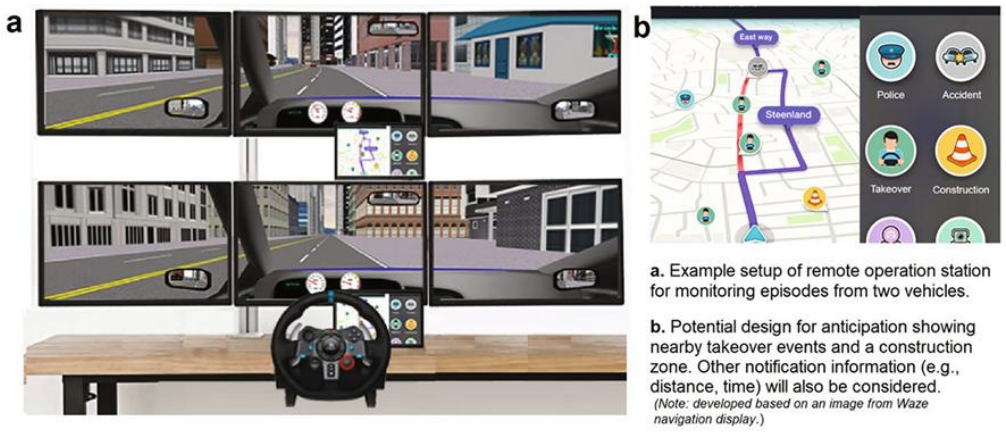


Figure 7 (a) A possible setup for remote operation and (b) display for anticipation

a – The Monitoring Station

An integrated multi-monitor setup allows for simultaneous monitoring of **two vehicles**. This is based on preliminary findings that show this is feasible without significant performance degradation. The upper/lower arrangement ensures perceptual separation.

b – The Anticipation Display

A separate map view displays augmented information to support anticipation. This includes:

- Known construction zones
- Reports of accidents or police presence
- Locations of recent takeover events from other vehicles in the fleet

Key Function: This design allows operators to maintain broad situational awareness across their assigned vehicles while receiving specific, actionable intelligence about emerging risks.

Pillar 2: Prediction to Assess Intervention Likelihood

This module analyzes a wide range of real-time and historical data to generate a probability score for each upcoming vehicle episode, answering the question: “How likely is human intervention needed?”

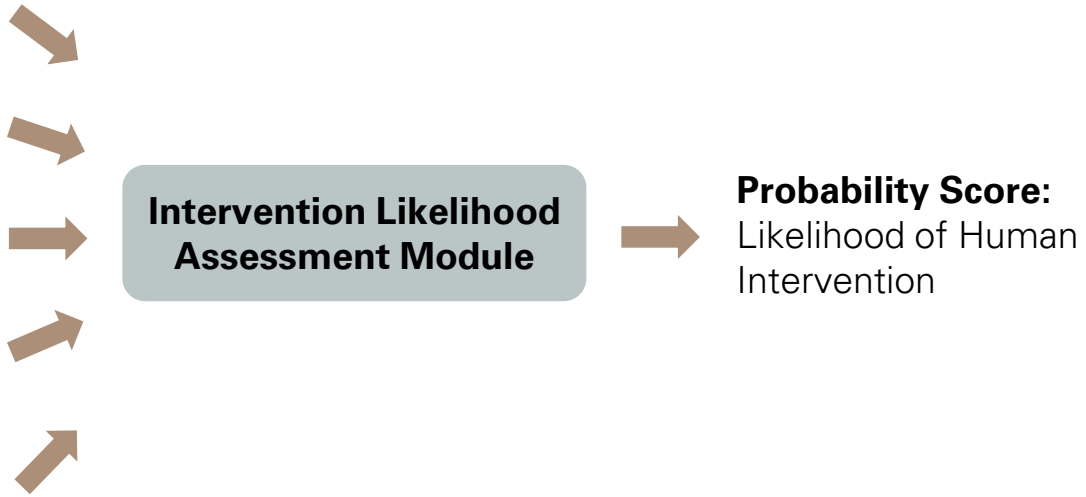
Traffic Data: Real-time and predicted traffic volumes and congestion patterns.

Facility Type & Condition: Road complexity, lane configurations, construction, and crashes.

Environmental Conditions: Weather, lighting, and pedestrian density.

Historical Disengagement Data: Analyzes the frequency, duration, and reasons for past interventions.

Automation Confidence: The vehicle’s own assessment of its ability to handle the current situation.



Pillar 3: Operation Research for Optimized Task Allocation

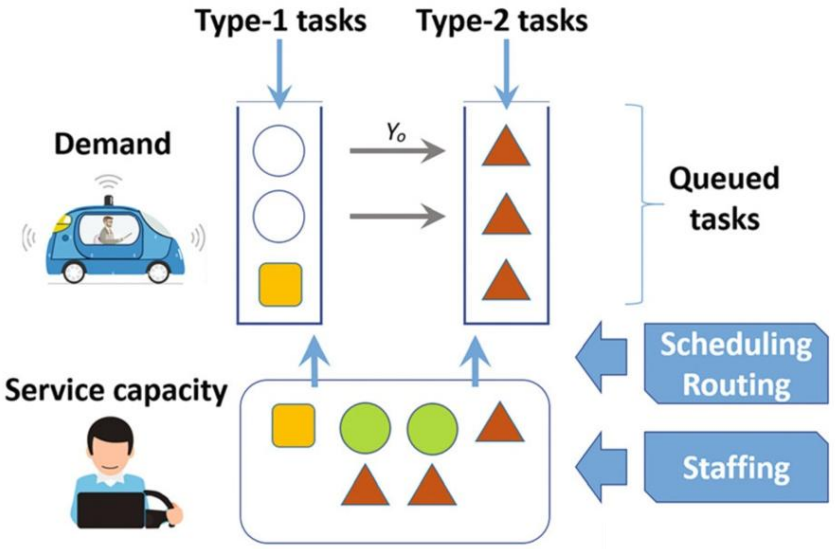


Figure 8 The service model for task allocation

Model's Goal: The model dynamically optimize for three balanced outcomes: Safety, Efficiency, and Cost.

The Service Model

- Operators are treated as a pooled resource, not dedicated to a single vehicle.
- **Type-1 Tasks (Monitoring):** Low-risk episodes where one operator can monitor multiple vehicles (up to a validated limit).
- **Type-2 Tasks (Intervention):** High-risk episodes or active interventions that require a dedicated operator.

Model's Logic: The model uses scheduling and routing algorithms to match the right operator to the right task at the right time, informed by both the intervention likelihood and the operator's current state (e.g., fatigue, workload).

Insights from Preliminary Studies

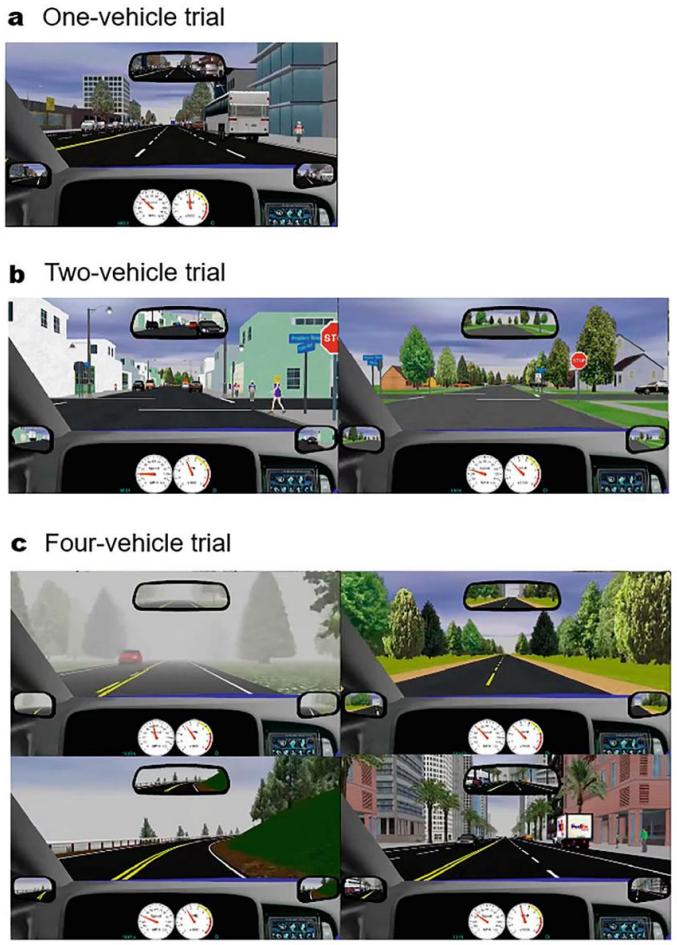


Figure 9 Example of each number of vehicle condition in[9]

Not all automation failures are equal

Our video-based remote operation task revealed that operators are much more likely to **miss "silent" failures** (like a vehicle missing a stop sign) compared to more obvious ones (like a lane departure)[8]. This highlights the need for tailored interface support.

There is a clear cognitive limit to monitoring but monitoring more than one vehicle is possible

- Operators was comparable when monitoring one or two vehicles[9].
- Performance degraded significantly when monitoring four vehicles, with higher workload and more errors[9].
- This finding directly informs the design of our **multi-vehicle interface** and the parameters of the task allocation model.

[8] Morrison, D., Cui, L., & Feng, J. (2022). An online method to study remote operation of automated vehicles. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 66*(1), 923–927.
[9] Shoffner, L. D., & Feng, J. (2024). Simultaneous remote monitoring of multiple automated vehicles. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 68*(1), 1752–1755.

The Future of Remote Operation is a Proactive Human-AI Ecosystem

By structing remote monitoring through manageable episodes, anticipating intervention needs, and aligning with operator attention, the proactive approach has the potential to improve safety and enable real-time human controllability. In such approach, operators retain meaningful oversight and influence over the system's behavior.

The understanding of human factors in this context is just in its infancy. Much more work is needed to explore the remote operation task setup, operation interface design, operator cognitive capabilities and effective strategies, task allocation, operator training, and rider experience.

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