Proactive Remote Operation of Automated Vehicles: Supporting human controllability

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W. Xu (ed.), *Handbook of Human-Centered Artificial Intelligence*,
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Abstract

This chapter explores the emerging field of remote operation of automated vehicles, with the focus on integrating human factors, traffic engineering, and operation research to enhance safety and efficiency. As automated vehicles become more prevalent, but before the full autonomy is achieved, the role of remote operators is emphasized as crucial for managing potential automation failures and ensuring human controllability. The chapter discusses the challenges of maintaining vigilance, managing cognitive load, and ensuring timely interventions in dynamic environments in remote operation. Innovative approaches are introduced to address these challenges, including the development of proactive operation systems that utilize advanced artificial intelligence (AI) for predictive traffic management and optimized task allocation. By enhancing operator interfaces and improving system responsiveness, these advancements aim to create a more reliable and intuitive framework of remote operation that safeguards human oversight and control. This research sets the groundwork for future developments in automated vehicle operations and highlights the importance of human-centered design in achieving safe and efficient transportation solutions with AI assistance.

Keywords

Automated vehicles · Remote operation · Human-centered design · Controllability · Operator engagement · Proactive system design

1 Introduction

1.1 Overview of Remote Operation of Automated Vehicles

Transportation services using automated vehicles are poised for exponential growth (Ambadipudi et al., 2017; Lanctot et al., 2017; Fig. 1). In the USA alone, Waymo, Tesla, Zoox, Cruise, and Uber have tested their robotaxis in select cities (Kerr, 2023; Lopez, 2022; Ohnsman, 2023; Paris, 2024; Shirouzu & Roy, 2025). Because vehicle automation is still far from full autonomy, a remote operator as a safety driver or

Fig. 1 Rapid growth of transportation with vehicle automation and reliance on remote operation (Nunes, 2018; Mobileye, 2020; Kim, 2020; Abuelsamid, 2021; Levy, 2022; Hyundai Motor Company, 2023; Bellan & Korosec, 2022; Shirouzu & Roy, 2025; Burnett, 2025)

supervisor is leveraged (California Code of Regulations, 2023; Reuters, 2024; Zhang, 2020; The Waymo Team, 2024; Zoox, 2020). This technology shift from a driver inside a vehicle to remote operation could quickly take place in transportation services. By 2030, the remote operation of automated vehicles as an industry is expected to grow to 38 billion (Abhay et al., 2021), with 4.9 trillion total traveled miles (Ambadipudi et al., 2017). Artificial intelligence (AI) can play an important role in realizing this, such as road scenario comprehension and intelligent decisions, traffic prediction, operator monitoring, task allocation, and optimization for resource and safety.

When collaborating with AI-powered automation, tasking a remote operator has several clear advantages as compared to tasking a driver in the vehicle. First, it is easier to ensure sufficient and standardized training for remote operators compared to in-vehicle drivers who vary widely in experience and preparedness. This is a significant advantage, given training is critical for handling emergencies (National Business Aviation Association, 2017). Second, it can increase accessibility for passengers who may be unable to take control of the vehicle themselves, such as children, individuals with blindness, and older adults who have ceased driving. Remote operation can ensure that a trained operator is always available to intervene if needed. Third, shift-taking among multiple remote operators can prevent fatigue in long trips to improve safety. Relying on a single in-vehicle driver for extended periods increases the risk of fatigue-related errors that lead to compromised safety and performance. While in-vehicle drivers can also alternate shifts to combat this issue, doing so introduces logistical challenges as drivers must be physically present at planned locations which requires careful coordination and often limits flexibility and increases operational cost due to the need of travel, staging, and idle time. In contrast, remote operators can transition between shifts seamlessly without stopping the vehicle, enabling continuous operation and improved scalability. This is especially beneficial for long-distance travel or time-sensitive services, where maintaining movement and operator alertness is essential.

Remote operation is considered a critical component of automated driving, a prerequisite of Level 4 automation (SAE, 2021), and a regulation priority in the USA, Canada, Israel, Germany, and the UK (Podhurst, 2021; UNECE, 2020). However, industry applications (Hundal, 2023; Zipper, 2022) for public road driving are just emerging with very limited research studying the remote operation of automated vehicles. For example, despite research on remote operation in other contexts such as aerial vehicles or rovers (Bilimoria et al., 2014; Chen et al., 2011; Schilling et al., 2002), remotely operating a passenger or freight vehicle inside mixed traffic poses different challenges given the dynamic environment and the time constraint for a remote operator to intervene on vehicle control. Existing trials of robotaxi services have already led to discoveries of unexpected difficulties. For example, sudden braking or prolonged stops caused traffic congestion and even collisions with a vehicle and a pedestrian in San Francisco (Kerr, 2023), while vehicle stopping at improper locations and occasionally driving on the wrong side of the road were observed in Austin (Turek, 2025). Additionally, a vehicle getting confused with its path circling a parking lot (Bacon, 2025) and a lack of human support to intervene when harassment from other cars taking place (Bonos, 2024) can leave riders frustrated and feel helpless.

With the profound change in mobility service, remote operators could begin replacing traditional in-vehicle drivers for taxis, buses, and trucks. This will take place alongside rapid advances in vehicle automation and supporting infrastructure.

As AI continues to enhance automation functions and enable new capabilities, it will also intensify the automation paradox, which states that the better automation becomes, the more humans struggle when it fails (Bainbridge, 1983). Operators will face growing risks such as overtrust, inappropriate reliance, incorrect mental models, misuse, out-of-the-loop, inattention, and decreased task engagement. While many of these issues are also being researched in the context of human-vehicle collaborative driving with in-vehicle drivers (e.g., Xing et al., 2021) and the findings can inform the human factors design of remote operation, simulated experiments and interviews with current remote operators have shown fundamental differences between the tasks involved in remote operation and in-vehicle driving (Mutzenich et al., 2021; Tener & Lanir, 2022). Little is known about the work of remote operation of automated vehicles, the specific challenges remote operators face, and how to make technology better for operators to conduct this remote operation (Hampshire et al., 2020), especially considering AI's involvement in assisting various aspects of the system. It is critical to understand human capabilities and limitations to enable the human-centric design of remote operation and its interface.

1.2 Motivation for a Proactive Approach

In the remote operation of automated vehicles, AI-powered automation poses significant challenges related to operator task engagement and performance. One of the critical issues arising from these highly automated systems is the "out-of-the-loop" phenomenon (Merat et al., 2019). This issue reflects a situation where operators, due to minimal active engagement in the operational process, become less effective in maintaining situational awareness and responding efficiently and effectively when required (Greenlee et al., 2018). Increased involvement in non-driving-related activities due to higher automation levels can reduce engagement in driving (de Winter et al., 2014). It is reasonable to speculate that the same could happen with remote operators. As shown in a recent study (Bai & Feng, 2025), both maintaining a proper workload and processing of driving-related information are critical to promote driver cognitive engagement and takeover performance when using partial automation. This points to an important consideration for remote operation that a proper task load should be identified and maintained to keep the operators cognitively engaged for proper situation awareness and the ability to anticipate.

Despite these findings, current remote operation systems generally adopt a reactive approach, in which human operators either control the vehicle throughout the trip or intervene only when requested by automation. These systems typically lack support for continuous monitoring and instead focus on replicating the driving environment, leaving remote operators vulnerable to impaired situation awareness and delayed responses. Following the reactive approach, existing research on the remote operation of automated vehicles has predominantly concentrated on enabling the control of a single vehicle from a distance by recreating the in-vehicle driving experience for remote operators (DriveU.auto, 2025a; Kettwich et al., 2021; Ottopia, 2025; Phatom Auto, 2025). However, this approach fails to address the cognitive and attentional demands to keep remote operators alert and responsive. Under this method, remote operators face similar challenges as in-vehicle drivers, such as vigilance decrement and passive fatigue due to underload, where prolonged periods of monitoring without active engagement lead to reduced attention and slower reaction times (Clark & Feng, 2017; Körber et al., 2015; Merat et al., 2019). Furthermore, remote operators are also impacted by their physical separation from the vehicle environment, which can exacerbate these issues (Tener & Lanir, 2022). Additional challenges include latency in the transmission of control commands and sensory feedback (Georg & DIergeyer, 2019; Zhang, 2020), and a general lack of situation awareness, which is critical for safe and efficient vehicle operation (Mutzenich et al., 2021). These factors collectively hinder the ability of remote operators to maintain a high level of control and responsiveness, thereby compromising traffic safety and operational efficiency. Moreover, the current reactive approach, where a human operator intervenes only upon the system's request, is problematic. AI-powered automation can lead to even worse out-of-the-loop and disengagement from ongoing vehicle monitoring tasks. Out-of-the-loop performance problems occur when operators are less involved in the control process, leading to delayed response times and reduced situation awareness when they are suddenly required to intervene with vehicle control. Additionally, cognitive disengagement can result in operators paying less attention to their monitoring tasks, which is critical for ensuring safety and effective intervention when necessary. In these systems, it is essential that human operators are not merely serving as a fallback but as an integral part of system oversight.

To mitigate these issues, a shift toward a proactive approach is needed. Instead of waiting for the system to request assistance after detecting a problem and then a remote operator reacts, a proactive approach would enable the operator to actively anticipate and avoid hazardous situations. A proactive system is designed to enable control of the system when needed and keep the human operator cognitively engaged by supporting continuous monitoring, decision-making, and forward planning, even when direct intervention is not immediately required. For example, such a system might present evolving traffic predictions or highlight emerging risks before the automation reaches its performance limits. One promising strategy to support this proactive engagement is assigning operators to manage multiple vehicles rather than a single one. Monitoring a single highly automated vehicle can result in extended periods of low workload and passive observation, which increases the risk of cognitive disengagement. In contrast, overseeing multiple vehicles introduces variability, complexity, and a more consistent demand on attention, helping operators stay alert and mentally invested in the task. This approach involves not only multi-vehicle monitoring but also system design considerations that actively keep operators engaged and support their anticipation of potential intervention.

Similar approaches are being explored in civil aviation under the concept of single pilot operations, where an aircraft would be operated by a single onboard pilot with support from remote operators (Bilimoria et al., 2014; Xu et al., 2022a). The remote operators are responsible for monitoring multiple flights, stepping in when needed due to pilot incapacity or system anomalies. These efforts show that with the right system architecture, remote operators can effectively manage their tasks across multiple flights, supporting the feasibility of remote operation of multiple automated ground vehicles.

In addition to supporting operator engagement and anticipation, proactive monitoring also reinforces human operators' control of the system by ensuring that they remain aware of system status and can intervene when necessary. Even as AI handles complex coordination and monitoring tasks, operators must retain the ability to redirect system behavior based on context or judgment. With a proactive strategy, the entire system, not just the human-automation interface, is designed to maintain continuous operator engagement, situation awareness, and controllability, thereby enhancing overall system effectiveness and safety.

Shifting toward a proactive model of remote operation could improve operator engagement, performance, system efficiency, and safety. A proactive system would involve operators more consistently, such as through periodic checks or required inputs that ensure they remain part of the decision-making loop and retain a high level of system awareness. This could also involve predictive analytics that anticipates potential traffic or operational issues before they become critical. Such a proactive approach would not only mitigate the risks associated with sudden interventions but also improve the overall efficiency and safety of vehicle operation in mixed-traffic environments.

1.3 Human-Centered Design Considerations

The human-centered artificial intelligence (HCAI) framework is designed to ensure that AI technologies support and enhance human capabilities, and aid rather than replace human decision-making processes (Shneiderman, 2022; Xu & Gao, 2025; Xu et al., 2022b; Xu et al., 2024). The HCAI framework emphasizes a synergistic relationship between AI and human intelligence, so systems are efficient, intuitive, and sensitive to human needs. Central to HCAI's approach is the concept of human-AI collaboration, where AI and humans operate as partners, each enhancing the other's strengths in cognitive tasks. This partnership is crucial in leveraging human intuition and AI's computational abilities to improve decision-making and system performance. Another essential aspect of the HCAI framework is human controllability. Systems should be designed to keep humans meaningfully involved, with the ability to supervise and intervene AI behavior when needed. This ensures human can maintain authority and stay actively engaged, especially in dynamic and safety-critical situations. Controllability also fosters a sense of confidence and psychological ownership, which could be vital for building trust in AI systems and enabling effective human-AI collaboration. Moreover, HCAI advocates for AI systems that are integrated within broader ecosystems, encompassing other technological entities, infrastructure, and diverse human roles. In the context of proactive remote operation with AI assistance, this holistic perspective ensures that AI systems are not isolated but function as part of a dynamic sociotechnical network, where the interaction is not just with operators but extends to passengers, other vehicles and their drivers, pedestrians, and road infrastructure.

However, there also presents challenges (Garibay et al., 2023), particularly in designing AI systems that respect and enhance human cognitive capacities. Incidents in AI applications, such as those documented in the AI Incident Database (McGregor, 2025), highlight the need for human oversight. Errors like automated vehicles causing accidents show the dangers of overly autonomous systems. These examples reinforce the HCAI's focus on keeping humans in the loop (Zanzotto, 2019; Zheng et al., 2017). This is not just simply to require humans to oversee AI operations, but the entire system should be designed to engage and support human to oversee. This foundational approach enhances the functionality and safety of AI applications and also ensures their sustainable and beneficial deployment (Shneiderman, 2022; Xu et al., 2024).

The proposed proactive remote operation approach is consistent with HCAI principles by creating a joint cognitive system where AI and remote operators work in tandem. The remote operation system considers the direct interaction between the operator and the automated vehicle, while it also integrates broader ecosystem components like task allocation, operator monitoring, and predictive traffic analysis. The proactive remote operation follows the human-in-the-loop approach by ensuring that remote operators maintain ultimate control over vehicle operation. The system is designed to engage operators continuously, leveraging AI and service models to assign remote operation tasks based on factors including traffic conditions, operator workload, and attentional states, thereby optimizing task allocation. This enhances operational efficiency and upholds safety and ethical standards by maintaining human oversight.

1.4 Objectives and Scope of the Chapter

This chapter attempts to tackle the problem of remote operation of automated vehicles in mixed traffic using an integrated approach to support human oversight and control. It presents a system that supports proactive operator monitoring, anticipation, and intervention through likelihood assessment, optimized task allocation, and an interface to achieve high usability. Specifically, Sect. 2 discusses the current advances and potential of AI use in intelligent transportation, in understanding and monitoring drivers and operators, and in task allocation in managing fleets and work shifts. Section 3 presents a new proactive approach as opposed to the current problematic reactive approach and discuss various considerations and research needed to understand operator cognitive capacities. This section also introduces a conceptual model of proactive remote operation of automated vehicles and its corresponding system architect. The following sections then discuss the potential human-centered interface design (Sect. 4), methods to extract intelligent traffic information (Sect. 5), and a novel human-factors-informed service model to enable proactive operation of automated vehicles for transportation services (Sect. 6). Lastly, Sect. 7 presents two preliminary studies that can contribute to the fundamental knowledge. At the end, Sect. 8 provides a conclusion and discussion of the challenges and future directions of this work.

2 AI Use in Vehicle Automation, Intelligent Transportation, Understanding the Operator, and Operation Research

This section reviews the current state of the art in AI applications relevant to remote operation of automated vehicles. It highlights three interconnected research fields: the use of AI in (1) vehicle automation and traffic systems, in (2) understanding human operators' cognitive and behavioral states, and in (3) optimizing task allocation. These domains represent the technological foundation needed to support safe, efficient, and scalable remote operation of automated vehicles. Together, they provide critical insights for designing future proactive systems that integrate automation with human oversight.

2.1 AI Use in Vehicle Automation, Intelligent Transportation, and Real-Time Traffic Prediction

The Society of Automotive Engineers (SAE, 2021) categorizes vehicle automation into six levels, from no automation (Level 0) to full automation (Level 5). At Level 1, vehicles have driver assistance features such as steering or acceleration support. Level 2 advances to partial automation, where the vehicle manages both steering and acceleration in specific scenarios, although driver oversight remains crucial. Level 3 automation allows vehicles to manage all driving tasks without driver input under specific conditions but requires the driver to take over if automation encounters conditions it cannot handle and requests human intervention. Level 4 vehicles can operate independently in most environments but may be geographically restricted. Level 5, which is the highest level, enables full autonomy in any condition, removing the need for a human driver altogether.

AI is revolutionizing vehicle automation by enhancing capabilities such as image processing, object recognition, and route prediction. These AI-powered functions allow vehicles to perceive and interact with their environment more effectively (Yang et al., 2024), which is essential for navigating complex traffic scenarios safely and efficiently. To enable individual vehicles to perform the driving task, both the modular and the end-to-end approaches have leveraged AI (Atakishiyev et al., 2024; Chen et al., 2023c; Jing et al., 2022). In a modular approach, separate but interconnected modules handle specific functions, including perception, localization, planning, and control, each of which are powered by AI (Atakishiyev et al., 2024). For example, perception modules utilize AI for image processing to interpret real-time data from cameras and sensors, which is crucial for identifying obstacles and navigating roads. Localization modules integrate GPS data and real-time traffic updates to position the vehicle accurately within its environment. Likewise, planning modules use AI to make strategic driving decisions, while control modules execute these plans through precise maneuvering (Chen et al., 2023c; Hu et al., 2023; Yurtsever et al., 2020). This structure allows for specialized processing and easier debugging and maintenance, as each module can be developed and refined independently (Chen et al., 2023c; Hu et al., 2023). More recent advancements use end-to-end methods, where a single AI model handles all driving tasks from data input to action output. This holistic approach allows for seamless decision-making and potentially quicker response times, as the system processes raw sensor inputs, such as camera feeds and LIDAR data, directly into driving actions without compartmentalization (Araluce et al., 2024; Chen et al., 2023c; Jing et al., 2022). The end-to-end approach excels in handling complex dependencies that might be missed when using separate modules. With either AI approach, there is a growing realization that the vehicle automation needs to be explainable, to foster the trust and transparency between the technology and the driver (Atakishiyev et al., 2024).

AI also plays a crucial role in traffic management to enhance the efficiency and safety of transportation networks (for reviews, see Almukhalfi et al., 2024; Shaygan et al., 2022). Through the analysis of extensive data from road sensors and cameras, GPS information, social media feeds, and weather data, AI can predict traffic patterns and optimize traffic flow (Miglani & Kumar, 2019; Shi et al., 2019; Yin et al., 2021). For example, there is a rapidly growing trend of using AI technologies via machine learning and deep learning to predict potential congestion to assist traffic management (Akhtar & Moridpour, 2021; Ranjan et al., 2023). These technologies analyze vast amounts of data from various sources to predict traffic patterns, detect anomalies, and even optimize traffic signals (Abbas, 2019; Balasubramanian et al., 2023; Lilhore et al., 2022). Additionally, AI can be used to detect and respond to emergencies or unusual traffic conditions, such as accidents or road closures, by rerouting traffic and informing drivers of alternative routes, thereby minimizing disruptions (Ravi et al., 2021; Saleem et al., 2022). In these AI traffic management applications, the integration of multisource, real-time data processing and predictive models enhances response strategies to improve the overall safety and efficiency of traffic flow. To date, many studies have been conducted to predict traffic state (Bekiaris-Liberis et al., 2016; Li et al., 2014; Seo et al., 2017; Wang & Papageorgiou, 2005), facility type (Hu et al., 2004; Li, 2015; Li et al., 2018b), and environmental conditions (Datla & Sharma, 2008; Jia et al., 2017; Maze et al., 2006; Seeherman & Liu, 2015; Smith et al., 2004).

2.2 AI Use in Understanding the Driver or Operator

Monitoring mental states of drivers is becoming more prevalent in vehicles (Aghaei et al., 2016; Ayas et al., 2023), and has become a requirement for vehicles with partial or conditional automation. These systems have already been developed and some commercially available. As an example, Tesla has implemented an advanced driver monitoring system that utilizes cabin cameras to detect if a driver is distracted or drowsy, to help drivers stay vigilant of the driving situations (Tesla, 2025).

Similarly, the Seeing Machines FOVIO Driver Monitoring System tracks drivers' faces and eyes to infer their mental states and performance (Seeing Machines, 2025).

AI is increasingly used in understanding the behaviors and states of drivers, facilitating more personalized and efficient operational strategies. For example, aftermarket driver monitoring systems are used to monitor truck drivers (Uffizio, 2024; Mekinec, 2023). AI can analyze real-time data such as steering patterns, braking habits, eye movements, and physiological indices such as EEG, ECG, and respiration rate to detect signs of fatigue or distraction. This capability allows for the implementation of adaptive safety systems that can alert drivers to potential hazards, or if necessary, bring the vehicle to a safe stop, to prevent accidents.

With the rapid advancement in AI, deep learning and data fusion are well suited to leverage these multimodal data to inform about driver mental states (Das et al., 2021; Tavakoli & Heydarian, 2022). AI is particularly useful with comprehensive datasets, with the potential to enable more accurate and reliable feedback to drivers. Previous research also proposed and demonstrated the effectiveness of adaptive driver monitoring and warning based on driving environment contexts (Fletcher & Zelinsky, 2008; Kujala et al., 2024). This approach requires the monitoring system capable of handling real-time processing of large data volumes, an area where AI excels. Indeed, recent literature review on AI use in driver monitoring call for inclusion of traffic context such as weather, road condition, vehicle dynamics, and traffic flow to enhance the understanding of driver mental states and behavior (Yang et al., 2024).

2.3 AI Use in Task Allocation

AI is becoming essential in logistics and manufacturing to enhance efficiency and productivity in logistic delivery service, manufacturing, and warehouse management (Rosário & Dias, 2023). AI algorithms optimize the distribution of tasks among resources, ensuring each task is appropriately matched with resources based on capability, availability, and operational efficiency. This approach is becoming vital in environments where precision in resource allocation can significantly impact overall outcomes (Yaiprasert & Hidayanto, 2024).

In logistics of delivery services, AI can be used for optimizing delivery routes and schedules, adapting to fluctuations in demand and operational challenges (Rosário & Dias, 2023). In transportation services, AI-driven algorithms schedule tasks such as parcel pickups and deliveries, dynamically adjusting routes in real-time to account for traffic conditions, vehicle availability, and delivery urgencies. For example, AI can effectively conduct route planning via analyzing road networks, traffic patterns, and customer locations to solve complex vehicle routing problems, thereby enhancing the cost efficiency and reliability of these transportation services (Schmitt, 2023). AI can also optimize resource allocation for the delivery service to make sure resources of vehicles, personnel, and facilities are utilized efficiently (Kumar et al., 2021). In a recent cost analysis, AI has been shown to significantly improve cost strategies and maximize profit in the logistics delivery sector (Yaiprasert & Hidayanto, 2024).

Similarly, AI-powered smart manufacturing can enhance the efficiency and quality of production lines and better optimized warehouse management (Sodiya et al., 2024; Wamba & Queiroz, 2022). Many manufactures are already leveraging AI. For example, Tesla uses AI applications to identify vehicle flaws to improve quality control. Toyota uses AI to optimize supply chain, and Bosch utilizes robotic process automation to improve the efficiency of repetitive tasks (Li et al., 2018a). Airbus has also implemented AI in its production lines (Ransbotham et al., 2017). Likewise, in warehouse management, AI can optimize various aspects such as demand casting, inventory management, and order fulfillment (Javaid et al., 2022; Sodiya et al., 2024). The adaptive nature of AI algorithms allows them to respond dynamically to changes in conditions and demands, streamlining operations and enabling businesses to react swiftly to market shifts and evolving customer needs (Dash et al., 2019). With vast amount of information collected via sensors and enterprise systems, AI-powered automation can identify patterns and anomalies to enhance order accuracy, fulfillment time, and real-time data-driven decisions (Sodiya et al., 2024; Wan et al., 2020).

As in the applications discussed above, much of the current research of utilizing AI in the logistics optimization in various sectors have primarily concentrated on nonhuman aspects such as predicting demands, managing inventory, optimizing delivery route planning, and inspection (for reviews, see Chen et al., 2024; Sodiya et al., 2024). While these AI applications can be transferred to managing human resources and optimizing human workload and performance, limited efforts have been made to explore these despite the critical need to consider a human-centric approach (Leng et al., 2024). A significant human-centered application in industrial and manufacturing settings is that AI can use operator mental state information to optimize task allocation and scheduling. By understanding the physical and cognitive loads experienced by operators, AI-powered systems can schedule breaks and adjust workloads in real time to prevent fatigue and enhance productivity. A recent review of operation research on fatigue monitoring and personnel scheduling (Xu & Hall, 2021) suggests that fatigue can be evaluated via productivity tracking (Delasay et al., 2019), movement data (Yi et al., 2016), physiological signals (Chowdhury & Nimbarte, 2017; Fu et al., 2016), and subjective report (Yildi et al., 2017). The review further pointed to research exploring shift scheduling as a mitigation to fatigue (Gunawan & Lau, 2013; Todovic et al., 2015; Wang & Liu, 2014). Although most of these research did not specifically investigate AI-powered scheduling methods, existing success suggests the potential value of AI implementation to solve these operation problems, especially pertaining to human resource, well-being, and performance.

3 A Framework of Proactive Operation

This section presents a human-centered framework for proactive remote operation of automated vehicles. It begins by describing three developmental stages of remote operation, as a remote operator can be a remote driver, remote monitor, or a remote commander. The section then contrasts reactive and proactive approaches in remote operation, advocating for systems that enable anticipation, engagement, and real-time oversight. Finally, it introduces a conceptual AI-assisted architecture designed to optimize operator involvement, task allocation, and safety in mixed traffic environments.

3.1 Stages of Remote Operation

To date, industry application is just emerging with very limited research examining remote operation of automated vehicles. Among these, efforts have been largely focused on recreating the driving environment for a remote operator to drive or navigate a single vehicle (Lightbown, 2023; Phantom Auto, 2025; DriveU.auto, 2025a; Kettwich et al., 2021). For example, a remote operator may operate a highly automated vehicle which requires the operator to monitor and takeover control when needed. This leads to the remote operator experiencing similar out-of-the-loop and vigilance problems as a human driver would in an automated vehicle (Clark & Feng, 2017; Körber et al., 2015; Merat et al., 2019) but the remote operator could further suffer from compromised situation awareness due to not physically being inside a vehicle (Mutzenich et al., 2021).

However, the future of remote operation can be much more than what has been currently developed. In a recently proposed framework of cloud-based remote operation of automated vehicles (Zhang, 2020), a cloud-based system is envisioned to be able to assist and guide remote operators, and allow the overall system to handle more vehicles than the number of available operators as long as the number of vehicles requiring control at any one moment does not exceed the number of operators available. Many unique problems arise in remote operation that need to be addressed. Figure 2 illustrates the three proposed stages with example human factors questions. Stage 1 involves direct remote driving or navigation, where an

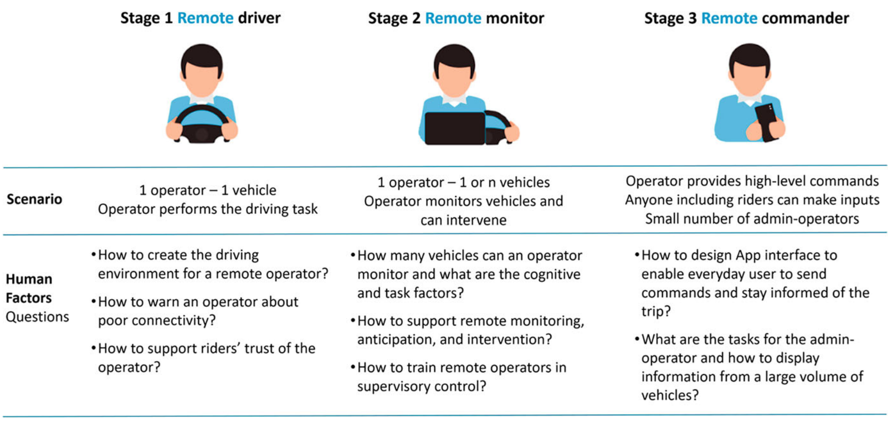

Fig. 2 Three stages of remote operation of automated vehicles

operator controls a vehicle in real time, either using pedals and a wheel or by specifying the vehicle's path. This setup can be used in low-speed or recovery scenarios as it requires continuous operator input and situation awareness through a remote operation interface. At stage 2, the operation shifts to supervisory control of one or more highly automated vehicles. The operator primarily monitors automation performance and only intervenes when necessary. For example, an operator may anticipate issues based on road conditions, update routes, resolve automation uncertainties, or take over to remotely drive or guide the vehicle. This supervisory stage enables proactive oversight without requiring constant manual input. Stage 3 extends to fleet-level management. An admin-level operator may oversee a large number of vehicles and provide higher-level inputs for route planning and coordination. Additionally, as private owners of automated vehicles may allow their vehicles to be used as robotaxis (Ingram, 2025), an interface is needed for owners to track their vehicle's status and set availability and preference, even when the vehicle is in active use. Some research has attempted to answer human factors questions for stage 1 but little research exists so far to explore stages 2 or 3. Systematic research needs to involve disciplines including human factors, cognitive psychology, operation research, artificial intelligence, traffic engineering, and smart infrastructure development and planning. In the currently discussed remote operation approach, this chapter focuses on stage 2 (remote monitor).

Similar to the stages described above, DriveU.auto recently proposed six modes of remote operation: direct drive (T0), low-level control (T1), high-level control (T2), guide (T3), advice (T4), and supervise (T5), where the first three modes are remote driving, and the latter three modes are remote assist (DriveU.auto, 2025b). In T0–T2, a remote operator can either directly activates the actuators in the vehicle or controls lateral and longitudinal positions through a remote controller, a driving wheels, or a joystick. In T3–T5, a remote operator may provide input assisting vehicle path planning, responds to assistance requests from a vehicle, or just monitors and intervene if needed. Mapping these to the focus of stage 2 remote operation, T3–T5 (guide, advise, and supervise), are more related to the focus of the current chapter.

3.2 "Proactive" Versus "Reactive" Approach in Human Automation Interaction

In human-automation interaction, a human operator can take either a reactive approach or a proactive approach (Parasuraman et al., 2000; Zhang et al., 2021). A reactive approach requires human assistance only when the system becomes aware of difficulties; while in a proactive approach, operators actively anticipate and avoid hazardous situations (Fig. 3). Even as AI enables high levels of automation or limited autonomy, the entire system will still require human involvement especially considering the potential for errors in complex situations and the need of oversight.

The typical setup in the current remote operation of automated vehicles assumes a reactive approach, with the remote operator stepping in only when the system

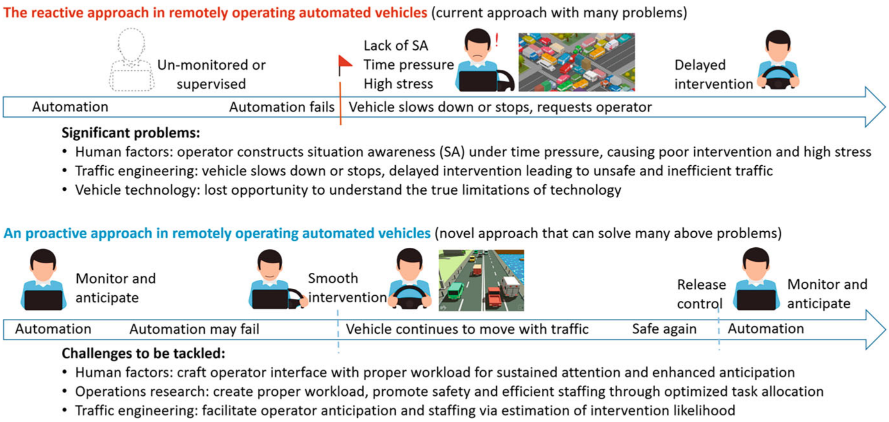

Fig. 3 A contrast between the current reactive approach and the novel proactive approach

requests assistance (DriveU.auto, 2025b; Ottopia, 2025; Phantom Auto, 2025; SAE, 2021). While this setup requires fewer human resources, it has several significant disadvantages, including missed opportunities to improve vehicle automation technology, poor intervention performance and high stress of the operator, as well as subsequently increased risk of crashes and traffic congestions. Specifically, from a technology perspective, incidents during which AI did not handle driving properly are missed if they did not lead to a crash or near crash; this suggests missed opportunities to identify and address edge cases and to improve automation. In current human-driven automated vehicles, one method to collect additional data related to potential edge cases is asking drivers to describe the incidents when they voluntarily deactivate automation. This can provide valuable information as human drivers supervise automation by offering immediate feedback (i.e., temporarily deactivate) and subsequently providing a description of what happened to ensure more explainable feedback. In reactive remote operation, this mechanism is lacking leading to a missed opportunity to collect valuable data for continuous improvement of AI.

From a human factors perspective, when intervening under time pressure, remote operators experience high stress (Tener & Lanir, 2022) and difficulty in constructing situation awareness (Linkov & Vanžura, 2021; Mutzenich et al., 2021), both leading to impaired intervention performance. "Hard and dubious," "overwhelming," "stressful," and "a huge effort" are words remote operators used to describe their job using a reactive approach (Tener & Lanir, 2022). This stress can diminish their ability to respond effectively, potentially increasing the likelihood of reduced quality of intervention. Furthermore, the lack of proactive engagement in remote operation can prevent operators from developing a deeper and intuitive understanding of vehicle behavior under various conditions, therefore hindering the overall system reliability and safety. Just as drivers in automated vehicles benefit from being notified in advance (Clark & Feng, 2017; Wan & Wu, 2018), remote operators could significantly improve their effectiveness and reduce workload when anticipatory information is provided. They would benefit from systems that not only alert them to immediate problems but also provide insights into ongoing vehicle performance and potential anomalies before they escalate into critical situations. The reactive approach places operators in a position where they primarily respond to emergencies, which can increase stress and hinder the development of comprehensive situational awareness, ultimately degrading both operator well-being and system performance.

From both traffic engineering and operations research perspectives, the prolonged interventions in the reactive approach would lead to traffic blockage and even rear-end collisions in mixed traffic (Zipper, 2022). When remote operators intervene only in response to system alerts for an immediate action, it can result in sudden, possibly erratic vehicle maneuvers that disrupt the flow of surrounding traffic. This disadvantage could occur regardless of whether the operator is using a wheel and pedals to remotely provide direct control or simply specifying a path for the vehicle to follow. Such disruptions contribute to short-term traffic and affect overall traffic patterns. Additionally, the reactive approach does not account for the collection and analysis of traffic data that could be used to optimize traffic flow and predict potential hotspots of congestion. Furthermore, task allocation is compromised due to the unpredictable nature of demand. Operators may experience periods of inactivity followed by sudden, intense bursts of required interventions when issues arise. This uneven distribution of tasks can lead to operational inefficiencies, with some operators overwhelmed and others underutilized, thereby increasing operational costs and reducing overall system effectiveness.

In contrast, a proactive approach would be much preferred. AI can benefit from oversight and feedback from remote operators, and the remote operator can benefit from enhanced operation familiarity with the automated system as a result of continuous interaction. An operator will likely be more engaged, confident, and competent while feeling less stressed in an intervention due to their ongoing participation rather than sporadic involvement in emergencies.

The proactive remote operation approach also enables operators to anticipate and adapt to changes in traffic dynamics in real-time therefore mixed traffic flows more smoothly with less disturbance. With support through human-centered interface and system design, remote operators can make informed decisions that align with the evolving road conditions, thereby preventing the abrupt maneuvers that typically result from reactive interventions. This approach leverages operators' understanding of automation and recognition of environmental factors that could trigger edge cases (see parallel literature on driver proactive thinking; Casner & Hutchins, 2019; Zhang et al., 2021), enabling supervision of a vehicle through anticipation and planning. The ability to preemptively address these situations enhances overall traffic management and reduces the risk of congestion and crashes. Indeed, data from on-road testing of automated vehicles with safety drivers already supports this. A recent analysis of data from automated vehicles in California found that those vehicles were less likely to be in a crash when a safety driver proactively takes over than those cases when automation signals its failure (Khattak et al., 2021).

Other evidence suggests greater satisfaction and engagement when operators have more control (Lyons et al., 2014), likely because they can utilize their skills and insights more effectively, leading to a more fulfilling work experience. This enhanced operator satisfaction also has implications for their long-term performance and the overall efficacy of the automated vehicle operation. Operators who feel in control and valued are more likely to stay alert and committed to their roles, which further contributes to the efficiency and safety of the automated systems they oversee.

Overall, a proactive approach not only can improve safety and traffic flow but also reduce work-related stress for operators, leading to better job satisfaction and lower turnover rates. This holistic improvement in both human and technical aspects underlines the significant advantages of moving away from a reactive operation model toward a more proactive and integrated approach in the management of automated vehicles. The following subsections present a novel approach that enables a remote operator to be engaged, proactively monitoring and anticipating potential events, without a substantial increase in the demand of human resource (i.e., number of remote operators).

3.3 A Conceptual Model of Proactive Remote Operation of Automated Vehicles with AI Assistance

The Three-Component System: Operator, Traffic, and Task Allocation

Figure 4 presents a conceptual model for a proactive remote operation system with AI assistance, designed to optimize the interaction based on traffic conditions and operator characteristics. This system comprises two key AI-driven components: the intervention likelihood assessment module and the task allocation module. These modules integrate and analyze vast amounts of data to support efficient and effective decision-making in remote vehicle operations.

The intervention likelihood assessment module utilizes AI to analyze collected traffic information, such as types of service facilities, current traffic patterns, reported detours, and nearby intervention events. This module evaluates these data

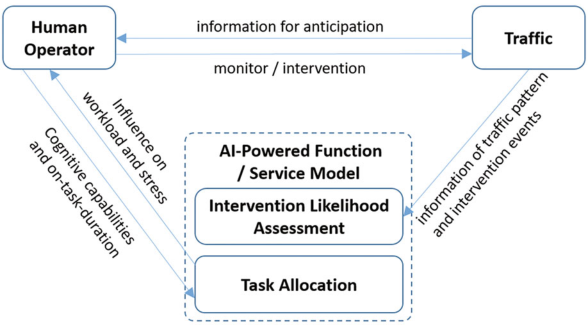

Fig. 4 General system components of proactive remote operation

to assess the likelihood of a vehicle needing a remote operator's intervention. For instance, if the system detects a complex traffic scenario or a potential hazard on the route, it can calculate an increased probability of intervention necessity. This predictive capability allows remote operators to prepare in advance, ensuring they are ready to intervene swiftly and safely if required.

Concurrently, the task allocation module leverages AI to understand and integrate information about the human operators themselves, such as their cognitive capabilities and the duration of their tasks. By assessing an operator's current cognitive load and how long they have been performing tasks, the model or AI can intelligently allocate control tasks among available operators, aiming to optimize their workload and minimize stress. This not only enhances the efficiency of the operation but also supports the well-being of the operators by preventing fatigue and overload.

Through the remote operation interface, operators receive real-time traffic information which aids them in anticipating and preparing for potential intervention scenarios. This interface plays a crucial role in how operators interact with the system, supporting them to anticipate and monitor. The system's design ensures that operators can effectively influence the vehicle's navigation and safety by either taking direct control or allowing automation to continue managing routine conditions (similar to Ottopia, 2025). Through monitoring and intervention, an operator can influence traffic via the operator's action (or no action).

Architecture of a System for Proactive Remote Operation of Automated Vehicles in Mixed Traffic

Based on the conceptual model, there are five potential scenarios. As illustrated in Fig. 5, continuous information of one vehicle is first segmented into multiple episodes, and each episode (e.g., 2-minute duration) is categorized as low or high likelihood of intervention necessity, based on the traffic information. For a low likelihood episode, it is assigned to either a human operator for monitoring, may be in combination with other vehicles' episodes (scenarios 1 and 2), or unmonitored (scenarios 3 and 4).

Specifically, in scenario 1, when there is an identifiable issue during monitoring, the remote operator proactively intervenes and other concurrently monitored low-likelihood episodes are assigned to other remote operators. When there is not any identifiable issue, the vehicle continues to travel without operator intervention until the end of the episode regardless whether it is monitored (scenario 2) or unmonitored (scenario 3). In scenario 4, the vehicle encounters an issue while unmonitored, thus requests operator assistance. The remote operator would reactively intervene. In scenario 5, when an episode is categorized as high risk (i.e., an intervention is likely), this episode is assigned to a dedicated human operator to anticipate an upcoming intervention. A vehicle's next episode goes through the same process.

Each vehicle's subsequent episodes undergo the same assessment and assignment process, ensuring continuous monitoring and intervention readiness. This model can be experimentally evaluated to determine the safety and efficiency of each scenario, which will help calibrate and refine the service operation model. Over time, this

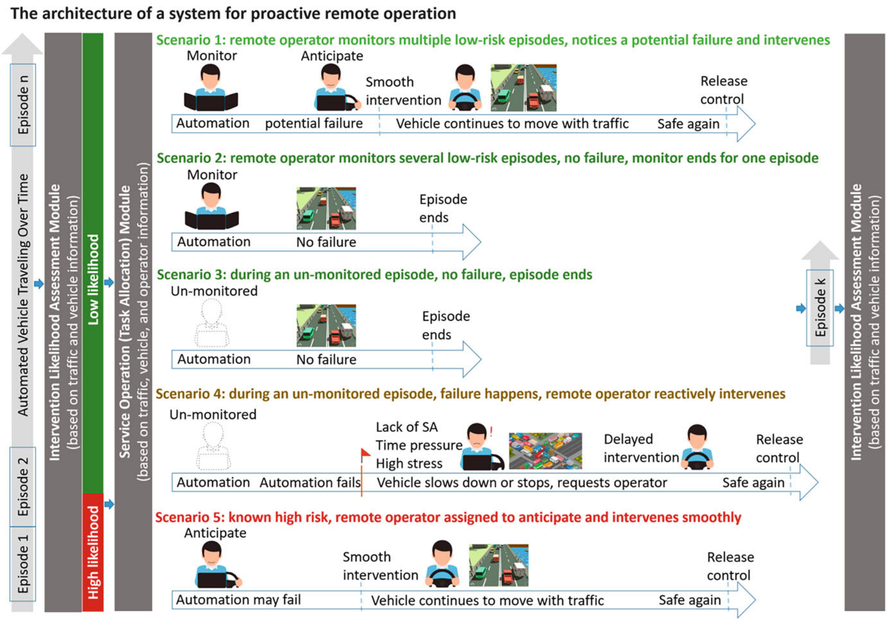

Fig. 5 The architecture of a system for proactive remote operation of automated vehicles in mixed traffic

structured approach could greatly enhance the overall system's ability to dynamically adapt to various traffic conditions and operator availability. By systematically categorizing episodes based on risk and managing them accordingly, the remote operation system ensures optimal safety and maximized operational efficiency.

Experimental validation of this model would provide crucial data on the effectiveness of proactive versus reactive interventions, enabling further optimization of the AI algorithms that support decision-making processes. This iterative improvement could lead to a more reliable and responsive service model, reducing the likelihood of accidents and improving user satisfaction with automated vehicle technologies. The preliminary research section (Sect. 7) describes some pilot work that the authors' team has been conducting as initial steps on this frontier. Over time, through continuous learning, three aspects of this entire human machine system will improve: operators' proactive intervention decision and performance, the accuracy of the likelihood assessment, and the efficiency of task allocation. These improvements will subsequently resulting in better remote operation and enhanced traffic safety and efficiency.

To realize the above conceptual model of proactive remote operation of automated vehicles and its corresponding system architect, the following sections (Sects. 4, 5, and 6) discuss the potential human-centered interface design (Sect. 4), methods to extract intelligent traffic information (Sect. 5), and a novel human-factors-informed service model to enable proactive operation of automated vehicles for transportation services (Sect. 6). Each of these sections begins with a review of relevant literature and the state-of-the-art of the specific domain (i.e., current knowledge), followed by proposed technical approaches to enable the conceptual model and system architecture (i.e., technical approach).

4 Human-Centered Remote Operation

4.1 Current Knowledge: Workload Management, Attentional State Monitoring, and Cognitive Engagement

Operators have cognitive limitations in space and time. They can only attend to about four visual targets simultaneously (Cavanagh & Alvarez, 2005; Feng et al., 2012; Sears & Pylyshyn, 2000), and their workload increases with task difficulty and information volume (Alvarez & Cavanagh, 2004; Rubio et al., 2004). Overload leads to impaired performance and elevated stress (Matthews & Campbell, 2009). Previous studies suggest that remote operators can handle multiple units, with up to 16 units in a missile management task (Cummings & Guerlain, 2007), and four robots in an inspection task (Olsen & Wood, 2004; Trouvain & Wolf, 2002). The cognitive constraints come from overlapping events (Chadwick, 2006), attentional demand (Chadwick, 2006), and switching among units that require different mental models or situation awareness (Goodrich & Olsen, 2003). Cognitive capacity is task-dependent, and some recent preliminary findings suggest that an operator can monitor two vehicles without performance degradation. In those studies (Morrison et al., 2022; Shoffner & Feng, 2024), a video-based approach was taken to simulate remote operation of automated vehicles. Preliminary evidence based on task accuracy suggests that remote operator can successfully monitor two vehicles showing little degradation from their performance on monitoring a single vehicle, while significant detriments were observed when operators monitored four vehicles simultaneously (Shoffner & Feng, 2024). This is encouraging evidence suggesting the possible scenario of multi-vehicle monitoring in remote operation. In addition, this research has found that certain types of silent automation failures such as missing a stop sign is much more difficult to detect than other failures such as deviating from the lane, highlighting the need to take specific road environment and traffic and weather conditions into consideration when designing the remote operation task.

Another type of cognitive limitations relates to time which can be categorized into two aspects: (1) a minimum time required to develop situation awareness (Linkov & Vanžura, 2021; Mutzenich et al., 2021), and (2) prolonged task exposure with underload and low prevalence of critical events causing boredom, passive fatigue, mind wandering (Geden et al., 2018; Saxby et al., 2013), and vigilance decrement (Wolfe et al., 2007). Boredom and vigilance decrement have been highlighted as potential issues in remote operation (Hampshire et al., 2020; HF-IRADS, 2020), although limited research has examined these very topics. Prolonged exposure to monotonous driving can lead to an increased rate of mind wandering and impairment of vigilance (Geden & Feng, 2015; Geden et al., 2018). In the context of proactive remote operation, the duration of each episode should be sufficient for a remote operator to establish situation awareness, while also not too long to prevent the loss of vigilance. The authors' preliminary study suggests operators did not seem to demonstrate any significant decrement in vigilance after viewing about 12 videos with each ranging from 35 to 120 seconds (Shoffner & Feng, 2024). Such data can be used to guide the design of shifts in remote operation and to determine what would be the optimal frequency of breaks during the remote operation task.

The relationship between workload and vigilance is crucial in remote operation. Both excessive and insufficient workload can negatively impact monitoring performance. A suitable load would not only promote monitoring success at the moment but also enhance vigilance. More research is needed to better understand operators' spatial and temporal cognitive capabilities and to assess their ability to monitor vehicles across different traffic facilities. Research on driver monitoring of and intervention failures of partial automation suggests that drivers may suffer from weaker capabilities in regulating their behavior when the workload is too high (Bai & Feng, 2025). This evidence further supports the importance in identifying a proper load for remote operators given the criticality of their monitoring and intervention performance. These are critical considerations for a human-centered design of the remote operation task.

An additional human-centered approach is to monitor the operators and understand their dynamic attentional state, workload, and cognitive engagement. Existing research has shown the feasibility to infer driver attentional state via various channels of data including task-based measures, eye movements and facial expressions, body movements and gestures, as well as physiological measures such as EEG, ECG, respiration, and galvanic skin response. For example, in the domain of driver state monitoring (for a review, see Aghaei et al., 2016), vehicle-based measures are steering and braking inputs from the driver (Dong et al., 2011; Bayly et al., 2009), vehicle speed and jerk (Yabuta et al., 1985), and lane deviation and headway distance (Bayly et al., 2009), which have been found to reflect a driver's mental state. Face and eye tracking can provide additional information of driver attentional state. For example, eye blink rate and percentage of eye closure have been found to indicate drowsiness (Dinges & Grace, 1998), while glance behavior and head movements can tell what the driver is paying attention to (Feng et al., 2023; Bergasa et al., 2006; Viola & Jones, 2001; Murphy-Chutorian & Trivedi, 2010). Tracking the body such as hand movements has also been used to detect driver distraction (Yan et al., 2015). Further measures include skin conductance level (Boucsein, 2012), respiratory frequency (Fairclough & Mulder, 2011), heart rate and heart rate variability (Zhao et al., 2012; Hjortskov et al., 2004), and brain activities (Borghini et al., 2014). More holistic measures based on driver behavior has also been used to assess driver cognitive engagement in monitoring automation (Bai & Feng, 2024, 2025). While many channels of data can be useful in inferring attentional states, it is essential to ensure accuracy in such inferences as occurrences of monitoring errors such as mistakenly identifying a driver being drowsy while in fact they are not can affect driver acceptance of monitoring systems (for a review, see Ayas et al., 2023).

Based on these knowledge, similar methods can be adopted to monitor remote operators' mental state. Compared to the moving vehicle environment for a driver, the static indoor workstation environment for a remote operator would facilitate easier continuous recording and analysis of many of the above measures due to less environmental noise leading to improved inference accuracy.

Based on the attentional monitoring outcomes, remote operators can be assigned to specific episodes and task scenarios (e.g., driving facilities and traffic conditions) considering the risk level and operator readiness. Work breaks can be scheduled based on fatigue level and episode duration and demand may be tuned based on the operator's attentional state.

4.2 Technical Approach: Facilitating Operator Monitoring and Anticipation in Remote Operation Through Interface Design

This subsection explores a technical approach to support proactive remote operation of automated vehicles through effective interface design. Drawing on human factors research from driving, automation, and other remote-control domains, it explores how interfaces can facilitate monitoring and anticipation when operators oversee multiple vehicles. Key considerations include visual layout, alert design, explainability of AI decisions, and support for both operators and riders. The goal is to create human-centered systems that enhance engagement, attention, situation awareness, trust, and performance in remote operation settings.

Despite cognitive limitations, humans can use knowledge and anticipation to overcome them. Anticipation is critical for safe driving (Stahl et al., 2014) and is a core skill to develop as one learns to drive (Taylor et al., 2011). Everyday tools aiding anticipation include traffic congestion warnings (D'Andrea & Marcelloni, 2017; Mehta, 2022) and safety warnings on navigation apps or dynamic message signs for incidents like police presence, broken down vehicles, or lane merge (Shakir, 2022). Other findings also show the power of anticipation such as understanding the upcoming road layout (Feng et al., 2018) or knowing the upcoming risk level (Sall & Feng, 2019) could effectively guide attention and hazard detection. Consistent with this, a recent article on challenges and guidelines of designing a remote operation interface suggests the integration of contextual road information and advanced alerts that explain the need and reason for interventions (Tener & Lanir, 2022), which can enhance operators' ability to anticipate and respond to changes.

Interface Design for Monitoring and Anticipation in Remote Operation

Research on interface design for remotely operating automated vehicles is just emerging (Gnatzig et al., 2012; Kettwich et al., 2021; Sheridan, 1995), with most focused on supporting situation awareness of a remote operator. In a proactive approach, an operator is actively monitoring the environment to recognize the factors that could trigger edge cases. Here we discuss designing the interface to support the monitoring of multiple vehicles and to anticipate potential interventions. Limited research has examined these in the context of remotely operating automated vehicles; thus, we summarize literature from other application domains as well.

Monitoring. To support an operator in monitoring multiple units, the interface should present all units' information simultaneously (Chadwick et al., 2004; Chen et al., 2011) and allow voluntary switching among units. However, switching between vehicles incurs a cost, which can be reduced by allowing operators to determine when and where to switch tasks (Squire et al., 2006). Prior findings point to the need of considering vehicle monitoring and selection, context switching, problem-solving, and command expression in interface design (Goodrich & Olsen, 2003).

Anticipation. Notifications based on the attentional demand of upcoming road environment have been used to better attend to the road (Kujala et al., 2016). When the upcoming attention demand is high (e.g., intersection), a notification is issued. Alerts to anticipate could be intrusive (Chen et al., 2011; Cummings, 2004), while augmented information overlaid to camera views is recommended if visual clutter could be avoided (Chen et al., 2011). Timing of alerts is also a critical factor (Clark & Feng, 2017). In general, information that is designed to facilitate anticipation should be intuitive, and easy to extract and interpret (Olson & Wuennenberg, 2001). Figure 6 shows two conceptual display illustrations. Example applications can be found from the industry (Demuynck, 2020; DriveU.auto, 2025a; Dröge, 2020).

The overall goal of the remote operation interface is to enable: (1) simultaneous monitoring of multiple vehicles given preliminary evidence suggesting its feasibility (Shoffner & Feng, 2024), and (2) anticipation of potential interventions through the presentation of traffic information and surrounding events. Information from traffic and surrounding interventions can be used to help remote operators anticipate and prepare for potential upcoming interventions. The following subsection presents a setup that promotes monitoring and anticipation in remotely operating automated vehicles. The effectiveness of such support can further enhance our understanding of what constitutes proactive human-automation interaction, what information do operators need, and when and how they would use it.

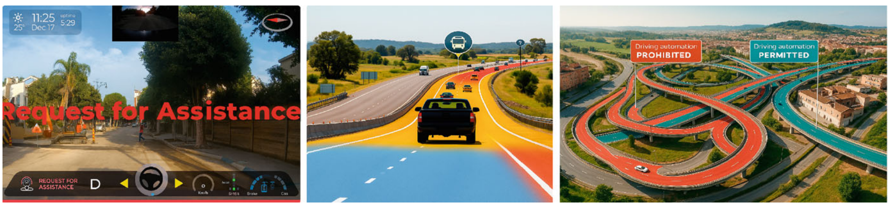

Fig. 6 (a) Conceptual illustration of a remote operation interface calling for human assistance. (b) Conceptual illustration of traffic and events shown as augmented information

A Potential Remote Operation Setup to Enable Multi-vehicle Monitoring

Figure 7 illustrates a possible setup consisting of three monitors for each vehicle, which is typical for desktop driving simulators and the current remote operation industry (DriveU.auto, 2025a; Ottopia, 2025; Phatom Auto, 2025; Tener & Lanir, 2022). In addition, there is a fourth monitor to display the road map with traffic and intervention information (similar to the method in prior studies, Cauffman et al., 2020; Feng et al., 2023). Given these research findings support simultaneous monitoring of two vehicles (Shoffner & Feng, 2024), Fig. 7 shows an example integrated six-monitor setup. The space gap between upper and lower monitors is to ensure perceptual separation of visual information from the two vehicles, also making focused attention on one easier (Harley, 2020). An upper-and-lower arrangement was chosen, instead of a left-and-right arrangement, considering the need to make all visual information accessible when monitoring multiple units (Chadwick et al., 2004), and the spatial alignment of control and display (Tsang et al., 2015). It is important to note that further research is needed to examine these interface design aspects, including the number of displays and the exact spatial arrangement, guided by existing models of human attention (e.g., SEEV model; Wickens, 2015). In the case of intervention, the remote operator can use a driving wheel and pedals to directly drive. If the intervention is to navigate the vehicle by specifying its path, the remote operator may use a touch screen and pointing device instead. While both direct driving using a wheel and pedals and navigation such as specifying one of the vehicle path options are used in today's remote operation (Ottopia, 2025; The Waymo Team, 2024), further research is needed to determine the control method based on the intuitiveness given it is an important factor emphasized in the literature (Olson & Wuennenberg, 2001). The current example illustrates the direct driving option; however, navigation (i.e., path specifying) could follow similar display setup with altered input devices. To support remote operators' anticipation, traffic information (e.g., congestion, known construction zone ahead) and intervention events from surrounding automated vehicles will be displayed as augmented information on the fourth monitor.

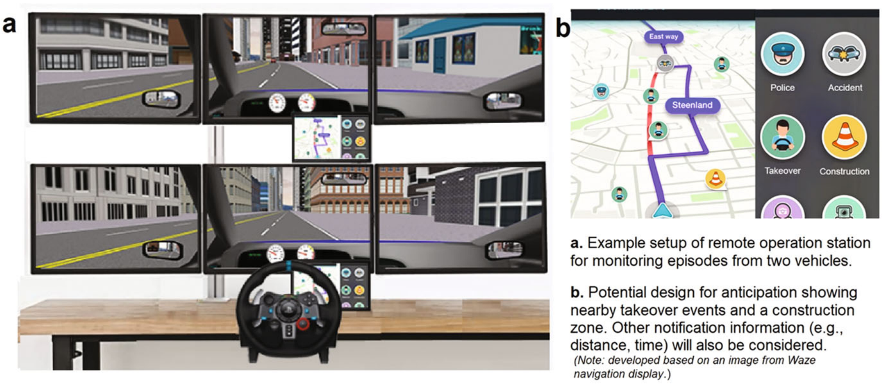

Fig. 7 (a) A possible setup for remote operation and (b) display for anticipation

Additional Considerations on Explainable AI Decisions and Operator Training

In the design of this proactive remote operation system, the cognitive aspects such as workload, attention, monitoring, and anticipation are critical issues to address. Additionally, considerations such as how to make the AI decisions explainable and how to effectively train remote operators are also highly important aspects of the human-centered design approach.

One significant technical challenge is the transparency of AI decisions, which is pivotal for operator trust and effectiveness (von Eschenbach, 2021; Zerilli et al., 2022). The AI systems controlling the vehicles often operate as "black boxes," with decision-making processes that are not transparent, making it difficult for operators to understand and predict the vehicle's behavior (Dong et al., 2023; Utesch et al., 2020). This lack of transparency can hinder the operator's ability to intervene appropriately, as they may not fully understand why the AI is acting in a certain way. Addressing this issue involves developing AI systems that not only perform well but also communicate their decision-making process in a manner that is understandable to humans. Techniques such as explainable AI can be instrumental in achieving this by providing insights into the AI's reasoning in predicting traffic conditions and potential intervention necessity, thus enhancing the operator's situational awareness and trust in the system (Sanneman & Shah, 2022; Hassija et al., 2024).

Another challenge on transparency is how AI identifies an operator's attentional state and cognitive engagement. Because a person's own attention and cognitive engagement involve a significant component of internal experience, AI can only make inferences based on indirect observations of explicit behavior or performance data. In attention, meta-awareness is an important aspect that allows the awareness of one's own attentional state (Smallwood et al., 2007). Attentional states and cognitive engagement involve subjective experiences that an external observer (i.e., another human or a system) can only infer based on action, eye movements and facial expression, and physiological signals, while the human being observed would consider own internal experiences instead of the inferences as the truth. For example, when a remote operator receives frequent alerts to take breaks (due to detected fatigue) but the operator still subjectively feels alert and capable of continuing the monitoring task especially if the operator feels under pressure to complete certain amount of work hours, the operator may view the system being intrusive and annoying. Because the perceived ground truth (i.e., subjective experience) only lies within the remote operator who is being observed, how the operator would perceive the trustworthiness and fairness the AI inferences would require highly transparent and explainable information. An additional factor that further complicates this issue is that while AI-powered inferences can be highly accurate, it is still possible to make errors including false recognition and misses. In current driver monitoring technologies, false identification of fatigue has already been recognized as a significant issue (Langer et al., 2016; Assuncao et al., 2019). Similarly, when an operator mind wanders but with eyes stay fixed on the road, AI-powered monitoring based on eye movements may not catch this mental state even though the operator might realize it later. Therefore, a future research direction on the design of remote operation is to produce AI assistance to remote operators in a convincing and explainable way.

Given remote operation of automated vehicles is not a traditional occupation, operator training is another important area that needs to be explored. This area of expertise draws parallels with professions such as air traffic control, unmanned aerial vehicle operation, robot teleoperation, and even esports. Insights from a recent interview study (Tener & Lanir, 2022) highlighted that significant video gaming experience was a common attribute among operators, demonstrating the relevance of gaming skills that overlap with remote vehicle operation. It is perhaps not surprising as playing games such as beamNG.drive and Starsector require overlapping skills with remote operation and share similar task interface, and that research has shown gaming can change cognitive capabilities (Spence & Feng, 2010; Wu et al., 2012; Feng & Spence, 2018; Green & Bavelier, 2003). In addition, professional drivers like truck and taxi drivers could transition into remote operation roles, with their valuable practical experience that could benefit their performance in remote operation. Therefore, training programs for these operators need to include not only advanced driving techniques but also interaction with AI-powered automation, decision-making, and managing high stress situations. Such training should emphasize understanding AI functions, the interface, traffic dynamics, and why and how the tasks are allocated. Simulation-based learning with realistic scenarios will likely play a crucial role in this training, similar to current practice in training pilots and air traffic controllers (Malakis & Kontogiannis, 2012; Zuluaga-Gomez et al., 2023; Mavin & Murray, 2010; Landman et al., 2018).

Enhance Rider Experience Through Rider Interface Design

Another aspect that should not be overlooked is the form of interaction between the rider and the remotely operated vehicle. With the recent deployment of robotaxi services in various cities in the USA, rider experience issues have emerged. For example, instances where a vehicle repeatedly circles a parking lot due to navigation errors (Bacon, 2025) or lacks human support to intervene during harassment from other vehicles (Bonos, 2024) can result in significant frustration and feelings of helplessness among passengers. Such experiences highlight critical areas where the interaction between riders and vehicles (or remote operators) needs enhancement to ensure both comfort and confidence in the technology.

There is a growing body of research that recognizes the importance of rider interface design for robotaxi service (Hua, 2022; Meurer et al., 2020; Paris, 2024; Yoo et al., 2024). These research have identified several key factors that can improve rider satisfaction and foster trust in the technology. To compensate for the absence of a human driver, riders should be provided with an intuitive in-vehicle interface that not only communicates information about the ride but also allows communication with remote assistance when needed and even limited control of certain vehicle actions (Paris, 2024; Yoo et al., 2024). This ensures that riders feel in control and secure throughout the ride. Another important consideration is the in-vehicle visual display design. By incorporating visual cues and contextual data that reflect the dynamics of the ride, such as graphical representations of the vehicle, its path, and the environmental information, the interface can explain the reasons for sudden stops or route changes in real time. Advanced alerts about road conditions and upcoming maneuvers can also improve rider awareness of the situation. These display elements can help riders to feel more involved and informed. Moreover, the interface needs to be adaptable, to support the diverse needs and preferences of various rider groups, including older adults, children, and individuals with sensory impairments such as vision loss. When a remote operator intervenes vehicle operation, informing riders about this intervention and its reasoning could also promote their trust and conform in using the service.

5 Real-Time Traffic Prediction

5.1 Current Knowledge: Automated Vehicles in Mixed Traffic and Prediction of Intervention Events

To ensure safe and effective intervention by remote operators, it is essential to predict the necessities of these events ahead of time. This prediction will allow for effective determination by a system on whether a dedicated remote operator should be assigned, while also allowing for sufficient preparation time for the remote operator to gather all relevant information and be ready to perform a safe and smooth intervention. In addition to preparation time as a major predictor of operator intervention performance (Clark & Feng, 2017), various traffic-related factors such as traffic level (Gold et al., 2018), facility type (Favarò et al., 2018), and environmental conditions (Favarò et al., 2018) can also influence intervention performance. Many "edge cases" that we know from on-road piloting of highly automated vehicles involve traffic- or environment-related triggers (Tener & Lanir, 2022). For example, a vehicle may encounter an unknown or unidentifiable object blocking the road. In other cases, a vehicle may face difficulty deciding the path due to perceived information conflicting with rules, such as crossing the separation line when the road is rerouted due to construction. These situations suggest that it is possible to use traffic and environmental predictors to estimate whether an operator intervention is likely needed.

AI-powered real-time traffic prediction can enhance the capabilities and safety of remote-operated automated vehicles. Real-time traffic information will be essential to allow human operators and the system to anticipate important events such as potential interventions and to enable a proactive approach. For example, comprehensive real-time data on traffic conditions and road incidents can enhance situation awareness of remote operators, augmenting their capability to anticipate knowing what information to look for when monitoring the vehicle performance. This predictive capability means they can anticipate potential challenges that vehicle automation may face thus needing intervention. This capability allows for better detection of anomalies and applying preemptive adjustments to the vehicle's path or speed, thereby enhancing safety and efficiency.

While a fair amount of research has been conducted on predicting traffic states (Bekiaris-Liberis et al., 2016; Li et al., 2014; Seo et al., 2017; Wang & Papageorgiou, 2005), facility types (Hu et al., 2004; Li, 2015; Li et al., 2018b), and environmental conditions (Datla & Sharma, 2008; Jia et al., 2017; Maze et al., 2006; Seeherman & Liu, 2015; Smith et al., 2004), very few studies have focused on using these factors to predict the likelihood of intervention in automated vehicles. This gap in the literature highlights the need for a comprehensive framework that can consider all relevant factors and accurately predict the likelihood of intervention under different traffic, facility, and environmental conditions.

5.2 Technical Approach: A Intervention Likelihood Assessment Module

This subsection describes the framework of the intervention likelihood assessment module in the remote operation model (Fig. 4). This module considers the following factors: (1) traffic data includes real-time and predicted traffic patterns to identify high-risk areas for automated vehicles due to traffic volumes and congestion; (2) facility type, including lane configuration and signal type, helps assess road complexity and infrastructure availability; (3) facility condition includes road surface, construction, and accidents that can increase the likelihood of operator intervention; (4) environmental condition data collects weather and lighting information that can affect vehicle sensors and cameras, as well as pedestrian and vehicle presence; (5) historical disengagement data (Favarò et al., 2018) analyzes the frequency, duration, reason, and outcome of intervention events to predict the likelihood of operator intervention in future scenarios; (6) microscopic, higher resolution data from surrounding vehicles is also incorporated, assuming low market penetration and uncertain service demand; and (7) confidence in automation describes how confident the automation software is in handling the driving task. The framework can develop probabilistic models to predict the likelihood of intervention, trained using historical and real-time data. The output is a probability score (likelihood, Fig. 4) fed into the service operation module.

Once developed, this hypothetical framework can be tested using traffic microsimulation tools such as SUMO (Lopez et al., 2018) to assess its effectiveness and reliability in a controlled environment. Real-world traffic data, facility information, and sampled vehicle trajectories can be incorporated into the simulations to test the accuracy of the framework. The use of traffic microsimulation allows for safe and controlled testing, enabling identification of potential improvements before deploying the framework in the real world. While macroscopic data allows prediction of long-horizon traffic states, meaningful prediction of traffic states and the need for operator intervention using microscopic data is challenging (Chang & Edara, 2017; Osman et al., 2019). As such, intervention likelihood will focus on short-term predictions that are sub-5-minute intervals.

This approach utilizes a holistic method by combining traffic engineering, facility analysis, and environmental assessments within a unified framework to predict the necessity for operator intervention. The development and testing of this framework via microsimulation can help to advance the operational safety and trustworthiness of remote operation of automated vehicles for transportation services. This will ensure to integrate remotely operated automated vehicles seamlessly and safely into transportation systems.

6 Operation Research to Support Proactive Remote Operation

6.1 Current Knowledge: Service Operations and Transportation Services with Automated Vehicles

Service systems are often studied by probabilistic models and queueing theory, which are important areas of the field of operations research. In service systems, determining a proper service capacity is perhaps the most critical operational decision. The service capacity may mean the number of nurses (or beds) in a hospital, the number of agents in a call center, or the number of drivers in a ride-hailing platform. According to the queueing-theory terminology, such a decision is referred to as "staffing" the right number of servers. Seeking the optimal staffing level in a service system is often quite challenging because it has to take into account several key factors rising from practice, including the heterogeneity in multiclass customers (Liu et al., 2022; Yang et al., 2022), the time variability of the demand process (Lee et al., 2021; Liu, 2018; Liu & Whitt, 2012, 2014), the stochasticity in the service times (Cao et al., 2021; Chen et al., 2023a), uncertain model parameters (e.g., Chen et al., 2023b), and the unpredictable issues in human behavior (e.g., customer abandonment, balking, and retrial; Sun & Liu, 2021; Wang et al., 2022).

Remote operation of automated vehicles is an emerging new industry that sits at the intersection of service systems and transportation. There is a very small body of literature on this subject. Some investigated a hybrid human-AI system for the automated vehicles (Hampshire et al., 2020) and another modeled a human-monitored automated driving system by a queueing model with batch arrivals and discussed several heuristic methods for setting the staffing levels (Daw et al., 2020). A recent study (Benjaafar et al., 2022) investigated system capacity of ride-hailing service when operated by in-vehicle drivers or remote operators. A number of benefits were identified for the remotely operated system including a significant reduction in the number of required drivers to maintain the same level of service and a more stable system for service. In a remote operation system, while the vehicles are still constrained by geographical locations, operators are not but can be treated as a pool of shared resources. These studies focus on improving the service levels objectives without considering any safety metrics. In addition, none of the abovementioned studies takes into account important human factors such as how many simultaneous tasks an operator can perform and how long an operator has been on a task which affects their level of fatigue and vigilance decrement.

Operation research can support the proactive remote operation by building a more practical service model for automated vehicles with remote servers informed by human factors research. This model is based on prior studies that examined ways to achieve desired service-level goals in service systems via optimized operational level decisions, including structural design (Cao et al., 2021; Nambiara et al., 2023), customer routing (Yang et al., 2022), scheduling (Lee et al., 2021; Liu et al., 2022), waiting time prediction (Garyfallos et al., 2024), and staffing of the service capacity (Chen et al., 2023a; Liu, 2018; Liu & Whitt, 2012; Sun & Liu, 2021). Using this new model, it is possible to understand the optimal operational decision-makings (e.g., staffing and control) that achieve a more balanced objective function that comprises a safety metric, service-level metric, and staffing cost.

6.2 Technical Approach: Task Allocation Module and a Novel Human-Factors-Informed Service Model

In the currently proposed system architecture (Figs. 4 and 5), the task allocation module can be designed to optimize among three outcome measures: (1) safety, (2) efficiency, and (3) cost. For calibrating the initial model for task allocation, we need to have a numerical measure of the safety of each scenario as described in Fig. 5. This safety measure is a collective reflection of the human factors indices (e.g., vehicle control measures during intervention, time to collision, and stress score) and traffic indices (e.g., extreme braking events and delay in traffic network), with a higher general safety rating suggesting the scenario being safer with more smooth intervention performance (if there was an operator intervention). Given scenarios 2 and 3 do not have any edge cases or intervention, thus would be rated the highest safety score. For scenarios 1, 4, and 5, this safety rating would be based on the empirical observations of operator intervention performance.

In service systems such as customer contact centers and ride-hailing platforms, a critical task is to properly match the demand with supply. Doing so involves decision-makings at the operational level, including (1) staffing policy (i.e., the total number of servers required), (2) scheduling method (i.e., prioritizing one customer class over another), and (3) routing (i.e., the way to allocate a task to a server) (Cao et al., 2021; Lee et al., 2021; Liu & Whitt, 2012, 2014; Liu, 2018; Liu et al., 2022; Sun & Liu, 2021). However, queueing systems used to model conventional service systems do not consider human factors such as how many simultaneous tasks an operator can perform and how long an operator has been on a task. These models treat both the servers and customers as “machines.” In addition, the goal of conventional service systems is centered at improving the system’s efficiency, for example, maximizing the system’s throughput and profitability or minimizing the queueing delay.

A novel service queueing model can be introduced for describing the dynamics of the remote operation system. This new model can be informed by human factors

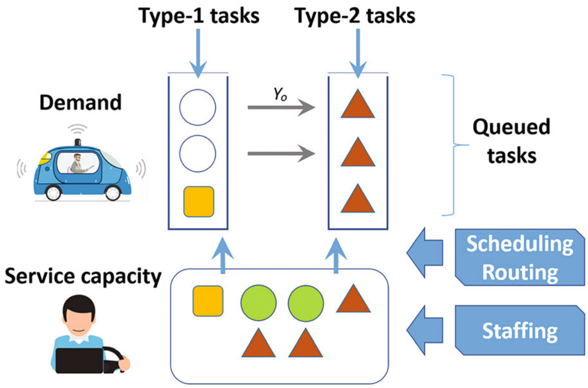

Fig. 8 The service model for task allocation

considerations as noted in Sect. 4 of this chapter. We consider a queueing model with n servers (each representing a remote operator). Each task corresponds to an automated vehicle that is in service (currently transporting a customer to the destination). New tasks arrive randomly. We classify the tasks into two types (Fig. 8): type-1 tasks are those currently unmonitored (white circles) or being monitored by a remote operator (yellow square), and type-2 tasks are those already having been intervened by a remote operator (red triangle).

Tasks waiting in a queue are processed in a first-come first-served fashion. Type-1 tasks may often evolve into type-2 tasks (corresponding to the instances that an automated car is unable to handle emergent events and needs to be overtaken by a remote driver; scenario 4 in Fig. 5). Unlike traditional queueing models that are adopted to model the transportation service systems where a server represents an in-vehicle driver, here a server in this new model is a remote operator. A major advantage of remote operators over in-vehicle drivers is that the former are shared or pooled resources while the latter are dedicated resources (i.e., the server is dedicated to a specific task). For example, as soon as a remote operator completes processing a task, the operator can be immediately reassigned to another task in the queue. The queueing model with pooled servers yields a much higher throughput than the one with dedicated servers. In addition, each server can work with at most k type-1 tasks at the same time (for example, a remote drive may be simultaneously monitoring k vehicles). However, the performance of each individual task degrades as k increases. We could use a risk function R(k) to measure the individual performance of each one of the k tasks. We dub this new model the queue with remote servers. For the queue with remote servers, we can then characterize several relevant performance metrics, including the throughput rate (rate at which tasks are completed), waiting time (time until a newly arrived task is processed), and intervention rate (rate at which unmonitored tasks require an operator to intervene).

This service model accounts for human factors such as operator multitasking and attention capabilities and fatigue level. Conventional queueing systems view servers and customers as machines, which lacks ecological validity when humans are providing service. In addition, this model incorporates safety as a core goal whereas conventional models only considered system efficiency and cost. For transportation services, safety is a critical factor to consider.

7 Preliminary Studies

As preliminary steps, the authors' team conducted human factors studies to develop a remote automated vehicle monitoring task and examine performance and attention of remote operators when they had to monitor one or multiple vehicles (Morrison et al., 2022; Shoffner & Feng, 2024).

The first study (Morrison et al., 2022) introduced a video-based remote operation task. In this task, participants viewed video clips of driving scenarios, taking on the role of a remote operator responsible for overseeing vehicle performance and identifying automation failures that required intervention. The videos depicted various driving scenarios, including potential automation failures such as close approaches to other vehicles, veering off the road or into an opposite lane, or missing a stop sign. Participants were informed that each video may or may not include an unsafe event in order to decrease the likelihood of growing anticipation for a critical event as the video progressed. Automation failures ranged from issues with lane selection and maintenance to problems with object recognition and collisions, occurring in a variety of environments from busy downtown areas to more straightforward country roads. The speed of vehicle travel in these scenarios ranged from 25 to 65 miles per hour, and video lengths varied from 32 to 125 seconds to ensure the unpredictability of timing of unsafe events. In each trial, participants monitored a single vehicle's performance and indicated the need for intervention by pressing a button and subsequently reported the reason for their action, with only timely and accurately explained interventions considered correct responses.

A total of 35 driving scenarios were assessed in this study, with participants' overall accuracies ranging from 40% to 100% (Table 2, Morrison et al., 2022). A 40% overall accuracy means that 40% of the participants successfully detected automation failure within the designated time frame (e.g., from the onset of an event to the occurrence of a collision) and correctly described the reason for it. The findings showed significant differences in unsafe event detection depending on the type of event, with particularly low detection rates when a vehicle disobeyed road signs, implying the need for stronger support to remote operator in these scenarios via training and interface design. This study introduced a method, although low-fidelity, to simulate the possible task of a remote operator monitoring an automated vehicle, where quick and accurate responses are crucial to maintain safety. Participants' overall accuracies in each scenario set the bases for further experimental designs to investigate various aspects of remote operation such as the number of vehicles that an operator can successfully monitor simultaneously and effective interface design to facilitate monitoring and anticipation.

The second study further examined how the number of vehicles an operator monitors affect their performance in identifying anomalies and cognitive workload overtime (preliminary results reported in Shoffner & Feng, 2024). Participants

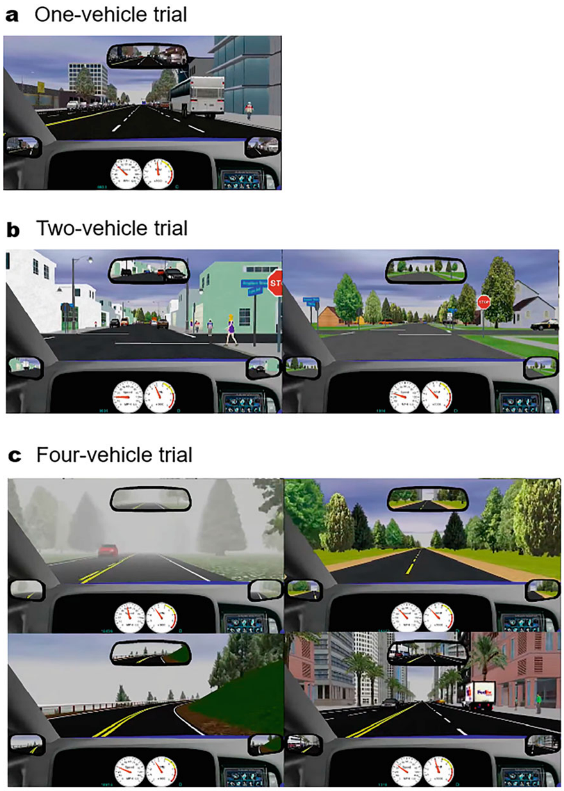

Fig. 9 Examples of each number of vehicle condition in Shoffner and Feng (2024)

assumed the role of remote operators overseeing the operation of one, two, or four simulated automated vehicles (Fig. 9), and pressed a button to indicate the need of intervention when they identified an automation failure. When more than one vehicle was monitored, each vehicle displays simulated a unique driving scenario, and only one unsafe event would occur in one of these vehicles. The other vehicles would travel safely, and those videos were created to match the duration of the video containing the critical event. Similar to the previous study, participants were informed that each trial might or might not contain an unsafe event to reduce the growing anticipation of an event as the video continued.

This study followed a 3x3 (block x vehicle number) repeated measures design, where participants completed a total of 18 trials, including 6 trials of monitoring 1 vehicle, 6 trials of monitoring 2 vehicles, and 6 trials of monitoring 4 vehicles. The 18 trials were divided into 3 blocks of 6 trials each to examine the effect of task duration on operator performance. Every block contained two trials for each vehicle number condition. The order of trials within each block was randomized for every participant. To ensure consistent difficult levels across blocks, we selected videos based on overall accuracies from the initial study (Morrison et al., 2022). Eighteen videos with accuracies ranging from 60% to 80% were chosen. We then formed six triads of videos with matching accuracies and randomly allocated one from every triad to each block.

Preliminary results from this study showed that participants were able to simultaneously monitor two vehicles as their accuracies in this condition was comparable to the one-vehicle condition. However, simultaneous monitoring of four vehicles was very challenging, leading to significantly degraded performance and higher workloads. Furthermore, the study observed a decline in correct interventions and an increase in false alarms in later trial blocks compared to the first, suggesting potential fatigue or vigilance decrement. This raises important considerations for determining the appropriate monitoring durations and work breaks for remote operators. This study is ongoing with current analyses focusing on operator visual behavior during remote operation to understand their scanning strategies and situation awareness.

8 Conclusion

The growing field of remote operation of automated vehicles presents both promising applications and notable challenges. It highlights a pivotal shift in how transportation services are envisioned and implemented. As automation in vehicles progresses, the role of the remote operator becomes increasingly crucial, not just as a fallback but as an integral part of the driving ecosystem to enhance safety, reliability, and human controllability when automation may fail. This transition is backed by significant investment forecasts suggesting a rapid growth in the industry, with expectations of substantial increases in both market value and operational miles by 2030. These advancements are paralleled by innovations in AI, which further enables the systems' ability to comprehend complex road scenarios, manage fleets, and optimize task allocation.

However, the shift from a traditional in-vehicle driver to a remote operator managing multiple vehicles introduces unique challenges. These include maintaining high levels of vigilance, managing increased cognitive loads, and ensuring timely interventions in dynamic traffic environments. Current robotaxi applications in pilot cities have uncovered practical difficulties such as unexpected stops leading to traffic disruptions and the systems' occasional failure to navigate correctly, which underscores the necessity for robust and reliable remote operation frameworks. In addition, the challenges of lacking physical connection to the driving environment while ensuring constant situation awareness further complicate these operations, demanding innovative solutions to enhance operator responsiveness and system integration.

This chapter explores a novel proactive approach to human interaction with automation, emphasizing a preventive rather than reactive perspective that is crucial for enhancing our engagement with highly automated systems. Two primary challenges associated with this approach are the substantial demand for human resources and maintaining operators' vigilance, especially when critical events are infrequent.

The presented architecture of the system capitalizes on operator cognitive capabilities, estimates of intervention likelihood, and an optimized service model to strike a balance between safety and efficiency. By managing short monitoring episodes, matching the task demand and operator attentional state, and scheduling work breaks as necessary, the system ensures that operators maintain sufficient vigilance throughout their remote operation tasks.

Looking ahead, the future directions of remote operation research and application are geared toward developing more proactive systems. This involves not only refining AI's predictive capabilities to better anticipate and address potential interventions but also enhancing the interfaces through which a remote operator interacts with the system. The goal is to create intuitive environments that can facilitate operator monitoring of and intervention to highly automated vehicles. When remote monitoring is structured proactively through manageable task durations, anticipation of intervention needs, and alignment with operator attention, it does more than maintaining situation awareness; it enables real-time human controllability. Through the structure, operators retain meaningful oversight and influence over the system's behavior. Such advancements could improve not only the safety and efficiency of automated vehicle operations but also the overall user experience for both operators and riders. They can set a new standard for how automated vehicles are integrated into our daily lives and infrastructure. As highlighted in the concept of human-AI joint cognitive ecosystems (Xu et al., 2024), the remote operation systems, including human operators, AI-powered functions and service models, and interfaces, should not function in isolation but as part of an interconnected ecosystem that involves vehicle automation, transportation infrastructure, drivers in automated and legacy vehicles, and other road users. 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. The proactive remote operation is a general framework that enables integration of human operator in a system with AI-powered functions. This framework, if proved to be successful in remote operation of automated vehicles, can also inform remote operation in other contexts such as drone operation that utilizes AI-powered automation where human oversight and controllability would be beneficial.

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References

Abbas, Q. (2019). V-ITS: Video-based intelligent transportation system for monitoring vehicle illegal activities. *International Journal of Advanced Computer Science and Applications (IHACSA), 10*(3), 202–208.

Abhay, S., Lalit, K., & Sonia, M. (2021). Global robo taxi market: By application, component used, propulsion, level of automation, and region. *Allied Market Research*, 1–266.

Abuelsamid, S. (July 28, 2021). *Ottopia to provide remote assistance for motional robotaxis*. Forbes. Retrieved from: https://www.forbes.com/sites/samabuelsamid/2021/07/28/ottopia-to-provide-remote-assistance-for-motional-robotaxis/?sh=20043b4d4a6e

Aghaei, A. S., Donmez, B., Liu, C. C., He, D., Liu, G., Plataniotis, K. N., Chen, H.-W., & Sojoudi, Z. (2016). Smart driver monitoring: When signal processing meets human factors in the driver's seat. *IEEE Signal Processing Magazine, 33*(6), 35–48. https://doi.org/10.1109/MSP.2016.2602379

Akhtar, M., & Moridpour, S. (2021). A review of traffic congestion prediction using artificial intelligence. *Journal of Advanced Transportation, 2021*, 1–18.

Almukhalfi, H., Noor, A., & Noor, T. H. (2024). Traffic management approaches using machine learning and deep learning techniques: A survey. *Engineering Applications of Artificial Intelligence, 133*, 108147.

Alvarez, G. A., & Cavanagh, P. (2004). The capacity of visual short-term memory is set both by visual information load and by number of objects. *Psychological Science, 15*, 106–111.

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.

Araluce, J., Bergasa, L. M., Ocaña, M., Llamazares, Á., & López-Guillén, E. (2024). Leveraging driver attention for an end-to-end explainable decision-making from frontal images. *IEEE Transactions on Intelligent Transportation Systems, 1*(1), 1–12.

Assuncao, A. N., Aquino, A. L., Câmara de, M., Santos, R. C., Guimaraes, R. L., & Oliveira, R. A. (2019). Vehicle driver monitoring through the statistical process control. *Sensors, 19*(14), 3059.

Atakishiyev, S., Salameh, M., Yao, H., & Goebel, R. (2024). Explainable artificial intelligence for autonomous driving: A comprehensive overview and field guide for future research directions. *IEEE Access, 12*, 101603–101625.

Ayas, S., Donmez, B., & Tang, X. (2023). Drowsiness mitigation through driver state monitoring systems: A scoping review. *Human Factors, 66*(9), 2218–2243.

Bacon, A. (January 7, 2025). *Waymo passenger nearly misses his flight after car drives in circles*. CNN. Retrieved on January 27, 2025: https://www.cnn.com/2025/01/07/business/waymo-circles-delay/index.html

Bai, X., & Feng, J. (2024). *Capturing the mind: Non-driving-related tasks as a window into cognitive engagement in automated driving*. In Proceedings of the human factors and ergonomics society annual meeting (Vol. 68, no. 1, pp. 1362–1364). SAGE Publications.

Bai, X., & Feng, J. (2025). Awakening the disengaged: Can driving-related prompts engage drivers in partial automation? *Human Factors, 67*(7), 731–752.

Bainbridge, L. (1983). Ironies of automation. *Automatica, 19*(6), 775–779.

Balasubramanian, S. B., Balaji, P., Munshi, A., Almukadi, W., Prabhu, T., Venkatachalam, K., & Abouhawwash, M. (2023). Machine learning based IoT system for secure traffic management and accident detection in smart cities. *PeerJ Computer Science, 9*, e1259.

Bayly, M., Young, K. L., & Regan, M. A. (2009). Chapter 12. Sources of distraction inside the vehicle and their effects on driving performance. In M. A. Gegan, J. D. Lee, & K. L. Young (Eds.), *Driver distraction: Theory, effects, and mitigation* (pp. 191–214).

Bellan, R., & Korosec, K. (2022, April 20). *Musk says Tesla aspires to mass produce robotaxis by 2024*. TechCrunch. Retrieved from: https://techcrunch.com/2022/04/20/elon-musk-mass-produce-robotaxi-by-2024/

Bekiaris-Liberis, N., Roncoli, C., & Papageorgiou, M. (2016). Highway traffic state estimation with mixed connected and conventional vehicles. *IEEE Transactions on Intelligent Transportation Systems, 17*(12), 3484–3497.

Benjaafar, S., Wang, Z., & Yang, X. (2022). *Human in the loop automation: Ride-hailing with remote (tele-) drivers*. Available at SSRN 4130757. https://doi.org/10.2139/ssrn.4130757.

Bergasa, L. M., Nuevo, J., Sotelo, M. A., Barea, R., & Lopez, M. E. (2006). Real-time system for monitoring driver vigilance. *IEEE Transactions on Intelligent Transportation Systems, 7*(1), 63–77.

Bilimoria, K. D., Johnson, W. W., & Schutte, P. C. (2014). *Conceptual framework for single pilot operations*. HCI-Aero'14: Proceedings of the international conference on human-computer interaction in aerospace, 4, pp. 1–8.

Bonos, L. (2024, December 22). Robot taxi riders in San Francisco targeted with a new form of harassment. *The Washington Post*. Retrieved on January 27, 2025: https://www.washingtonpost.com/technology/2024/12/22/waymo-robotaxi-passengers-harassment/

Borghini, G., Astolfi, L., Vecchiato, G., Mattia, D., & Babiloni, F. (2014). Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. *Neuroscience & Biobehavioral Reviews, 44*, 58–75.

Boucsein, W. (2012). *Electrodermal activity*. Springer Science & Business Media.

Burnett, S. (2025, July 31). *Germany sets out framework for teleoperated cars*. Automotive World. Retrieved on August 10, 2025: https://www.automotiveworld.com/articles/germany-sets-out-framework-for-teleoperated-cars/

California Code of Regulations Title 13., Division 1, Chapter 1, Article 3.7 – Testing of Autonomous Vehicles Section 227.38. 2023.

Cao, P., He, S., Huang, J., & Liu, Y. (2021). To pool or not to pool: Queueing design for large-scale service systems. *Operations Research, 69*(6), 1866–1885.

Casner, S. M., & Hutchins, E. L. (2019). What do we tell the drivers? Toward minimum driver training standards for partially automated cars. *Journal of Cognitive Engineering and Decision Making, 13*, 55–66.

Cauffman, S. J., Deng, Y., Lau, M., Cunningham, C., Kaber, D., & Feng, J. (2020). Driver logo sign detection and hazard responses during partially automated driving. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 64*(1), 1960–1964.

Cavanagh, P., & Alvarez, G. A. (2005). Tracking multiple targets with multifocal attention. *Trends in Cognitive Sciences, 9*, 349–354.

Chadwick, R. A. (2006). *Operating multiple semi-autonomous robots: Monitoring, responding, detecting*. In Proceedings of human factors and ergonomics society 50th annual meeting, pp. 329–333.

Chadwick, R. A., Gillan, D. J., Simon, D., & Pazuchanics, S. (2004). *Cognitive analysis methods for control of multiple robots: Robotics on $5 a day*. In Proceedings of the human factors and ergonomics society 48th annual meeting, 688–692.

Chang, Y., & Edara, P. (2017). *Predicting hazardous events in work zones using naturalistic driving data*. In Proceedings of the IEEE 20th international conference on intelligent transportation systems (ITSC), pp. 1–6.

Chen, J. Y. C., Barnes, M. J., & Harper-Sciarini, M. (2011). Supervisory control of multiple robots: Human-performance issues and user-interface design. *IEEE Transactions on Systems, Man, and Cybernectics, Part C: Applications and Reviews, 41*(4), 435–454.

Chen, X., Liu, Y., & Hong, G. (2023a). *An online learning approach to dynamic pricing and capacity sizing in service systems*. *Operations Research,72*(6), 2677–2697.

Chen, X., Hong, G., & Liu, Y. (2023b). *Online learning and optimization for queues with unknown arrival rate and service distribution.* arXiv:2303.03399.

Chen, L., Wu, P., Chitta, K., Jaeger, B., Geiger, A., & Li, H. (2023c). *End-to-end autonomous driving: Challenges and frontiers*. arXiv:2306.16927.

Chen, W., Men, Y., Fuster, N., Osorio, C., & Juan, A. A. (2024). Artificial intelligence in logistics optimization with sustainable criteria: A review. *Sustainability, 16*, 9145.

Chowdhury, S. K., & Nimbarte, A. D. (2017). Effect of fatigue on the stationarity of surface electromyography signals. *International Journal of Industrial Ergonomics, 61*(4), 120–125.

Clark, H., & Feng, J. (2017). Age differences in the takeover of vehicle control and engagement in non-driving-related activities in simulated driving with conditional automation. *Accident Analysis and Prevention, 106*, 468–479.

Cummings, M. L. (2004). The need for command and control instant message adaptive interfaces: Lesions learned from tactical tomahawk human-in-the-loop simulations. *Cyber Psychology and Behavior, 7*(6), 653–661.

Cummings, M. L., & Guerlain, S. (2007). Developing operator capacity estimates for supervisory control of autonomous vehicles. *Human Factors, 49*(1), 1–15.

D'Andrea, E., & Marcelloni, F. (2017). Detection of traffic congestion and incidents from GPS track analysis. *Expert Systems with Application, 73*(1), 43–56.

Das, K., Sharak, S., Riani, K., Abouelenien, M., Burzo, M., & Papakostas, M. (2021). *Multimodal detection of drivers drowsiness and distraction*. In Proceedings of the 2021 international conference on multimodal interaction, 416–424. Montreal, QC, Canada, October 18–21, 2021.

Dash, R., McMurtrey, M., Rebman, C., & Kar, U. K. (2019). Application of artificial intelligence in automation of supply chain management. *Journal of Strategic Innovation and Sustainability, 14*(3), 43–53.

Datla, S., & Sharma, S. (2008). Impact of cold and snow on temporal and spatial variations of highway traffic volumes. *Journal of Transport Geography, 16*(5), 358–372.

Daw, A., Hampshire, R. C., & Pender, J. (2020). *Beyond safety driver: Staffing a teleoperations system for autonomous vehicles*. Retrieved from: arXiv:1907.12650v2.

Delasay, M., Ingolfsson, A., Kolfal, B., & Schultz, K. (2019). Load effect on service times. *European Journal of Operational Research, 279*(3), 673–686.

De Winter, J. C., Happee, R., Martens, M. H., & Stanton, N. A. (2014). Effects of adaptive cruise control and highly automated driving on workload and situation awareness: A review of the empirical evidence. *Transportation Research Part F: Traffic Psychology and Behaviour, 27*, 196–217.

Demuynck, V. (2020). Understanding the latest breakthrough in safe automated driving. tomtom. Retrieved from: https://www.tomtom.com/newsroom/explainers-andinsights/operational-design-domain-automated-driving/

Dinges, D. F., & Grace, R. (1998). *Perclos: A valid psychophysiological measure of alertness assessed by psychomotor vigilance*. US Department of Transportation, Federal Highway Administration, Publication Number FHWA-MCRT-98-006, 58.

Dong, J., Chen, S., Miralinaghi, M., Chen, T., Li, P., & Labi, S. (2023). Why did the AI make that decision? Towards an explainable artificial intelligence (XAI) for autonomous driving systems. *Transportation Research Part C: Emerging Technologies, 156*, 104358.

Dong, Y., Hu, Z., Uchimura, K., & Murayama, N. (2011). Driver inattention monitoring system for intelligent vehicles: A review. *IEEE Transactions on Intelligent Transportation Systems, 12*(2), 596–614.

DriveU.auto. (2025a). *Deploy robot and autonomous vehicle fleets with confidence, using teleoperation*. Retrieved from: https://driveu.auto/

DriveU.auto. (2025b). *Teleoperation for autonomous vehicles*. Retrieved from: https://driveu.auto/teleoperation/

Dröge, O. (2020). Anticipating the road ahead with TomTom Hazard Warnings. tomtom. Retrieved from: https://www.tomtom.com/newsroom/product-focus/anticipate-roadahead-with-tomtom-hazard-warnings/

Fairclough, S. H., & Mulder, L. J. M. (2011). Psychophysiological processes of mental effort investment. In R. A. Wright & G. H. E. Gendolla (Eds.), *How motivation affects cardiovascular response: Mechanisms and applications* (pp. 61–76). American Psychological Association. https://doi.org/10.1037/13090-003

Favarò, F., Eurich, S., & Nader, N. (2018). Autonomous vehicles' disengagements: Trends, triggers, and regulatory limitations. *Accident Analysis & Prevention, 110*, 136–148.

Feng, J., Choi, H., Craik, F. I. M., Levine, B., Moreno, S., Naglie, G., & Zhu, M. (2018). Adaptive response criteria in road hazard detection among older drivers. *Traffic Injury Prevention, 19*(2), 141–146.

Feng, J., Deng, Y., Mei, Y. L., Cauffman, S. J., Johnson, E., Cunningham, C., & Kaber, D. B. (2023). Age differences in driver visual behavior and vehicle control when driving with in-vehicle and on-road deliveries of service logo signs. *International Journal of Industrial Ergonomics, 93*, 103386.

Feng, J., Pratt, J., & Spence, I. (2012). Attention and visuospatial working memory share the same processing resources. *Frontiers in Psychology, 3*, 103.

Feng, J., & Spence, I. (2018). Chapter 8. Playing action video games boosts visual attention. In C. J. Ferguson (Ed.), *Video game influences on aggression, cognition, and attention* (pp. 93–104). Springer International Publishing AG, part of Springer Nature.

Fletcher, L., & Zelinsky, A. (2008). Context sensitive driver assistance based on gaze – Road scene correlation. In O. Khatib, V. Kumar, & D. Rus (Eds.), *Experimental robotics. Springer tracts in advanced robotics* (Vol. 39). Springer. https://doi.org/10.1007/978-3-540-77457-0_27

Fu, R., Wang, H., & Zhao, W. (2016). Dynamic driver fatigue detection using hidden Markov model in real driving condition. *Expert Systems with Applications, 63*, 397–411.

Garibay, O., Winslow, B., Andolina, S., Antona, M., Bodenschatz, A., Coursaris, C., et al. (2023). Six human-centered artificial intelligence grand challenges. *International Journal of Human-Computer Interaction., 39*(3), 391–437.

Garyfallos, S., Liu, Y., Barley-Ros, P., & Cabellos-Aparicio, A. (2024). NeuraliNQ: A neural network method for the transient performance analysis in non-Markovian queues. Accepted at Queueing Systems.

Geden, M., & Feng, J. (2015). *Environment impacts mind wandering during driving*. In Proceedings of the 2015 international annual meeting of the human factors and ergonomics society, San Francisco, CA, USA.

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.

Georg, J. M., & DIergeyer, F. (2019). *An adaptable and immersive real time interface for resolving system limitations of automated vehicles with teleoperation*. In Proceedings of IEEE international conference on system man cybernetics, pp 2659–2664.

Gnatzig, S., Schuller, F., & Lienkamp, M (2012). *Human-machine interaction as key technology for driverless driving – A trajectory-based shared autonomy control approach*. In Proceedings of the IEEE international workshop on robot and human interactive communication, pp. 913–918.

Gold, C., Happee, R., & Bengler, K. (2018). Modeling take-over performance in level 3 conditionally automated vehicles. *Accident Analysis & Prevention, 116*, 3–13.

Goodrich, M. A., & Olsen, D. R. (2003). *Seven principles of efficient human robot interaction*. In Proceedings of IEEE international conference on systems, man and cybernetics, pp. 3943–3948.

Green, C. S., & Bavelier, D. (2003). Action video game modifies visual selective attention. *Nature, 423*, 534–537.

Greenlee, E. T., DeLucia, P. R., & Newton, D. C. (2018). Driver vigilance in automated vehicles: Hazard detection failures are a matter of time. *Human Factors, 60*(4), 465–476.

Gunawan, A., & Lau, H. C. (2013). Master physician scheduling problem. *Journal of the Operational Research Society, 64*(3), 410–425.

Hampshire, R. C., Bao, S., Lasecki, W. S., Daw, A., & Pender, J. (2020). Beyond safety drivers: Applying air traffic control principles to support the deployment of driverless vehicles. *PLoS One, 15*(5), e0232837.

Harley, A. (August 2, 2020). *Proximity principle in visual design*. Nielsen Norman Group. Retrieved from: https://www.nngroup.com/articles/gestalt-proximity/

Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., et al. (2024). Interpreting black-box models: A review on explainable artificial intelligence. *Cognitive Computation, 16*(1), 45–74.

Hjortskov, N., Rissén, D., Blangsted, A. K., Fallentin, N., Lundberg, U., & Søgaard, K. (2004). The effect of mental stress on heart rate variability and blood pressure during computer work. *European Journal of Applied Physiology, 92*, 84–89.

Hu, Y., Yang, J., Chen, L., Li, K., Sima, C., Zhu, X., Chai, S., … (2023). *Planning-oriented autonomous driving*. In Proceedings of IEEE/CVF conference on computer vision and pattern recognition (CVPR), pp 17853–17862.

Hu, W., Xiao, X., Xie, D., Tan, T., & Maybank, S. (2004). Traffic accident prediction using 3-D model-based vehicle tracking. *IEEE Transactions on Vehicular Technology, 53*(3), 677–694.

Hua, T. (2022). *How to establish robotaxi trustworthiness through in-vehicle interaction design*. [Master's thesis, University of Cincinnati]. OhioLINK Electronic Theses and Dissertations Center. http://rave.ohiolink.edu/etdc/view?acc_num=ucin1660818359697178

Human Factors in International Regulations for Automated Driving Systems (HF-IRADS). (2020). *Human factors challenges of remote support and control: A position paper from HF-IRADS*. Informal document GRVA-07-65. 7th GRVA, September 21–25, 2020, Agenda item 12.

Hundal, T. (March 2, 2023). *AAA reports that 68 percent of Americans are now afraid of autonomous cars*. The Autopian. Retrieved from: https://www.theautopian.com/aaa-autonomous-car-report-2023/

Hyundai Motor Company. (2023). *Hyundai x Motional – Bringing IONIQ5 robotaxis to the streets from 2023*. Retrieved from: https://www.hyundai.com/worldwide/en/brand-journal/mobility-solution/robotaxis

Ingram, D. (2025, June 21). *What to expect when (or if) Elon Musk launches a Tesla robotaxi service*. NBC News. Retrieved from: https://www.nbcnews.com/tech/innovation/expect-elon-musk-launches-tesla-robotaxi-service-rcna213546

Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2022). Artificial intelligence applications for industry 4.0: A literature-based study. *Journal of Industrial Integration and Management, 7*(01), 83–111.

Jia, Y., Wu, J., & Xu, M. (2017). Traffic flow prediction with rainfall impact using a deep learning method. *Journal of Advanced Transportation, 2017*, e6575947.

Jing, T., Xiao, H., Tian, R., Ding, H., Luo, X., Domeyer, J., Sherony, J., & Ding, Z. (2022). *Interaction: Interpretable action decision making for autonomous driving*. In Proceedings of the European conference on computer vision, pp. 370–387.

Kerr, D. (2023, December 30). *Driverless car startup Cruise's no good, terrible year*. NPR. Retrieved from: https://www.npr.org/2023/12/30/1222083720/driverless-cars-gm-cruise-waymo-san-francisco-accidents

Kettwich, C., Schrank, A., & Oehl, M. (2021). Teleoperation of highly automated vehicles in public transport: User-centered design of a human-machine interface for remote-operation and its expert usability evaluation. *Multimodal Technologies and Interaction, 5*, 26.

Khattak, Z. H., Fontaine, M. D., & Smith, B. L. (2021). Exploratory investigation of disengagements and crashes in autonomous vehicles under mixed traffic: An endogenous switching regime framework. *IEEE Transactions on Intelligent Transportation Systems, 22*(12), 7485–7495.

Kim. F. (September 222, 2020). *The future of rideshare is a remote control rental car*. VentureBeat. Retrieved from: https://venturebeat.com/transportation/the-future-of-rideshare-is-a-remote-control-rental-car/

Körber, M., Cingel, A., Zimmermann, M., & Bengler, K. (2015). Vigilance decrement and passive fatigue caused by monotony in automated driving. *Procedia Manufacturing, 3*, 2403–2409.

Kujala, T., Grahn, H., Mäkelä, J., Silvennoinen, J., & Tokkonen, T. (2024). Effects of context-sensitive distraction warnings on drivers' smartphone use and acceptance: A long-term naturalistic field study. *International Journal of Human-Computer Studies, 186*, 103247.

Kujala, T., Karvonen, H., & Häkelä, J. (2016). Context-sensititve distraction warnings – Effects on drivers' visual behavior and acceptance. *International Journal of Human-Computer Studies, 90*, 39–52.

Kumar, S., Kar, A. K., & Ilavarasan, P. V. (2021). Applications of text mining in services management: A systematic literature review. *International Journal of Information Management Data Insights, 1*(1), 100008.

Lanctot, R., Ambrosio, C., Cohen, H., & Riches, I. (2017). Accelerating the future: The economic impact of the merging passenger economy. *Strategy Analytics*, 1–30.

Landman, A., van Oorschot, P., van Paassen, M. M., Groen, E. L., Bronkhorst, A. W., & Mulder, M. (2018). Training pilots for unexpected events: A simulator study on the advantage of unpredictable and variable scenarios. *Human Factors, 60*(6), 793–805.

Langer, I., Abendroth, B., & Bruder, R. (2016). Driver condition detection. In H. Winner, C. Singer, S. Hakuli, & F. Lotz (Eds.), *Handbook of driver assistance systems* (pp. 871–889). Springer.

Lee, C., Liu, X., Liu, Y., & Zhang, L. (2021). Optimal control of a time-varying double-ended production queueing model. *Stochastic Systems, 11*(2), 140–173.

Leng, J., Zhu, X., Huang, Z., Li, X., Zheng, P., Zhou, X., et al. (2024). Unlocking the power of industrial artificial intelligence towards industry 5.0: Insights, pathways, and challenges. *Journal of Manufacturing Systems, 73*, 349–363.

Levy, K. (December 6, 2022). *Robo truckers and the AI-fueled future of transport*. Wired Retrieved from: https://www.wired.com/story/autonomous-vehicles-transportation-truckers-employment/

Li, L., Chen, X., & Zhang, L. (2014). Multimodel ensemble for freeway traffic state estimations. *IEEE Transactions on Intelligent Transportation Systems, 15*(3), 1323–1336.

Li, J., Cheng, H., Guo, H., & Qiu, S. (2018a). Survey on artificial intelligence for vehicles. *Automotive Innovation, 1*(1), 2–14.

Li, R. (2015). Traffic incident duration analysis and prediction models based on the survival analysis approach. *IET Intelligent Transport Systems, 9*(4), 351–358.

Li, R., Pereira, F. C., & Ben-Akiva, M. E. (2018b). Overview of traffic incident duration analysis and prediction. *European Transport Research Review, 10*(2), 1–13.

Lightbown, S. (2023, October 18). *Remote driving is a sneaky shortcut to the robotaxi*. WIRED. Retrieved from: https://www.wired.com/story/a-sneaky-shortcut-to-driverless-cars/

Lilhore, U. K., Imoize, A. L., Li, C.-T., Simaiya, S., Pani, S. K., Goyal, N., Kumar, A., & Lee, C.-C. (2022). Design and implementation of an ML and IoT based adaptive traffic management system for smart cities. *Sensors, 22*(8), 2908.

Linkov, V., & Vanžura, M. (2021). Situation awareness measurement in remotely controlled cars. *Frontiers in Psychology, 12*, 592930.

Liu, Y. (2018). Staffing to stabilize the tail probability of delay in service systems with time-varying demand. *Operations Research, 66*(2), 514–534.

Liu, Y., Sun, X., & Hovey, K. (2022). Scheduling to differentiate service in a multiclass service system. *Operations Research, 70*(1), 527–544.

Liu, Y., & Whitt, W. (2012). Stabilizing customer abandonment in many-server queues with time-varying arrivals. *Operations Research, 60*(6), 1551–1564.

Liu, Y., & Whitt, W. (2014). Algorithms for time-varying networks of many-server fluid queues. *INFORMS Journal on Computing, 26*(1), 59–73.

Lopez, J. (December 1, 2022). *GM's cruise seeking to test driverless origin robotaxi on San Francisco streets*. GMAuthority. Retrieved from: https://gmauthority.com/blog/2022/12/gms-cruise-seeking-to-test-driverless-origin-robotaxi-on-san-francisco-streets/

Lopez, P., Behrisch, M., Bieker-Walz, L., Erdmann, J., Flötteröd, Y.-P., Hilbrich, R., Lücken, L., Rummel, J., Wagner, P., & Wießner, E. (2018). *Microscopic traffic simulation using SUMO*. In Proceedings of the 2019 IEEE intelligent transportation systems conference (ITSC), pp 2575–2582.

Lyons, J. B., Marinier, R. P., Coovert, M. D., & Stankiewicz, K. (2014). *Reactive autonomy for human-robot teams: Trust and reliance in a dynamic environment*. Proceedings of the 9th ACM/IEEE international conference on human-robot interaction, pp 197–198.

Malakis, S., & Kontogiannis, T. (2012). Refresher training for air traffic controllers: Is it adequate to meet the challenges of emergencies and abnormal situations? *The International Journal of Aviation Psychology, 22*(1), 59–77.

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.

Mavin, T. J., & Murray, P. S. (2010). The development of airline pilot skills through simulated practice. In *Learning through practice: Models, traditions, orientations and approaches* (pp. 268–286). Springer Netherlands.

Maze, T. H., Agarwal, M., & Burchett, G. (2006). Whether weather matters to traffic demand, traffic safety, and traffic operations and flow. *Transportation Research Record, 1948*(1), 170–176.

McGregor, S. (2025). *AI incident database*. Retrieved on January 28, 2025 from https://incidentdatabase.ai/

Mehta, I. (2022, June 16). *Google maps has a new Andriod widget to show live traffic around you*. TechCrunch. Retrieved from: https://techcrunch.com/2022/06/16/google-maps-has-a-new-android-widget-to-show-live-traffic-around-you/

Mekinec, D. (2023, February 20). *Truck driver monitoring – how it works, and why it's important*. Accessed 2025/01/13: https://visagetechnologies.com/truck-driver-monitoring-system/

Merat, N., Seppelt, B., Louw, T., Engström, J., Lee, J. D., Johansson, E., et al. (2019). The "out-of-the-loop" concept in automated driving: Proposed definition, measures and implications. *Cognition, Technology & Work, 21*, 87–98.

Meurer, J., Pakusch, C., Stevens, G., Randall, D., & Wulf, V. (2020, July). *A wizard of oz study on passengers' experiences of a robo-taxi service in real-life settings*. In Proceedings of the 2020 ACM designing interactive systems conference (pp. 1365–1377).

Miglani, A., & Kumar, N. (2019). Deep learning models for traffic flow prediction in autonomous vehicles: A review, solutions and challenges. *Vehicular Communications, 20*, 100184.

Mobileye. (November 11, 2020). *Robotaxis on the road to the fully autonomous future*. Retrieved from: https://www.mobileye.com/blog/how-robotaxis-will-lead-the-way-toward-the-fully-autonomous-future/

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.

Mutzenich, C., Durant, S., Helman, S., & Dalton, P. (2021). Updating our understanding of situation awareness in relation to remote operators of autonomous vehicles. *Cognitive Research: Principles and Implications, 6*, 9.

Murphy-Chutorian, E., & Trivedi, M. M. (2010). Head pose estimation and augmented reality tracking: An integrated system and evaluation for monitoring driver awareness. *IEEE Transactions on Intelligent Transportation Systems, 11*(2), 300–311.

Nambiara, S., Mayorga, M. & Liu, Y. (2023) *Routing and staffing in emergency departments: A multiclass queueing model with workload dependent service times*. Accepted at IISE Transactions on Healthcare Systems Engineering.

National Business Aviation Association (NBAA). (2017). *Training for automated flight decks is essential*. Retrieved from: https://nbaa.org/aircraft-operations/safety/training-automated-flight-decks-essential/

Nunes, A. (November 12, 2018). *Robotaxis are coming. So why are we still so unprepared?* Wired. Retrieved from: https://www.wired.com/story/robotaxis-are-coming/

Ohnsman, A. (February 27, 2023). *Waymo's L.A. robotaxi fleet is going fully driverless*. Forbes. Retrieved from: https://www.forbes.com/sites/alanohnsman/2023/02/27/exclusive-waymos-la-robotaxi-fleet-is-going-fully-driverless/?sh=24cb0121706d

Olsen, D. R., & Wood, S. B. (2004). *Fan-out: Measuring human control of multiple robots*. In Proceedings of SIGCHI Conference on Human Factors Computer Systems, 231–238.

Olson, W. A., & Wuennenberg, M. G. (2001). *Autonomy based human-vehicle interface standards for remotely operated aircraft*. In Presentation at the 20th Digital Aviation Systems Conference. Daytona Beach, Florida.

Osman, O. A., Hajij, M., Bakhit, P. R., & Ishak, S. (2019). Prediction of near-crashes from observed vehicle kinematics using machine learning. *Transportation Research Record, 2673*(12), 463–473.

Ottopia (2025). https://ottopia.tech/

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 30*(3), 286–297.

Paris, M. (2024, November 18). *How robotaxis are trying to win passengers' trust. BBC*. https://www.bbc.com/future/article/20241115-how-robotaxis-are-trying-to-win-passengers-trust

Phatom Auto. (2025). https://phantom.auto/

Podhurst, A. (August 3, 2021). *Teleoperation: The "picks and shovels" of the autonomous vehicle gold rush*. Forbes. Retrieved from: https://www.forbes.com/sites/forbestechcouncil/2021/08/03/teleoperation-the-picks-and-shovels-of-the-autonomous-vehicle-gold-rush/?sh=265100976c54

Ranjan, S., Kim, Y.-C., Ranjan, N., Bhandari, S., & Kim, H. (2023). Large-scale road network traffic congestion prediction based on recurrent high-resolution network. *Applied Sciences, 13*(9), 5512.

Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping business with artificial intelligence: Closing the gap between ambition and action. *MIT Sloan Management Review, 59*(1), 1–23.

Ravi, A., Nandhini, R., Bhuvaneshwari, L., Divya, J., & Janani, K. (2021). Traffic management system using machine learning algorithm. *International Journal of Innovative Research in Technology, 150994*, 304–308.

Reuters. (December 9, 2024). *Tesla aims to launch robotaxi with teleoperator backup, Deutsche Bank says*. Retrieved on January 27, 2025: https://www.reuters.com/business/autos-transportation/tesla-aims-launch-robotaxi-with-teleoperator-backup-deutsche-bank-says-2024-12-09/

Rosário, A. T., & Dias, J. C. (2023). How has data-driven marketing evolved: Challenges and opportunities with emerging technologies. *International Journal of Information Management Data Insights, 3*(2), 100203.

Rubio, S., Díaz, E., Martín, J., & Puente, J. M. (2004). Evaluation of subjective mental workload: A comparison of SWAT, NASA-TLX, and workload profile methods. *Applied Psychology, 53*(1), 61–86.

SAE International. (2021). *Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles (J3016_202104)*. SAE International. https://www.sae.org/standards/content/j3016_202104/

Saleem, M., Abbas, S., Ghazal, T. M., Khan, M. A., Sahawneh, N., & Ahmad, M. (2022). Smart cities: Fusion-based intelligent traffic congestion control system for vehicular networks using machine learning techniques. *Egyptian Informatics Journal, 23*(3), 417–426.

Sall, R., & Feng, J. (2019). Dual-target hazard perception: Could identifying one hazard hinder a driver's capacity to find a second? *Accident Analysis & Prevention, 131*, 213–224.

Sanneman, L., & Shah, J. A. (2022). The situation awareness framework for explainable AI (SAFE-AI) and human factors considerations for XAI systems. *International Journal of Human–Computer Interaction, 38*(18–20), 1772–1788.

Saxby, D. J., Matthews, G., Warm, J. S., Hitchcock, E. M., & Neubauer, C. (2013). Active and passive fatigue in simulated driving: Discriminating styles of workload regulation and their safety impacts. *Journal of Experimental Psychology: Applied, 19*(4), 287–300.

Schilling, K., Roth, H., & Lieb, R. (2002). Remote control of a "Mars rover" via internet – To support education in control and teleoperations. *Acta Astroautic, 50*(3), 173–178.

Schmitt, M. (2023). Deep learning in business analytics: A clash of expectations and reality. *International Journal of Information Management Data Insights, 3*(1), 100146.

Sears, C. R., & Pylyshyn, Z. W. (2000). Multiple object tracking and attentional processing. *Canadian Journal of Experimental Psychology, 54*, 1–14.

Seeherman, J., & Liu, Y. (2015). Effects of extraordinary snowfall on traffic safety. *Accident Analysis & Prevention, 81*, 194–203.

Seeing Machines. (2025). Retrieved from: https://seeingmachines.com/products/automotive/

Seo, T., Bayen, A. M., Kusakabe, T., & Asakura, Y. (2017). Traffic state estimation on highway: A comprehensive survey. *Annual Reviews in Control, 43*, 128–151.

Shakir, U. (December 28, 2022). *Waze tests new alerts warning drivers about roads with a "history of crashes"*. The Verge. Retrieved from: https://www.theverge.com/2022/12/28/23529380/waze-history-of-crashes-beta-release-traffic-crash-data

Shaygan, M., Meese, C., Li, W., Zhao, X., & Nejad, M. (2022). Traffic prediction using artificial intelligence: Review of recent advances and emerging opportunities. *Transportation Research Part C, 145*, 103921.

Sheridan, T. B. (1995). Teleoperation, telerobotics and telepresence: A progress report. *Control Enigneering Practices, 3*, 205–214.

Shi, Y., Feng, H., Geng, X., Tang, X., & Wang, Y. (2019). *A survey of hybrid deep learning methods for traffic flow prediction*. In Proceedings of the 3rd international conference on advances in image processing, pp 133–138.

Shirouzu, N., & Roy, A. (June 23, 2025). *Tesla rolls out robotaxis in Texas test*. Reuters. Retrieved on June 30, 2025: https://www.reuters.com/business/autos-transportation/tesla-tiptoes-into-long-promised-robotaxi-service-2025-06-22/

Shneiderman, B. (2022). *Human-centered AI*. Oxford University Press.

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. https://doi.org/10.1177/10711813241269256

Smallwood, J., McSpadden, M., & Schooler, J. W. (2007). The lights are on but no one's home: Meta-awareness and the decoupling of attention when the mind wanders. *Psychonomic Bulletin & Review, 14*(3), 527–533.

Smith, B. L., Byrne, K. G., Copperman, R. B., Hennessy, S. M., & Goodall, N. J. (2004, January). *An investigation into the impact of rainfall on freeway traffic flow*. In Proceedings of the 83rd Annual Meeting of the Transportation Research Board, Washington DC.

Sodiya, E. O., Umoga, U. J., Amoo, O. O., & Atadoga, A. (2024). AI-driven warehouse automation: A comprehensive review of systems. *GSC Advanced Research and Reviews, 18*(2), 272–282.

Spence, I., & Feng, J. (2010). Video games and spatial cognition. *Review of General Psychology, 14*, 92–104.

Squire, P., Trafton, G., & Parasuraman, R. (2006). *Human control of multiple unmanned vehicles: Effects of interface type on execution and task switching times*. In Proceedings of 2006 ACM conference on human robot interaction, pp. 26–32.

Stahl, P., Donmez, B., & Jamieson, G. (2014). Anticipation in driving: The role of experience in the efficacy of pre-event conflict cues. *IEEE Transactions on Human-Machine Systems, 44*(5), 603–613.

Sun, X., & Liu, Y. (2021). Staffing many-server queues with autoregressive inputs. *Naval Research Logistics, 68*(3), 312–326.

Tavakoli, A., & Heydarian, A. (2022). Multimodal driver state monitoring through unsupervised learning. *Accident Analysis and Prevention, 170*, 106640.

Taylor, T. G., Masserang, K. M., Pradhan, A. K., Divekar, G., Samuel, S., Muttart, J. W., Pollatsek, A., & Fisher, D. L. (2011). *Long term effects of hazard anticipation training on novice drivers measured on the open road*. In Proceedings of the 2011 international driving symposium on human factors in driver assessment, training and vehicle design, pp. 187–194.

Tener, F., & Lanir, J. (2022). *Driving from a distance: Challenges and guidelines for autonomous vehicle teleoperation interfaces*. CHI 22, New Orleans, LA, USA.

Tesla. (2025). *Model Y Owner's Manual*. Retrieved from: https://www.tesla.com/ownersmanual/modely/en_us/GUID-EDAD116F-3C73-40FA-A861-68112FF7961F.html

The Waymo Team. (2024, May 21). *Fleet response: Lending a helpful hand to Waymo's autonomously driven vehicles*. The official Waymo blog. Retrieved from: https://waymo.com/blog/2024/05/fleet-response/

Todovic, D., Makajic-Nikolic, D., & Kostic-Stankovic, M. (2015). Police officer scheduling using goal programming. *Policing: An International Journal of Police Strategies & Management, 38*, 295–313.

Trouvain, B., & Wolf, H. (2002). Evaluation of multi-robot control and monitoring performance. *Proceedings of IEEE International Workshop Robot Human Interactive Communication*, 111–116.

Tsang, N. H., Ho, J. K. L., & Chan, A. H. S. (2015). Interface design and display-control compatibility. *Measurement and Control, 48*(3), 81–86.

Turek, S. E. (2025, July 21). *Tesla robotaxi riders raise red flags after experiencing concerning safety issues: "The car didn't behave correctly"*. Yahoo!tech. Retrieved from: https://tech.yahoo.com/transportation/articles/tesla-robotaxi-riders-raise-red-104516640.html?guccounter=1

Uffizio. (2024, January 8). *Enhancing road safety with truck driver monitoring system*. Retrieved from: https://www.uffizio.com/blog/enhancing-road-safety-with-truck-driver-monitoring-system/

UNECE. (2020). *Human factors challenges of remote support and control: A position paper from HF-IRADS*. Informal Document No. 8-September 2020 session of WP.1(8), 1–9. Retrieved from: https://unece.org/fileadmin/DAM/trans/doc/2020/wp29grva/GRVA-07-65e.pdf

Utesch, F., Brandies, A., Pekezou Fouopi, P., & Schießl, C. (2020). Towards behaviour based testing to understand the black box of autonomous cars. *European Transport Research Review, 12*(1), 48.

Viola, P., & Jones, M. (2001, December). *Rapid object detection using a boosted cascade of simple features*. In Proceedings of the 2001 IEEE computer society conference on computer vision and pattern recognition. CVPR 2001 (Vol. 1, p. I).

Von Eschenbach, W. J. (2021). Transparency and the black box problem: Why we do not trust AI. *Philosophy & Technology, 34*(4), 1607–1622.

Wamba, S. F., & Queiroz, M. M. (2022). Industry 4.0 and the supply chain difitalisation: A blockchain diffusion perspective. *Production Planning & Control, 33*(2–3), 193–210.

Wan, J., Li, X., Dai, H. N., Kusiak, A., Martinez-Garcia, M., & Li, D. (2020). Artificial-intelligence-driven customized manufacturing factory: Key technologies, applications, and challenges. *Proceedings of the IEEE, 109*(4), 377–398.

Wan, J., & Wu, C. (2018). The effects of lead time of take-over request and nondriving tasks on taking-over control of automated vehicles. *IEEE Transactions on Human-Machine Systems, 48*(6), 582–591.

Wang, T. C., & Liu, C. C. (2014). Optimal work shift scheduling with fatigue minimization and day off preferences. *Mathematical Problems in Engineering, 2014*, 1–8.

Wang, Y., & Papageorgiou, M. (2005). Real-time freeway traffic state estimation based on extended Kalman filter: A general approach. *Transportation Research Part B: Methodological, 39*(2), 141–167.

Wang, Z., Liu, Y., & Fang, L. (2022). Pay to activate service in vacation queueing systems. *Production and Operations Management, 31*, 2609–2627.

Wickens, C. D. (2015). Noticing events in the visual workplace: The SEEV and NSEEV models. In R. R. Hoffman, P. A. Hancock, M. W. Scerbo, R. Parasuraman, & J. L. Szalma (Eds.), *The Cambridge handbook of applied perception research* (Vol. 2, pp. 749–768). Cambridge University Press.

Wolfe, J. M., Horowitz, T. S., Van Wert, M. J., Kenner, N. M., Place, S. S., & Kibbi, N. (2007). Low target prevalence is a stubborn source of errors in visual search tasks. *Journal of Experimental Psychology: General, 136*(4), 623–638.

Wu, S., Cheng, C. K., Feng, J., D'Angelo, L., Alain, C., & Spence, I. (2012). Playing a first-person shooter video game induces neuroplastic change. *Journal of Cognitive Neuroscience, 24*, 1286–1293.

Xing, Y., Lv, C., Cao, D., & Hang, P. (2021). Toward human-vehicle collaboration: Review and perspectives on human-centered collaborative automated driving. *Transportation Research Part C: Emerging Technologies, 128*, 103199.

Xu, S., & Hall, N. G. (2021). Fatigue, personnel scheduling and operations: Review and research opportunities. *European Journal of Operational Research, 295*(3), 807–822.

Xu, W., Cheng, Y., Dong, W., Dong, D., & Ge, L. (2022a). Human factors engineering research on single pilot operations for large commercial aircraft: Progress and prospect. *Advances in Aeronautical Science and Engineering, 13*(1), 1–18. (in Chinese).

Xu, W., Dainoff, M. J., Ge, L., & Gao, Z. (2022b). Transitioning to human interaction with AI systems: New challenges and opportunities for HCI professionals to enable human-centered AI. *International Journal of Human-Computer Interaction, 39*(3), 494–518.

Xu, W., & Gao, Z. (2025). An intelligent sociotechnical systems (iSTS) framework: Enabling a hierarchical human-centered AI (hHCAI) approach. *IEEE Transactions on Technology and Society, 6*(1), 31–46.

Xu, W., Gao, Z., & Dainoff, M. (2024). *An HCAI methodological framework (HCAI-MF): Putting it into action to enable human-centered AI*. airXiv, December 2024. Retrieved on January 27, 2025: https://airxiv.org/2311.16027

Yabuta, K., Iizuka, H., Yanagishima, T., Kataoka, Y., & Seno, T. (1985). *The development of drowsiness warning devices* (No. 856043). SAE Technical Paper.

Yaiprasert, C., & Hidayanto, A. N. (2024). AI-powered ensemble machine learning to optimize cost strategies in logistics business. *International Journal of Information Management Data Insights, 4*(1), 100209.

Yan, C., Coenen, F., & Zhang, B. (2015). Driving posture recognition by convolutional neural networks. *IET Computer Vision, 10*(2), 103–114.

Yang, G., Ridgeway, C., Miller, A., & Sarkar, A. (2024). Comprehensive assessment of artificial intelligence tools for driver monitoring and analyzing safety critical events in vehicles. *Sensors, 24*, 2478.

Yang, J., Huang, J., & Liu, Y. (2022). Mind your own customers and ignore the others: Asymptotic optimality of a local policy in multiclass queueing systems with customer feedback. *IISE Transactions, 54*(4), 363–375.

Yi, W., Chan, A., Wang, X., & Wang, J. (2016). Development of an early-warning system for site work in hot and humid environments: A case study. *Automation in Construction, 62*, 101–113.

Yildi, B. C., Gzara, F., & Elhedhli, S. (2017). Airline crew pairing with fatigue: Modeling and analysis. *Transportation Research Part C: Emerging Technologies, 74*, 99–112.

Yin, X., Wu, G., Wei, J., Shen, Y., Qi, H., & Yin, B. (2021). Deep learning on traffic prediction: Methods, analysis, and future directions. *IEEE Transactions on Intelligent Transportation Systems, 23*(6), 4927–4943.

Yoo, S., Lee, S., Kim, S., Kim, E., Hwangbo, H., & Kang, N. (2024). The anxiety consumers feel about using robotaxis: HMI design for anxiety factor analysis and anxiety relief based on field tests. *Archives of Design Research, 37*(3), 47–62.

Yurtsever, E., Lambert, J., Carballo, A., & Takeda, K. (2020). A survey of autonomous driving: Common practices and emerging technologies. *IEEE Access, 8*, 58443–58469.

Zanzotto, F. M. (2019). Human-in-the-loop artificial intelligence. *Journal of Artificial Intelligence Research, 64*, 243–252.

Zerilli, J., Bhatt, U., & Weller, A. (2022). How transparency modulates trust in artificial intelligence. *Patterns, 3*(4), 100455.

Zipper, D. (December 8, 2022). *Self-driving taxis are causing all kinds of trouble in San Francisco*. Slate. Retrieved from: https://slate.com/technology/2022/12/san-francisco-waymo-cruise-self-driving-cars-robotaxis.html

Zhang, T. (2020). Toward automated vehicle teleoperation: Vision, opportunities, and challenges. *IEEE Internet of Things Journal, 7*(12), 11347–11354.

Zhang, Y., Angell, L., & Bao, S. (2021). A fallback mechanism or a commander? A discussion about the role and skill needs of future drivers within partially automated vehicles. *Transportation Research Interdisciplinary Perspectives, 9*, 100337.

Zhao, C., Zhao, M., Liu, J., & Zheng, C. (2012). Electroencephalogram and electrocardiograph assessment of mental fatigue in a driving simulator. *Accident Analysis & Prevention, 45*, 83–90.

Zheng, N., Liu, Z., Ren, P., Ma, Y., Chen, S., Ye, S., Xue, J., Chen, B., & Wang, F. (2017). Hybrid-augmented intelligence: Collaboration and cognition. *Frontiers of Information Technology & Electronic Engineering, 18*(2), 153–179.

Zuluaga-Gomez, J., Prasad, A., Nigmatulina, I., Motlicek, P., & Kleinert, M. (2023). A virtual simulation-pilot agent for training of air traffic controllers. *Aerospace, 10*(5), 490.

Zoox, (2020). How Zoox Uses TeleGuidance to Provide Remote Human Assistance to its Autonomous Vehicles. YouTube. Retrieved from: https://www.youtube.com/watch?v=NKQHuutVx78&t