A taxonomy and systematic review of driving automation failure scenarios

Song Yan [1], Ange Wang [2], Jiyao Wang [1], Chunxi Huang [1], Dengbo He [*1,2,3]

1. Thrust of Robotics and Autonomous Systems, The Hong Kong University of Science and Technology (Guangzhou); 2. Thrust of Intelligent Transportation, The Hong Kong University of Science and Technology (Guangzhou); 3. HKUST Shenzhen-Hong Kong Collaborative Innovation Research Institute, Shenzhen, China.

*Corresponding author. Email: dengbohe@hkust-gz.edu.cn

Abstract

Before human drivers are fully removed from the vehicle control loop, the transition of control from automation to human drivers in safety-critical scenarios remains a critical challenge. Although existing research has proposed several taxonomies to categorize safety-critical scenarios from technical and human-factors perspectives, gaps remain across approaches, hindering the transfer of the control process. To bridge this gap, we propose a framework compatible with previous taxonomies from both technical and human-automation interaction perspectives. This framework considers technological difficulties, the nature of driving tasks, and drivers' capabilities. Three dimensions were included in the taxonomy: the source of harm, the urgency level, and the trigger conditions. Then, a systematic literature review of safety-critical scenarios in existing empirical studies (N=292) was conducted using our proposed taxonomy. We summarized the types of scenarios adopted in previous studies, driver performance in these scenarios, and the intervention strategies to enhance takeover quality. Several major research gaps were identified, including the highly unbalanced types of scenarios adopted in previous studies, a lack of understanding of information needs across scenarios, and the lack of appropriate strategies to improve takeover performance in specific scenarios. These findings underscore the need for a unified framework to categorize and analyze safety-critical scenarios, which can support researchers, practitioners, and policymakers in testing and improving the safety of automated vehicles.

Keywords: Traffic safety, driving automation, takeover scenarios, human factors, system failure

1. Introduction

With the advent and growing adoption of driving automation technologies, the automotive industry is undergoing a transformative shift expected to benefit the traffic system, including reduced driver stress, increased road safety, and greater traffic efficiency. However, due to the long deployment cycle of vehicle technologies (Highway Loss Data Institute, 2022), it is estimated that till the 2030s and potentially the 2040s, partially or conditionally driving automation that is classified as Levels 2 and 3 by the Society of Automotive Engineers (SAE) (SAE International, 2021) may still be the mainstream in the consumer market. Thus, in critical scenarios, human intervention will still be needed for driving automation in the near future (Litman, 2023). This poses the challenge of ensuring a safe control transition in complex, dynamic driving scenarios, especially during system-initiated takeovers.

Previous research has attempted to tackle this challenge by providing drivers with warnings when a takeover is required, for example, via takeover requests (TORs) (Jansen et al., 2022). However, it takes some time for drivers to build up their situation awareness and successfully take over control of the vehicle. It is recommended that at least 8 seconds are needed for a fully distracted driver to safely take control of the vehicle (Samuel et al., 2016). This is technically challenging, as on a 100 km/h highway, an 8-second pre-warning requires the system to detect hazards at least 222 meters ahead. Hence, researchers also sought to provide driver training to help drivers be aware of their responsibilities and the limitations of driving automation (e.g., Boelhouwer et al., 2019; Ebnali et al., 2019; Hergeth et al., 2017) so that they can proactively take control of the vehicle. However, drivers may still struggle to determine when a takeover is necessary, given the highly diverse traffic environment and the uncertainty

in driving automation performance. In particular, the SAE taxonomy is primarily based on the responsibility for driving automation and drivers. With technological advancement, the boundaries between SAE Levels 2 and 3 have become increasingly vague. For example, vehicle manufacturers have started using terms such as "L2+ automation" (Mobileye, 2020) or "AutoPilot" (Tesla, 2024) to describe advanced driver assistance systems (ADAS). This poses further challenges for drivers to correctly identify when a takeover is needed. Thus, it becomes necessary to categorize takeover scenarios more systematically to guide the labeling of driving automation, evaluate the human-machine interface, and help drivers better understand the system boundaries of their vehicles.

Approaches from the driving automation testing domain may provide some insights. The safety and efficacy of driving automation depend heavily on the accurate perception, understanding, and response to scenarios. Thus, scenario-based methods were proposed as a systematic approach to identifying the full range of conditions that automated driving systems may handle. Unlike traditional bumper-to-bumper testing or statistical analysis of crash data, scenario-based methods decompose complex traffic situations into discrete, reproducible scenarios characterized by road geometry, traffic participants, environmental conditions, and ego vehicle states, enabling targeted safety evaluation and validation of driving automation systems (ISO, 2022b; Staplin et al., 2018). In recent years, extensive research has been conducted on identifying (Neelofar & Aleti, 2022; Zhang et al., 2022), generating (Ding et al., 2023), and evaluating (Chia et al., 2022; Y. Li et al., 2021) safety-critical scenarios that serve the scenario-based methods.

However, the research on the transfer of control between driving automation and human

drivers rarely considered this scenario-based approach. On one hand, most existing research has focused on a few relatively simple takeover scenarios (e.g., following a decelerating vehicle or approaching a static obstacle) without fully justifying the rationale for their selection (e.g., W. Chen et al., 2023; Ko et al., 2022; Shahini et al., 2023). Some adopted a taxonomy of hazardous scenarios from non-automated driving research, without considering the driving automation capabilities. For example, the high-risk scenarios in the NHTSA pre-crash scenario topology (Najm et al., 2007) have been adopted by some studies (Morando et al., 2021; Yamani et al., 2023) to investigate driver takeover behaviors, although the topology was proposed solely based on crash statistics among non-automated vehicles. This poses challenges in evaluating TORs or driver training programs and may impede drivers' judgment about whether a takeover is necessary. On the other hand, the existing scenario-based methods were designed for testing driving automation and did not account for driver intervention from a human-factors perspective. For example, the taxonomy of scenarios in driving automation testing (e.g, ISO, 2022b; UNECE, 2021) did not consider the time required for drivers to rebuild situation awareness (J. Zhang et al., 2025) and the influence of driving experience (Sun & He, 2025) on drivers' perception of traffic hazards, which are vital influential factors of takeover performance.

Thus, the objective of this study is to review the safety-critical scenarios used in existing takeover-related research and propose an updated taxonomy that accounts for both technical difficulties and human user uncertainty. The main contributions of this study are as follows: First, we proposed a novel taxonomy of safety-critical scenarios that integrates both technical perspectives (i.e., FuSa, SOTIF, and scenario-based safety evaluation) and human-automation interaction perspectives (i.e., driving task hierarchy and temporal constraints on drivers),

bridging a gap between technology-oriented and behavior-oriented taxonomies. Second, we conducted a systematic review of 292 empirical studies to summarize safety-critical scenarios in existing takeover research and identified critical imbalances and gaps in the current literature. Third, based on the proposed taxonomy and the systematic review findings, we identified actionable research directions and discussed how different intervention strategies can be tailored to specific safety-critical scenarios, providing insights for the design of driving automation systems.

2. Key concepts and existing frameworks for characterizing safety-critical scenarios

This section reviews the key concepts and existing frameworks for characterizing safety-critical scenarios with driving automation, identifies their limitations, and motivates the need for a new taxonomy.

2.1. Key concepts related to safety-critical scenarios

The SAE taxonomy of driving automation has defined several key concepts related to safety-critical scenarios, namely Operation Design Domain (ODD), Dynamic Driving Task (DDT), and DDT fallback (SAE International, 2021). The ODD and DDT are the two key concepts that describe the capabilities and limitations of driving automation with different SAE levels. ODD outlines the specific circumstances under which driving automation can operate and is characterized by static and dynamic traffic elements, as well as environmental conditions. At the same time, DDT describes the tactical and operational maneuvers required to operate the vehicle, including maneuver planning, object and event detection and response (OEDR), and

vehicle motion control. When driving automation operates outside the ODD or when a system malfunction occurs, a DDT fallback is triggered, prompting the fallback-ready user (either the driver or the backup system, depending on the level of automation) to take over some or all DDTs to achieve the minimal-risk condition.

Table 1 provides an overview of the ODD range and the DDT allocation between the driver and the system with different levels of automation. According to the SAE taxonomy, for Levels 0 to 2, the driver is consistently engaged in the DDT and must proactively resume control in the event of DDT fallbacks. At Level 3, the driving automation can manage the entire DDT within its ODD and may issue TORs if a fallback occurs. Drivers are expected to respond to TORs or initiate a takeover themselves if the driving automation fails to issue a TOR. In Levels 4 and 5, the driving automation fully executes the DDT fallback to reach a minimum risk condition. However, the SAE taxonomy fails to address real-world complexities, and system boundaries are often vague in practice. For example, TORs (a non-mandatory feature of the SAE Level 2 system according to the SAE taxonomy) are commonly used in commercialized Level 2 systems such as Tesla Autopilot and Huawei Advanced Driving System to prompt driver intervention (AITO, 2025; Tesla, 2025). In contrast, although SAE Level 4 systems should theoretically handle all system failures and achieve minimum-risk conditions within their ODD, current Level 4 vehicles may still fail to respond to hazards and be involved in crashes (NHTSA, 2022). Thus, while the SAE taxonomy defines automation levels from a driver-responsibility perspective, it may not accurately reflect actual technological development.

Table 1. SAE Levels of Driving Automation (SAE International, 2021).

Level	Name	DDT			ODD
		Sustained Lateral and Longitudinal Vehicle Motion Control	OEDR	DDT Fallback	
0	No Driving Automation	Driver	Driver	Driver	n/a
1	Driver Assistance	Driver and System	Driver	Driver	Limited
2	Partial Driving Automation	System	Driver	Driver	Limited
3	Conditional Driving Automation	System	System	Driver	Limited
4	High Driving Automation	System	System	System	Limited
5	Full Driving Automation	System	System	System	Unlimited

2.2. Technical frameworks for characterizing safety-critical scenarios

Functional safety (FuSa) (ISO, 2018) and safety of the intended functionality (SOTIF) (ISO, 2022a) are two complementary frameworks for managing the risks associated with driving automation. FuSa addresses risks related to electrical and electronic system faults, including random hardware faults and systematic faults, through fault tolerance or fault prevention (FuSa). A major limitation of FuSa is that it assumes system risks can be completely specified, which becomes increasingly challenging as driving automation incorporates complex AI components (X. Zhang et al., 2022; Y. Zhang et al., 2021).

SOTIF complements FuSa by addressing non-fault-related risks arising from functional insufficiencies—situations in which the system operates as designed but its intended

functionality is insufficient to ensure safety. SOTIF considers two types of functional insufficiency: specification insufficiency (incomplete specifications) and performance insufficiency (inadequate functional capability) (ISO, 2022a).

Building on FuSa and SOTIF, the Scenario-based Safety Evaluation Framework (ISO 34502) provides a systematic approach for safety testing by instantiating the ODD through pre-defined scenarios (ISO, 2022b). However, ISO 34502 primarily focuses on the inherent physical principles of DDT, categorizing them into perception-related, traffic-related, and vehicle-control-related, without considering the timing and urgency of scenarios from a driver's perspective. Thus, taxonomies from a human-centered perspective should also be proposed to enhance the evaluation of human-automation interaction.

2.3. Human factors perspectives on safety-critical scenarios

Several studies have attempted to classify safety-critical situations, taking human factors into account. For example, McCall et al. (2016) categorized takeover scenarios into five types based on whether a takeover is scheduled, who initiates it, and whether it is urgent, with each type necessitating different levels of driver responsibility, skill, and situational awareness. This taxonomy primarily focuses on the control transition process in takeover scenarios and has the potential to inform Human-Machine Interface (HMI) design for ensuring safe and seamless control transitions. Chen et al. (2023) introduced a taxonomy that categorizes takeover scenarios based on whether the ODD boundary is reached and whether the causes of failure are recognized by the system or the human driver. This taxonomy has demonstrated effectiveness in guiding improvements in driving automation features, HMIs, and driver training programs.

Similar to the concept of ODD boundary by Chen et al. (2023), Kanaan & Donmez (2024) focuses on whether the automation failures are triggered by unknown and unscheduled conditions. Through a scoping review of takeover scenarios, they find that most existing studies have considered only relatively simple scheduled ODD exit situations (e.g., unclear lane markings or road obstacles). Moreover, in studies of automation failures, the underlying mechanisms were often described ambiguously, making accurate classification challenging.

2.4. Synthesis of existing frameworks and gaps

The review above reveals several critical gaps in existing frameworks for characterizing safety-critical scenarios. First, technology-oriented taxonomies (e.g., ISO, 2018, 2022a, 2022b) focus primarily on system-level failures and do not account for the role of human drivers in the control transition process. Second, human-factor-oriented taxonomies (e.g., K.-T. Chen et al., 2023; Kanaan & Donmez, 2024; McCall et al., 2016) provide valuable insights into driver behavior but are limited in their coverage of technical failure types and lack alignment with industry standards. Third, existing taxonomies generally treat scenario urgency and trigger conditions as secondary factors, without systematically integrating them into a unified framework. These gaps highlight the need for a comprehensive taxonomy that bridges the technical and human factors perspectives while providing higher resolution in terms of scenario urgency and trigger conditions.

3. A taxonomy of safety-critical scenarios with technical challenges and human factors considered

Based on the gaps identified in Section 2, this section presents our proposed taxonomy of safety-critical scenarios that integrates technical and human-automation interaction perspectives across three complementary dimensions. The safety-critical scenario in our taxonomy is defined as *a situation wherein the driving automation fails to execute the DDT as intended, necessitating human intervention to ensure driving safety*.

3.1. Motivation for the taxonomy

Based on our review of existing frameworks, we believe that focusing solely on drivers' responsibilities as defined by SAE Levels cannot adequately differentiate the challenges drivers face when automation fails. In such conditions, understanding how drivers interact with automation failures is vital to the safety of driving automation, regardless of SAE levels. Our taxonomy primarily characterizes automation failures from a human–automation interaction perspective. This framework facilitates the identification of human–automation interaction challenges in automation failure scenarios and supports adaptive HMI strategies and driver training programs.

Figure 1 illustrates our taxonomy of safety-critical scenarios, which has three dimensions: the source of harm, the urgency level, and the trigger phase. The proposed taxonomy is grounded in three complementary theoretical foundations. First, the source of harm dimension draws on the distinction between system malfunction (ISO, 2018) and functional insufficiency (ISO, 2022a), a distinction widely adopted in the automotive industry for classifying

automation failures. Second, the trigger phase dimension aligns with the three-phase driving task model (Michon, 1985) and the functional modules of the driving automation (i.e., perception, planning, and control) (Pendleton et al., 2017), providing a theoretically grounded basis for categorizing driving challenges. Third, the urgency-level dimension is informed by the takeover-request literature (K.-T. Chen et al., 2023; McCall et al., 2016) and reflects the temporal constraints drivers face during control transitions. The combination of these three dimensions provides a comprehensive characterization of safety-critical scenarios: the source of harm identifies where the failure originates, the trigger phase describes the nature of the driving challenge, and the urgency level quantifies the time pressure on the driver. Together, these dimensions capture the technical challenges of driving automation and the human factors challenges drivers face when cooperating with automation.

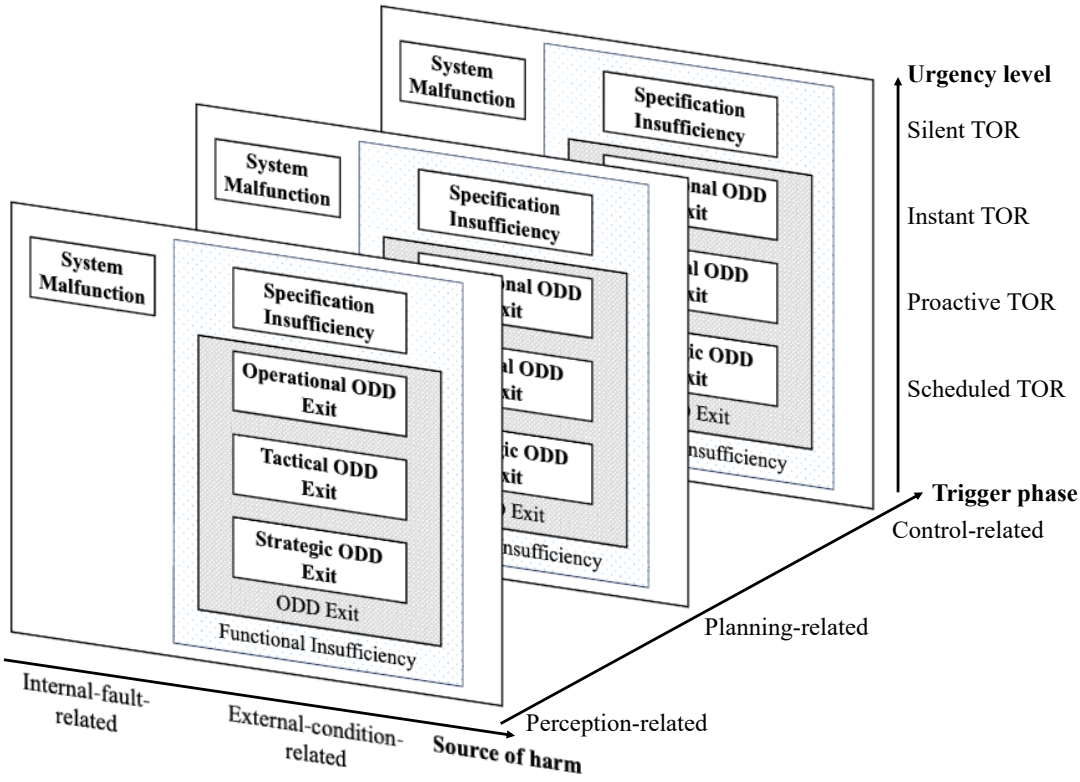


Figure 1. Taxonomy of safety-critical scenarios.

3.2. Source of harm

The source of harm explains where a critical event originates from. This dimension is considered because it can inform which skills or knowledge drivers need to anticipate a critical scenario.

3.2.1 Internal-fault-related and External-condition-related Scenarios

Being compatible with FuSa and SOTIF, internal-fault-related scenarios cover system malfunction in FuSa, and external-condition-related scenarios cover functional insufficiency in SOTIF. It should be noted that, according to FuSa, the system malfunction can be further categorized as a random hardware fault or systematic fault. However, as discussed in ISO 21448 (ISO, 2022a), the systematic fault can sometimes be regarded as functional insufficiency. For instance, the Uber automated driving vehicle incident (NTSB, 2019), where the driving automation failed to recognize a pedestrian, can be regarded as either a systematic software fault according to FuSa or a functional insufficiency of the machine learning component according to SOTIF. From a user's perspective, the drivers may not be able to tell whether it is a malfunction or functional insufficiency, but they may care more about whether the hazard is induced by internal faults (i.e., hardware, software, or mechanical faults) or external conditions (e.g., scenery, traffic, or environmental elements). In other words, internal-condition-related scenarios are mostly technically oriented and unpredictable to users, but external-condition-related scenarios can be predicted based on drivers' understanding of the system boundaries (or ODD) and the perception of the environment. Research has already found that drivers' takeover performance differs in internal-fault-related and external-condition-related scenarios (Kanaan

& Donmez, 2024). Thus, we have internal-fault-related and external-condition-related scenarios in this dimension.

3.2.2 External-condition-related scenarios: ODD exit and specification insufficiency

Building on the concept of functional insufficiency in SOTIF, we further defined different types of external-condition-related scenarios. Specifically, depending on whether the functional insufficiency and its trigger conditions are acknowledged and specified in the ODD, we subdivided the functional insufficiency scenarios into specification-insufficiency scenarios and ODD-exit scenarios. For instance, in a situation where the driving automation is unable to operate in heavy rain due to sensor limitations, if this sensor limitation and its trigger condition have been acknowledged in the ODD, the heavy rain scenario will be classified as an ODD exit scenario; conversely, if the ODD does not explicitly acknowledge this limitation, this scenario would be classified as a specification insufficiency scenario. Previous research aimed at improving drivers' mental models of driving automation, by nature, sought to help drivers be more aware of the ODD, and they found that drivers with stronger mental models can perform better in ODD exit events (e.g. Ebnali et al., 2019; Hergeth et al., 2017; Zhou et al., 2019). This indicates that the takeover performance can differ between ODD exit and functional insufficiency scenarios.

3.2.3 ODD Exit Scenarios: Strategic, tactical, and operational ODD exit

Based on when the system can detect the ODD exit, in line with the three levels of driving tasks (Michon, 1985), we define the three levels of ODD exit as follows:

1) Strategic ODD exit: A scenario in which the conditions that will cause the driving automation to exit its ODD are known at the route planning stage. This corresponds to the strategic level of driving, which involves global route planning and high-level decisions (e.g., exiting a highway at a predetermined location).
2) Tactical ODD exit: A scenario in which the ODD boundary is detected during the tactical driving phase, which involves OEDR and local trajectory planning. The system can identify the upcoming ODD exit at least seconds in advance (e.g., by detecting a new construction zone ahead or a vehicle cutting in from an adjacent lane).
3) Operational ODD exit: A scenario in which the ODD boundary is only reached during the operational driving phase, which involves real-time vehicle motion control. No advance warning can be provided, as the system only detects the ODD exit when it occurs (e.g., when suddenly encountering black ice or an unexpected change in road surface).

Note that we abandoned the term planned or unplanned event in previous studies (Hong et al., 2022) and adopted the 3-level driving task hierarchy to label driving scenarios (Michon, 1985), matching the DDT types in driving automation (i.e., globla route planning, OEDR and local trajectory planning, and motion control, SAE International, 2021). These 3-level ODD exits can also provide higher-resolution information on the available timing of the TOR, thereby enabling the establishment of the relationship between technical difficulties and drivers' perceived urgency. For example, the driving automation may only work on highways, and thus, when the route is planned, this strategic ODD exit is known. In contrast, detecting tactical ODD (e.g., a sudden cut-in vehicle initiated the ODD exit) is more challenging for drivers, given that drivers will need to perceive or even anticipate the hazards in order to take over the vehicle,

which is cognitively demanding, especially for those with little driving experience (He, 2020). Whereas the operational ODD is even more safety-critical, as no TOR can be provided in advance and the vehicle may exhibit unstable dynamics when the operational ODD exit occurs.

3.3. Urgency levels of safety-critical scenarios

The urgency level of safety-critical scenarios is widely recognized as a crucial factor affecting drivers' takeover performance and has been extensively studied. For example, McCall et al. (2016) categorized takeover situations into scheduled and non-scheduled, claiming that all scheduled takeovers are non-emergent, whereas non-scheduled takeovers could be either urgent or non-urgent. Similarly, K.-T. Chen et al. (2023) classified takeover situations into planned ODD exit, unplanned ODD exit, driving automation operation failure, and mechanical failure, suggesting that all these situations, except for planned ODD exit scenarios, have high urgency. Depending on whether a takeover request (TOR) is issued before or after the ODD exit, Yao et al. (2021) categorized safety-critical scenarios into ODD exit situations and system failure situations – the latter led to longer driver response time and lower takeover quality.

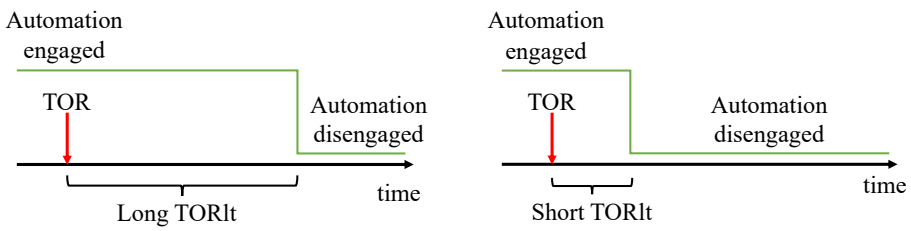
The source of harm is intrinsically associated with the urgency levels of scenarios. As depicted in **Figure 1**, we divide the scenarios into four levels based on the presence of TOR and the length of takeover request lead time (TORlt), i.e., scheduled TOR, proactive TOR, instant TOR, and silent TOR. The control transition process of each urgency level is illustrated in **Figure 2**.

- The scheduled TOR can only be triggered by strategic ODD exit, which usually has a long TORlt, and the drivers can be informed before the scenarios are encountered (**Figure 2a**, e.g., know the foggy weather kilometers away). More specifically, the scheduled TORs are those that can be known when the route is planned (e.g., knowing the highway exit when setting the navigation and knowing bad weather tens of kilometers ahead when planning the route).
- The proactive TOR can be triggered by strategic and tactical ODD exit and can only be up to tens of seconds ahead, given that the system can only realize the boundary of the ODD when planning the tactical level DDT (**Figure 2b,** e.g., detect a cutting-in vehicle when planning the vehicle motion in the next few seconds).
- The instant TOR can be triggered by all ODD exit scenarios (**Figure 2c,** e.g., detect the icy road when turning the steering wheel) and has no lead time.
- System malfunction scenarios and specification insufficiency scenarios have the highest urgency levels, and the system may not even detect them, leading to silent TOR (**Figure 2d;** i.e., the system may not disengage but continue operating in an unintended manner).

It should be noted that the urgency level is not entirely independent of the source of harm. However, they are conceptually distinct, capture different aspects of safety-critical scenarios, and connect the technical challenges and human factors challenges. Specifically, the source of harm describes the origin of the failure, the trigger phase characterizes the nature of the driving challenge, and the urgency level reflects the temporal constraint on the driver - each dimension provides unique information essential to understanding and addressing safety-critical scenarios. Further, the same source of harm may trigger different TORs with different levels of urgency.

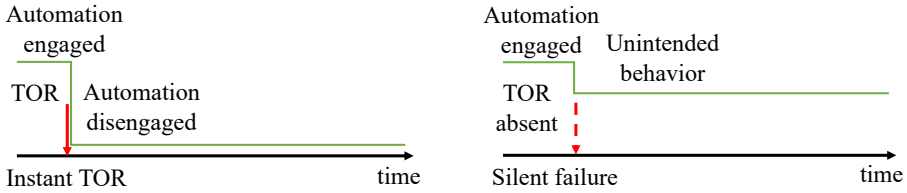
For example, a strategic ODD exit (e.g., a highway exit) can trigger a scheduled TOR, informing drivers of the upcoming takeover several kilometers in advance. However, the system can still issue a proactive TOR later, when the vehicle approaches the highway exit. In contrast, an operational ODD exit cannot trigger a scheduled TOR because the system cannot detect the situation in advance. Thus, we still opt to keep both dimensions, despite the inter-dependencies.

This dimension of scenario urgency is compatible with the taxonomy of safety-critical scenarios proposed by McCall et al. (2016), K.-T. Chen et al. (2023), and Yao et al. (2021), but provides higher resolution from the driving-task perspective, which can better inform how takeover quality can be improved. For example, for the scheduled TOR, a multi-stage warning may be helpful for drivers to anticipate the upcoming takeovers (i.e., not just inform drivers of the ODD exit right before the ODD boundary is reached, but also at the beginning of the drive) (W. Liu et al., 2022; Tan & Zhang, 2023; W. Zhang et al., 2023). For the proactive TOR, existing research focuses on how to help drivers build situation awareness more quickly within a limited time budget to quickly take over the vehicle (Wright et al., 2017; Y. Yang et al., 2018). The instant TOR is urgent; hence, guidance on how to better execute takeover action to reach minimum-risk conditions may be critical (Kalb et al., 2018). For the silent TOR, enhancing the transparency of driving automation and keeping drivers informed of the system status so they can detect failures in time are crucial (Jung et al., 2023a; Kraus et al., 2020).



a. Scheduled TOR

b. Proactive TOR



c. Instant TOR

d. Silent TOR

Figure 2. Control transition process with different urgency levels.

Note that although urgency can be conceptualized as a continuous variable (e.g., time-to-collision or takeover request lead time), we opted for a categorical classification of urgency levels for several reasons. First, in the context of a systematic review, a categorical taxonomy is more practical for classifying and comparing scenarios across studies, as different studies report urgency in different ways (e.g., some report exact lead times while others only describe the scenario type), and specific thresholds can vary with traffic conditions such as vehicle speed and traffic density. Second, the four-level classification (scheduled TOR, proactive TOR, instant TOR, and silent TOR) aligns with the information available to drivers and the type of cognitive and behavioral challenges they face, which is the primary focus of our taxonomy.

3.4. Trigger phase

The difficulty of handling takeover scenarios is not just determined by the TORlt, but also by the trigger conditions. Previous research usually categorized the trigger conditions of critical scenarios into scenery-related, environment-related, and traffic-related (Ito, 2021). However, such a taxonomy can hardly inform drivers of the capability of driving automation. For example, in the same scenario (e.g., heavy rain), different driving automation may fail for different

reasons (e.g., vehicles that rely heavily on LiDAR may be unable to detect road agents, while another vehicle may exit ODD due to a slippery road).

Thus, inspired by ISO 34502, which classifies driving automation testing scenarios into perception-related, traffic-related, and control-related categories (ISO, 2022b), and aligning with the three phases of the driving automation DDT (Pendleton et al., 2017), we categorize the trigger conditions into perception-, planning-, and control-related categories. The perception-related triggers are associated with the perception of information related to driving; the planning-related triggers are associated with planning the vehicle maneuver and trajectory; and the control-related triggers are associated with conditions that impede execution of the planned trajectory. **Table 2** lists example scenarios of all combinations of the dimensions in our taxonomy.

Depending on the trigger conditions, drivers may need different information even in the same scenario. Let us take a classical scenario that has been that has led to a number of fatal accidents in recent years as an example and explain it, i.e., whether the ACC can respond to stationary objects. All three trigger phases can lead to an unstopped vehicle in this scenario. First, the system may fail to identify the stationary object – in this case, to facilitate a successful takeover, the system should highlight all objects they have detected. Second, the system may fail to plan a motion to avoid the collision – in this case, the system should inform the drivers of the planned trajectory. Finally, the system may not be able to brake in time – in this case, it should inform the drivers of the braking system's capacity.

However, it should be noted that simply informing the system states may not be enough for a driver to take action in time, as a comparison between the system's ODD and anticipated

traffic development (i.e., hazard prediction) is needed to determine whether a takeover is required. A taxonomy of the hazardous scenarios has been proposed by Yan et al. (2024), in which the perception of cues informing hazard is critical for handling perception-related scenarios, and the understanding and prediction of hazards are critical for handling planning-related scenarios.

Table 2. Example scenarios with different sources of harm and trigger phases.

Source of harm	Urgency level	Trigger phase	Example Scenarios
System Malfunction	Silent TOR	Perception	Highway driving with ACC engaged. The ego vehicle's LiDAR sensor experiences a hardware malfunction, failing to detect a stationary truck ahead. The system continues operating without issuing any warning, creating an imminent collision risk.
		Planning	Urban arterial road with LCC engaged. A software bug causes the path planning algorithm to generate an incorrect trajectory, resulting in gradual lane departure toward the adjacent lane without any system alert.
		Control	Rural road with LCC engaged. A mechanical fault in the steering actuator causes sudden loss of steering control while the vehicle is negotiating a gentle curve, with no prior warning to the driver.
Specification insufficiency	Silent TOR	Perception	Suburban road with ACC engaged. The system fails to recognize an unconventional obstacle (e.g., a fallen tree branch with irregular shape) as it falls outside the trained object classification categories, despite clear visibility conditions.
		Planning	Highway driving with ACC engaged. The system cannot plan appropriate deceleration for a slippery road because the reduced tire-road friction coefficient under such conditions was not explicitly specified in the system's operational parameters.
		Control	Approaching a signalized intersection with ACC engaged. The braking system's maximum deceleration capacity is insufficient to stop before a lead vehicle that brakes abruptly, as the vehicle's braking performance with a worn brake was not accounted for in the system specifications.
Operational ODD exit	Instant TOR	Perception	Curved highway with LCC engaged. The vehicle suddenly enters a construction zone where lane markings have been temporarily removed. The lane detection function immediately loses tracking capability and issues an instant TOR with no lead time.
		Planning	Urban intersection with green light. A vehicle from the cross street runs a red light at high speed. The system detects the conflict too late to plan an evasive maneuver and issue an instant TOR.

		Control	Highway driving with ACC engaged. A vehicle cuts in aggressively from an adjacent lane at close distance. The system applies maximum braking but reaches its deceleration limit before achieving a safe following distance, triggering an instant TOR.
Tactical ODD exit	Proactive TOR	Perception	Highway at 100 km/h in clear weather. The radar detects a dense fog bank approximately 200 meters ahead. The system issues a proactive TOR with approximately 7 seconds lead time, allowing the driver to prepare for manual control before entering reduced visibility conditions.
		Planning	Rural road at 50 km/h. The forward-facing cameras detect a transition to an unpaved section with no lane markings. The system recognizes this upcoming ODD boundary exit and issues a proactive TOR with approximately 10 seconds lead time.
		Control	Urban street at 30 km/h. The system detects an upcoming with a curvature radius that exceeds the vehicle's maximum safe cornering speed at the current velocity. A proactive TOR is issued 5 seconds before the curve, warning the driver to reduce speed and take manual control.
Strategic ODD exit	Scheduled TOR	Perception	The navigation system identifies a fog zone along the planned highway route based on weather forecast data at route planning stage before departure. A scheduled TOR notification is displayed 1 kilometer before the fog zone
		Planning	Highway journey with L3 automation. The navigation system shows a scheduled toll station in 15 kilometers. The system provides a scheduled TOR notification at the start of the journey, with another reminder at 1 kilometer before the station.
		Control	Route planning for a mountain pass. The system identifies a series of sharp bends on the planned route that exceed the automation's handling capabilities. A scheduled TOR is issued kilometers before the bends, informing the driver of the upcoming challenging road section.

4. Review of safety-critical scenarios

Following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 approach (Page et al., 2021), this section presents the results of a systematic literature review regarding safety-critical scenarios in existing empirical takeover research. We aim to investigate the safety-critical scenarios used in existing empirical studies, examine findings on their influence on drivers' takeover behavior, and explore implications for driving automation design.

4.1. Literature search and screening

The systematic review followed the PRISMA 2020 approach (**Figure 3**). Given the focus on safety-critical scenarios in empirical studies related to driving automation, the key search terms were designed as follows: *("automated driving" OR "autonomous driving" OR "automated vehicle" OR "autonomous vehicle" OR "driving automation" OR "ADAS") AND ("TOR" OR "takeover" OR "take over" OR "fail*" OR "disengage*" OR "fallback") AND ("experiment*" OR "empirical" OR "field study" OR "naturalistic driving")*. The literature search was conducted on July 14, 2025, within title, abstract, and keywords, across four databases, including Web of Science, Scopus, IEEE Xplore, and ACM Digital Library, with no limits or filters applied. The total number of records identified was 3543, and 2299 were retained after removing duplicates. The abstracts of the remaining records were evaluated for eligibility based on the following inclusion criteria:

1) The research must involve an empirical study of driving automation with human

participants.

2) The ego vehicle in the experiment should be equipped with SAE Level 2 or higher automation.

3) The experiment should involve situations that require the driver's intervention.

In total, 368 records were found to be eligible, and the full papers were further screened. As a result, 4 reports were removed as they were not in English or Chinese, 69 reports were removed as they did not provide sufficient information about the safety-critical scenarios (e.g., the TORs are triggered based on time or location, not by specific scenarios, or the report did not provide description about the scenario), and 3 reports were removed as they only considered driver-initiated non-critical takeovers. Finally, 292 reports were identified as eligible for further assessment and review.

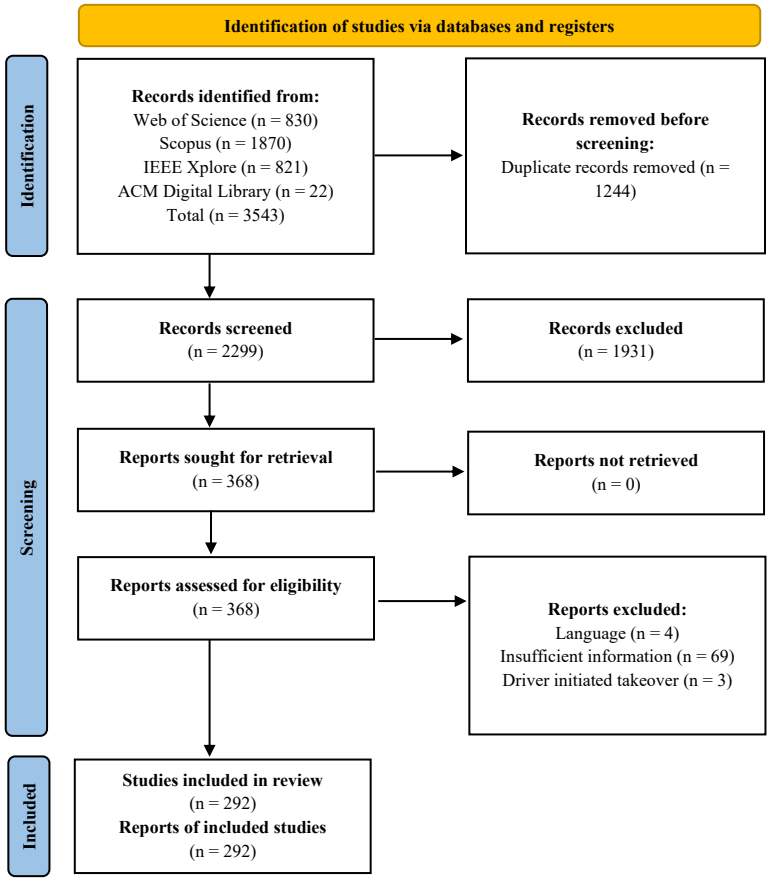


Figure 3. PRISMA process for literature selection.

4.2. Experiment settings

Figure 4 summarizes the experimental settings of the 292 included studies. The majority (n=277, 94.9%) of these studies were conducted in a driving simulator context, while a small percentage (n=12, 4.1%) were conducted on roads or tracks, and a few (n=3, 1%) were based on video simulation.

Additionally, it was found that the automation levels involved in the identified studies ranged from SAE L2 to L4, with the majority focusing on L3 automation (n=225, 77.1%), and 3 studies (1.0%) investigated takeover situations in L4 vehicles. It is noteworthy that some of the included studies did not specifically mention SAE levels (marked as NA in **Figure 4**),

although the ODD boundary and safety-critical scenarios are closely tied to the automation levels of driving systems. If both L2 and L3 systems were used in an experiment, the study was marked as L2&L3 in **Figure 4**.

Regarding non-driving related tasks (NDRTs), the majority (n=232, 79.5%) of the included studies allowed drivers to engage in NDRTs, while only a few (n=38, 13.0%) required drivers to continuously monitor the driving automation. Some studies (n=22, 8.5%) did not indicate whether NDRTs were allowed or not (NA in **Figure 4**).

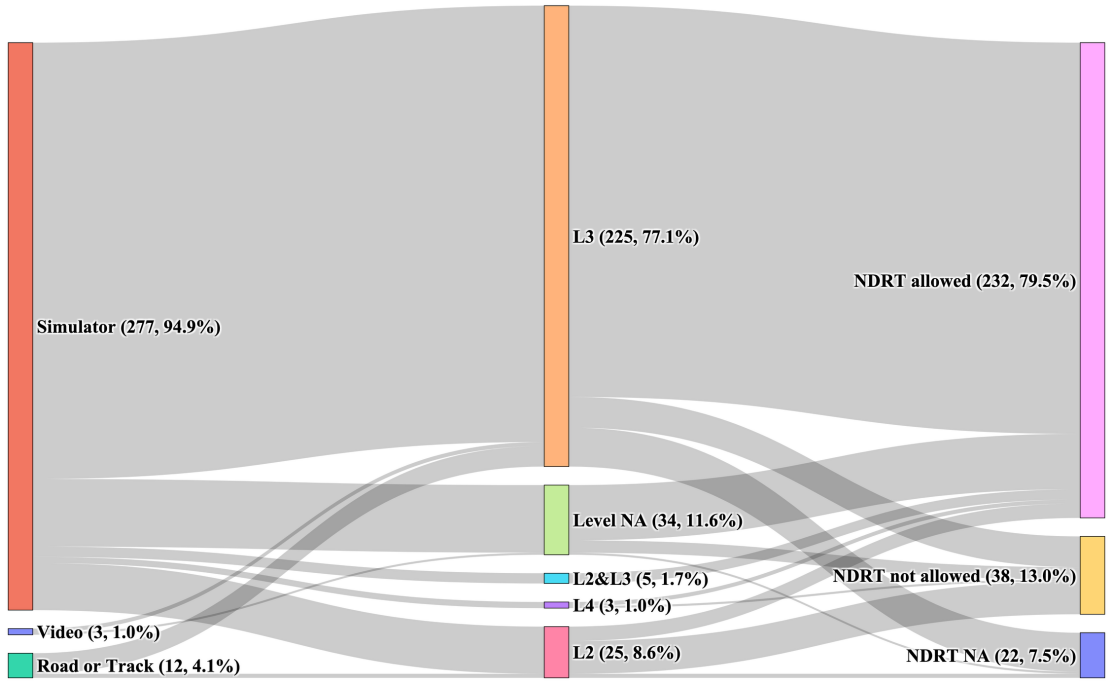


Figure 4. Sankey Diagram of experiment context, automation level, and NDRT.

4.3. Safety-critical scenarios involved in existing research

We further reviewed the safety-critical scenarios in the included studies. As shown in **Figure 5**, only 32% of studies clearly indicated the source of harm, with external-condition-related scenarios (particularly tactical ODD exits) receiving more attention than internal-fault-related scenarios. A large proportion of studies (66%) did not provide sufficient information to

categorize scenarios (see Section 5.3 for further discussion).

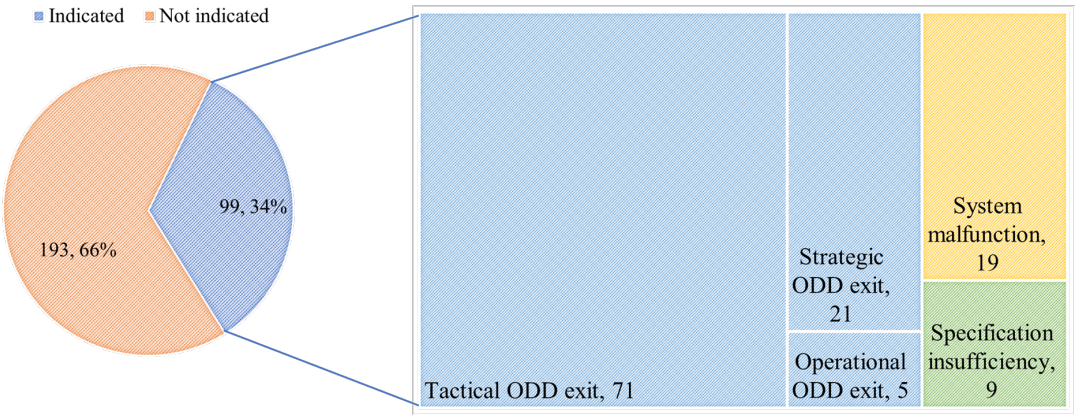


Figure 5. Source of harm of safety-critical scenarios. (Note: among the 99 studies that indicated their scenario types, a single study may involve multiple scenario types, so the sum in the right area chart exceeds the total number of studies.)

To better understand the distribution of safety-critical scenarios in prior studies, we also list them in **Table 3**. Notably, a single scenario may arise from either a single trigger condition or a combination of multiple conditions outlined in the taxonomy. Thus, a single trigger condition might manifest across several scenarios within a single study, and in such instances, it was counted only once. It can be observed that scenarios in which external conditions contribute to planning-related failures dominate. Among these scenarios, encountering a static obstacle on the road has been extensively studied (n=170), followed by infrastructure-related scenarios (n=128) and scenarios involving surrounding vehicle maneuvers (n=86). Additionally, factors such as foggy or rainy weather (n=34), unclear lane markings (n=24), and curved roads (n=15) have attracted significant attention in previous studies.

Table 3. Frequency of trigger conditions in the included studies.

	Internal-fault-related	External-condition-related
Perception-related	Sensor error: 7 ***Total: 7*** ***(L2: n=3; L3: n=4)***	Unclear or missing lane markings: 24 Occlusions: 8 Weather (e.g., fog or rain): 34 Unrecognizable traffic signs: 3 Missing GPS signal in certain road sections: 3 ***Total: 64*** ***(NA: n=2; L2: n=9; L3: n=52; L4: n=1)***
Planning-related	False alarm: 5 False trajectory planning: 3 Cyber-attack: 1 HMI fault: 1 ***Total: 10*** ***(NA: n=1; L2: n=1; L3: n=8)***	Static obstacles: 170 Infrastructures (e.g., highway exit, parking area, intersection): 128 Surrounding vehicle maneuvers: 86 Vulnerable road users' maneuvers: 34 Ego maneuvers (e.g., exceeds speed limit): 1 ***Total: 419*** ***(NA: n=48; L2: n=41; L3: n=327; L4: n=3)***
Control-related	Lose steering or acceleration: 3 Erroneous steering torque: 5 ***Total: 8*** ***(NA: n=2; L2: n=2; L3: n=4)***	Curved road: 15 External force (e.g., side wind): 1 ***Total: 16*** ***(NA: n=2; L2: n=3; L3: n=11)***

Figure 6 demonstrates the urgency levels of the safety-critical scenarios involved in the included studies. It is important to note that among the four urgency levels, both scheduled and proactive TOR involve a TORlt greater than zero. However, there is no universally agreed-upon TORlt threshold to differentiate between them, as it is subject to various conditions such as traffic density, lighting conditions, and vehicle velocity. Therefore, in determining whether a TOR is proactive or scheduled, we primarily rely on the experimental settings rather than an absolute TORlt value (i.e., whether a TOR can be scheduled when a route is planned). The result indicated that most (83%) studies focused on proactive TOR situations, while scenarios involving scheduled, instant, or silent TORs have been under-investigated. Additionally, a few

studies have attempted to compare takeover scenarios across varying levels of urgency.

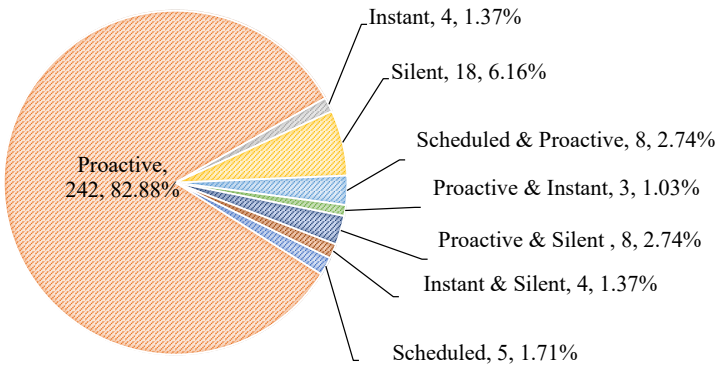


Figure 6. Urgency level of safety-critical scenarios.

4.4. Human performance in safety-critical scenarios

This section examines how the source of harm and urgency level influence drivers' takeover performance, drawing on the studies that reported scenario-related outcome measures. As previously mentioned, most existing research has focused on strategic or tactical ODD exit scenarios involving scheduled or proactive TORs. Only a few studies have examined drivers' takeover performance across scenarios with varying sources of harm and urgency levels. **Table 4** provides a comprehensive list of these studies, detailing the source of harm, urgency levels, and their impacts on drivers' takeover performance.

Given the varying terminology used across studies to describe failure types, we categorized the scenarios according to our proposed taxonomy for clarity. As shown in Table 4, drivers generally exhibit better lateral control quality, a higher intervention rate, and greater accuracy (i.e., successful intervention rate) in proactive TOR scenarios compared to instant or silent TOR scenarios. Nevertheless, conflict results have been found regarding the influence of

the source of harm and urgency level on reaction time and longitudinal control quality (DeGuzman et al., 2020; Mishler & Chen, 2023; Payre et al., 2023; Yao et al., 2020, 2021; Y. Zhang et al., 2023; Zhou et al., 2020)

Table 4. The effect of the source of harm and urgency levels on takeover performance.

Reference	Failure type indicated in the paper	Source of harm	Urgency level	Scenario Description	Findings
Yao et al. (2021)	System failure ODD exit	Operational ODD exit Tactical ODD exit	Instant TOR Proactive TOR	The scenarios for both failure types had the same roadworks, freeway exit ramp, and fog. In the system failure condition, the TOR was issued as soon as automation deactivation (Operational ODD exit and Instant TOR); while in ODD exit condition, the TOR was issued 7s ahead (Tactical ODD exit and Proactive TOR).	• Less reaction time (RT) in system failure scenarios compared to ODD exit scenarios • Better lateral control in ODD exit scenarios compared to system failure scenarios • No significant difference in longitudinal control
Yao et al. (2020)	System failure ODD exit	Operational ODD exit Tactical ODD exit	Instant TOR Proactive TOR		• Less RT in system failure scenarios • Better lateral control in ODD exit scenarios compared to system failure scenarios • No significant difference in longitudinal control
Mishler & Chen (2023)	System malfunction System limit	System malfunction Tactical ODD exit	Silent TOR Proactive TOR	The scenarios for both failure types are the same, which was a construction site appeared after the vehicle crested a hill. In the system limit condition, a TOR was issued as soon as the hazard became visible (Tactical ODD exit and Proactive	• Less RT in system limit failures compared to system malfunction failures • Higher accuracy in system limit failures compared to system malfunction failures

				TOR); while in the system failure condition, no TOR was issued (System malfunction and Silent TOR).	
Y. Zhang et al., (2023)	Silent failure Alerted failure	System malfunction System malfunction	Silent TOR Instant TOR	The scenarios for both failure types were the same, which was a steering loss situation. In the alerted failure condition, a TOR was issued at the time of steering loss (System malfunction and Instant TOR); while in the silent failure condition, no TOR was issued (System malfunction and Silent TOR).	• Less RT in alerted failures compared to silent failures • Better lateral control in alerted failures compared to silent failures • Better longitudinal control in silent failures compared to alerted failures
Payre et al. (2023)	Silent failure Explicit failure	System malfunction System malfunction	Silent TOR Instant TOR	In the silent failure condition, a system malfunction occurred during an overtaking maneuver (System malfunction and Silent TOR). In the explicit failure condition, a cyber-attack happened during an overtaking maneuver and a ransomware appeared on the screen (System malfunction and Instant TOR).	• Higher intervention rate in explicit failures compared to silent failures
Zhou et al. (2020)	Un-cognizable limitation Cognizable limitation	Specification insufficiency Tactical ODD exit	Silent TOR Proactive TOR	In the cognizable limitation condition, the system failed to detect the lane due to fog, unclear lane marking or snow, and a TOR was triggered 5 seconds	• Less RT in cognizable limitation scenarios compared to un-cognizable failures

				before automation failure (Tactical ODD exit and Proactive TOR). In the un-cognizable limitation condition, the lane is closed due to a fallen object, construction site, or stopped car, and the system fails with no TOR (Specification insufficiency and Silent TOR).	• Higher accuracy in cognizable limitation scenarios compared to un-cognizable failures
DeGuzman et al. (2020)	System malfunction System limit	System malfunction Tactical ODD exit	Silent TOR Silent TOR	In the system limit condition, the lane keeping system followed the solid line and entered the right-turn lane, failing to drive straight through an intersection (Tactical ODD exit and Silent TOR). In the system malfunction condition, the ego vehicle failed to keep in the lane and veered to the right (System malfunction and Silent TOR).	• Less RT in system limit failure • Less NDRT engagement before system limit failures compared to system malfunction failures • Longer on-road glance before system limit failures compared to system malfunction failures
Merlhiot & Yousfi (2024)	Urgent TOR Planned TOR	Tactical ODD exit Strategic ODD exit	Proactive TOR Scheduled TOR	Bothe failure types involved the same scenarios (a construction zone, and a lane reduction) but with different time budget. In the planned TOR condition, a TOR was presented with a TTC of 30 seconds (Strategic ODD exit and Scheduled TOR); while in the urgent TOR situation, a TOR was	• Less RT during urgent TORs • Less visual attention on road and more at the left mirror during urgent TORs

				triggered with a TTC of 7 seconds (Tactical ODD exit and Proactive TOR).	
Bai & Feng (2023)	No notification Notification	Specification insufficiency Tactical ODD exit	Silent TOR Proactive TOR	There are two scenarios. One was a lane reduction with no notification (Specification insufficiency and Silent TOR). Another one was a construction zone with a notification presented 620 ft (around 189 meters) ahead the hazard (Tactical ODD exit and Proactive TOR.	• Lower mental workload when takeover notification was presented

1

In addition to the source of harm and urgency level, NDRTs represent another important factor influencing drivers' takeover performance. As reported in Section 4.2, the majority (79.5%) of the included studies allowed drivers to engage in NDRTs, reflecting the real-world conditions under which partial and conditional driving automation operates. Previous research has shown that drivers' situation awareness, reaction time, and takeover quality during a takeover can be associated with the NDRT availability (e.g., X. Li et al., 2020, Minhas et al., 2022, Wandtner et al., 2018). At the same time, different NDRTs compete for drivers' visual, cognitive, and physical resources differently, thereby influencing takeover readiness and performance at different levels (Kim et al., 2022; S. C. Lee et al., 2021). In general, NDRTs that demand high levels of visual and cognitive attention can result in delayed takeovers (Kim et al., 2022). Further, cognitive demands have been found to have a stronger negative impact on takeover quality than physical or visual demands (S. C. Lee et al., 2021). Recent research also suggests that drivers' takeover readiness, which is shaped by the type and duration of NDRT engagement, interacts with scenario complexity to impact takeover performance (Lai et al., 2026; Lai, Kuo, et al., 2025). Therefore, it is essential to consider the types of NDRTs drivers are allowed to engage in when failures happen and propose different countermeasures if necessary, either to minimize certain types of distraction or to further support drivers. However, the interactions between NDRT types and scenario characteristics are under-investigated. For example, the influence of different NDRTs on drivers' performance in silent failure scenarios may differ from that in scenarios with proactive TORs, but empirical evidence is rare. Future research should systematically examine how NDRTs influence takeover performance across different takeover scenarios to inform the design of adaptive takeover request systems.

4.5. Intervention strategies for safer control transition

This section reviews the intervention strategies proposed to support safer control transitions in the included studies. These interventions typically fall into two main categories: driver education and human-machine interfaces (HMIs) (Roberts, 2024). For HMIs, according to K.-T. Chen et al. (2023), the essential information for facilitating safer takeover transitions can be classified into four types: ODD boundary information, environment and traffic information, automation transparency (e.g., the status, operations, and uncertainties of the system), and vehicle diagnostics (e.g., hardware or software faults). The included studies involving the above-mentioned intervention strategies are summarized in **Table 5** by intervention type and the type of information delivered to the driver. In Table 5, we have further divided HMIs into two types based on whether information is provided on an ongoing basis (i.e., sustained HMI) or only when a TOR is issued. Besides, a Sankey diagram (Figure 7) illustrates the relationship between scenarios and intervention strategies. This diagram incorporates data from 37 studies, with some studies featuring multiple combinations of scenarios and intervention strategies. Consequently, the width of the links and nodes in the Sankey diagram represents the frequency of these combinations rather than the number of individual studies.

4.5.1. Prevalence of intervention strategies

Interestingly, our investigation revealed distinct preferences among various intervention strategies regarding the type of information they provide. Notably, information about the ODD boundary is primarily conveyed through driver education before driving automation is used.

Conversely, automation transparency-related information is primarily conveyed through HMIs in real time, and environmental and traffic information is mostly provided when the TOR is issued. Besides, in terms of the scenarios, it is observed that the ODD boundary information has been utilized to assist drivers in all types of scenarios, the environment and traffic information plays an important role in tactical ODD exit scenarios, and the automation transparency information is preferred in more urgent scenarios, including the operation ODD exit and malfunction scenarios. Finally, none of the studies explored the impact of providing vehicle diagnostics information on drivers' takeover behaviors.

Table 5. Studies on intervention strategies to support control transition.

	Drive education	HMI (TOR)	HMI (sustained)
ODD boundary information	(Boelhouwer et al., 2019; Chai et al., 2025; DeGuzman & Donmez, 2024; Ebnali et al., 2019; Hergeth et al., 2017; C. Huang et al., 2024; T. Liu et al., 2018; Meteier et al., 2020; Roberts et al., 2024; Zhou et al., 2019, 2020; Zhou, Itoh, et al., 2021a, 2021b; Zhou, Kamijo, et al., 2021)	(Matsuo et al., 2024)	(Seppelt & Lee, 2007)
Environment and traffic information	NA	(An et al., 2020; Q. Chen et al., 2023; Forster et al., 2017; W.-C. Huang et al., 2024; Körber et al., 2018; Lai, Tsai, et al., 2025; Merlhiot & Yousfi, 2024; Qiu et al., 2025; Saito et al., 2022; Wang et al., 2022; Wright et al., 2017, 2018; Wu et al., 2023)	(Meteier et al., 2020; Pratticò et al., 2025; B. Yang et al., 2022; Yu et al., 2025)

Automation transparency	NA	(Zang & Jeon, 2025)	(Cohen-Lazry et al., 2020; Jung et al., 2023a; S. Lee et al., 2023; Ono et al., 2019; Pratticò et al., 2025)
Vehicle diagnostics	NA	NA	NA

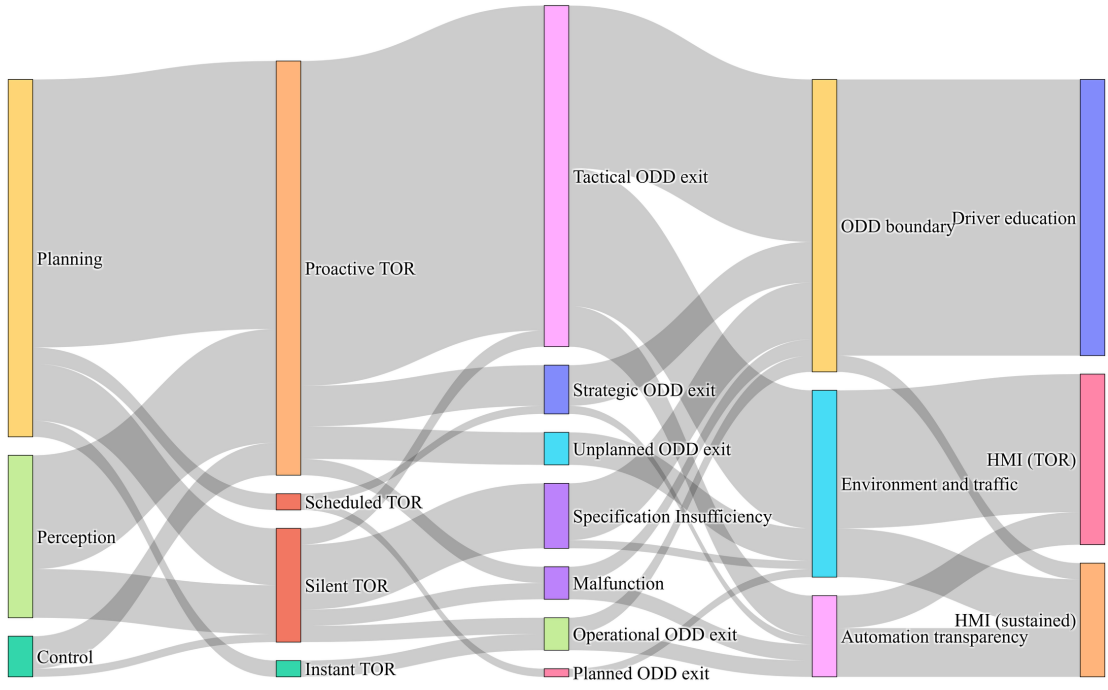


Figure 7. Sankey Diagram of intervention strategies in different scenarios (with each column indicating trigger phase, urgency level, source of harm, information type, and type of intervention).

4.5.2. Effects of intervention strategies

It is generally found that adequate information regarding the ODD boundary of driving automation can enhance drivers' situation awareness (Meteier et al., 2020), takeover performance (Ebnali et al., 2019; Hergeth et al., 2017; Zhou et al., 2019; Zhou, Itoh, et al., 2021b), and trust in the system (Hergeth et al., 2017). However, the degree of enhancement

varies depending on factors such as the form of training (e.g., video vs. simulator), and the explicit level of the information (e.g., general introduction of the possibility of failures; functional operations that the automation cannot perform, such as an automatic lane change; or specifical scenarios that the system cannot handle, such as a fog zone). It has also been found that providing illustrative examples of the limitations of driving automation can enhance drivers' ability to generalize learned knowledge to unfamiliar scenarios, thereby improving their takeover performance (T. Liu et al., 2018; Zhou et al., 2020; Zhou, Itoh, et al., 2021a). Besides, the positive effect of ODD boundary information was observed to be more significant at the early stage of driving automation use (Hergeth et al., 2017; Zhou et al., 2019).

In terms of HMI, providing additional environment and traffic information along with TOR was found to be able to draw drivers visual attention back to the road (Saito et al., 2022), enhance their hazard perception ability (Wright et al., 2017), situation awareness (Wang et al., 2022), takeover quality (An et al., 2020; Forster et al., 2017; Wu et al., 2023), and lead to more defensive driving behaviors (i.e., more brake pedal application and lower speed) (Wright et al., 2018). Drivers' self-reported understanding of the driving automation also increased when environment and traffic information were provided (Körber et al., 2018). However, drivers' reaction to the TOR can be delayed in proactive ODD exit scenarios when the HMI is provided (An et al., 2020; Saito et al., 2022). Providing automation transparency information along with TORs can benefit drivers' situation awareness and takeover performance, but the amount of information should be controlled to avoid distraction or suboptimal performance (Zang & Jeon, 2025). At the same time, providing ODD boundary information, along with TORs and the reason for the system failure, can enhance drivers' understanding of the situation and facilitate

earlier response. Specifically, after experiencing TORs with ODD boundary information, drivers can initiate a takeover more actively when the system fails to issue TORs in the future (Matsuo et al., 2024).

Additionally, the positive effects of providing sustained information through HMIs were also observed. Specifically, sustained information about the environment and traffic has been found to be associated with higher perceived safety (B. Yang et al., 2022) and takeover quality (Meteier et al., 2020), without delaying drivers' reactions (Meteier et al., 2020; B. Yang et al., 2022). Sustained information about the status and planned maneuvers of the driving automation (i.e., automation transparency) can improve drivers' visual attention allocation strategy (Cohen-Lazry et al., 2020) and takeover quality (Jung et al., 2023a; S. Lee et al., 2023; Ono et al., 2019), and even shorten their reaction time in takeover events (Jung et al., 2023a; S. Lee et al., 2023; Ono et al., 2019).

5. Discussion and Implications

To bridge the gap between technical difficulties and users' perceptions of takeover scenarios, we proposed a new taxonomy of safety-critical scenarios that require transferring control from driving automation to human drivers. This taxonomy considers the reasons leading to safety-critical scenarios from a technology perspective (i.e., source of harm), the nature of driving tasks (i.e., trigger phase), and the time buffer for drivers to respond (i.e., urgency level). It is thus compatible with both technology-oriented and behavior-oriented taxonomies in industry and academia. Based on the new taxonomy, a systematic review of safety-critical scenarios in existing empirical studies was conducted.

5.1. Safety-critical scenarios adopted in previous research

First, although previous research has investigated approaches to improving takeover quality in various safety-critical scenarios, most existing studies have focused on a limited set of scenarios. The planning-related scenarios characterized by simple external trigger conditions, such as encountering a static obstacle ahead or approaching a highway exit, are the most common in previous research. Further, a majority of the studies focused on external-condition-related critical scenarios but rarely considered internal faults of the driving automation. Research has found that when users are aware of or informed about the causes of a system failure, their trust in the system is less affected by the failure (Petersen et al., 2019). Thus, though both internal-fault-related and external-condition-related failures may lead to the same outcome (e.g., a crash into the front vehicle), drivers may perceive these two types of failures differently and take different strategies to handle the scenarios (DeGuzman et al., 2020; Mishler & Chen, 2023; Payre et al., 2023; Yao et al., 2020, 2021; Y. Zhang et al., 2023; Zhou et al., 2020). As such, drivers' performance and the effects of the countermeasures should be evaluated across different scenarios.

However, very few studies have investigated how scenario heterogeneity affects drivers' behavior and, in turn, performance in safety-critical scenarios. For those we identified (see **Table 4**), different terminology and taxonomies were used, and the descriptions of the scenarios were incomplete in some studies, making meta-analysis infeasible. Thus, a systematic approach to categorizing these scenarios in human-driving-automation research is crucial and can guide the design and strategies for driving automation to facilitate better transfer of control in safety-critical scenarios. Our taxonomy can thus guide the selection and justification of scenarios for

researchers and industry, ensuring that choices of safety-critical scenarios in experimental designs and evaluations of driving automation are theoretically motivated rather than arbitrary.

Further, we defined the urgency level based on the lead time/existence of TOR in the scenario. It was found that most scenarios adopted proactive TOR, which can be initiated anywhere from a few seconds to tens of seconds before a crash. As we mentioned in our taxonomy, such a TOR is only possible with a strategic or tactical ODD exit. However, the driving automation at this stage is not good at handling tactical driving tasks (Llorca, 2021), and initiating proactive TOR might be practically difficult (except for initiating proactive TOR based on strategic ODD exit). In most of the driving-automation-involved accidents in recent years, the system failed to initiate TOR (NTSB, 2017). Thus, although technological advances may facilitate proactive TOR in the future, instant and silent TOR may be more safety-critical and warrant greater attention. Future research should prioritize these underexplored scenario types to develop a more complete understanding of takeover challenges.

5.2. Approaches to improve the takeover performance in safety-critical scenarios

Scenarios with varying failure types and urgency levels pose distinct challenges for drivers, necessitating specific knowledge, skills, and levels of situational awareness (McCall et al., 2016). Thus, different information may be needed to support drivers in these scenarios (K.-T. Chen et al., 2023; Roberts, 2024). For example, vehicle diagnostics information may be preferred for internal faults (S.-H. Chen et al., 2011); but automation transparency information (S. Lee et al., 2023), environment and traffic information (Zhou, Kamijo, et al., 2021), and ODD boundary information (Zhou, Kamijo, et al., 2021) may be needed for drivers to judge

the necessity of actions in external-fault-related scenarios. These strategies can complement each other to improve drivers' takeover performance in various safety-critical situations.

Further, in previous research, educating drivers about the ODD boundary of driving automation has been found to enhance their takeover performance in ODD exit (Boelhouwer et al., 2019; Meteier et al., 2020), specification insufficiency (T. Liu et al., 2018; Zhou et al., 2020), and malfunction scenarios (Zhou, Itoh, et al., 2021a; Zhou, Kamijo, et al., 2021). However, the effectiveness of driver education may diminish over time. Thus, providing sustained ODD boundary information through in-vehicle HMIs may also work (Seppelt & Lee, 2007), but has been underinvestigated. Previous research also found that providing environment and traffic information (Wu et al., 2023; B. Yang et al., 2022; Zhou, Kamijo, et al., 2021) or automation-transparency-related information (Cohen-Lazry et al., 2020; Jung et al., 2023b; S. Lee et al., 2023; Ono et al., 2019) through HMIs can improve drivers' takeover performance. However, additional information during TOR issuance (e.g., verbal messages or visual cues that inform drivers of potential hazards) has been found to delay drivers' reactions (An et al., 2020; Saito et al., 2022), possibly due to increased mental workload. Thus, enhancing drivers' own capability to anticipate and respond to external hazards may help.

Thus, vehicle manufacturers should adjust their warning strategies for driving automation accordingly, for example, providing progressive alerts for scheduled TORs, clear environmental and traffic information for instant TORs, and automation transparency information and fail-safe mechanisms for silent TORs. They should also consider the joint effects of safety-critical scenarios and driver states (e.g., whether the driver is engaging in NDRT, Pan et al., 2025; Shahini et al., 2023) on takeover performance, and adjust warning strategies based on driver

state monitoring. Further, for regulatory agencies, our taxonomy and review highlight the need for standardized training programs to help drivers understand the various challenges they may encounter when using driving automation, as driver expectations and mental models of automation capabilities have been found to influence takeover performance (Zhou, Itoh, et al., 2021c; Zhou, Kamijo, et al., 2021). This is especially urgent, as we currently lack widely accepted procedures for training and evaluating users of driving automation.

6. Conclusion

The rapid advancement of driving automation technologies has raised the concern of traffic safety. While scenario-based methods have been widely adopted to evaluate the safety of driving automation, existing approaches predominantly focus on the technical aspects of safety-critical scenarios. For systems with partial and conditional automation, where human intervention may be necessary, integrating human factors is essential. In response, we introduced a structured taxonomy of safety-critical scenarios for partially and conditionally automated vehicles, aiming to bridge gaps in the existing literature. This taxonomy provides a comprehensive framework that considers technological difficulties, the nature of driving tasks, and drivers' capabilities. It is thus compatible with previous taxonomies from both academia and industry. We then conducted a systematic review of safety-critical scenarios in empirical studies, using our proposed taxonomy. We identified several major research gaps, including highly unbalanced scenario types used in previous studies, insufficient understanding of discrepancies in information needs across scenarios, and a lack of diversity in interventions for specific scenarios. Overall, this study offers valuable insights for researchers, manufacturers,

and policymakers, though further empirical research is needed to validate the effectiveness of our taxonomy.

List of Abbreviations

Abbreviation	Terminology
ADAS	Advanced driving assistant system
TOR	Takeover request
TORlt	Takeover request lead time
HMI	Human-machine interface
ODD	Operational design domain
DDT	Dynamic driving task
OEDR	Object and event detection and response
FuSa	Functional safety
SOTIF	Safety of the intended functionality

Acknowledgments

This research was funded by the National Natural Science Foundation of China (Grant No. 52202425).

CRediT AUTHORSHIP CONTRIBUTION STATEMENT

Song Yan: Writing – Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing - original draft; Ange Wang: Formal analysis, Methodology; Jiyao Wang: Formal analysis, Validation; Chunxi Huang: Conceptualization, Formal analysis, Investigation; Dengbo He: Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing.

Data Availability

The data that support the findings of this study are openly available in GitHub at https://github.com/songyan8/Driving-Automation-Failure-Scenarios.

Conflict of Interest

No potential competing interest was reported by the authors.

References

AITO. (2025). *AITO M5 owner's manual*. AITO. https://hima.auto/dam/hima-site/cn/wenjie/service/pdf/m5-new-product-manual-20250208.pdf

An, S., Maeda, M., Mao, X., & Itoh, M. (2020). Effects of request-to-intervene message contents on driver performance and safety under conditionally automated driving system. In *IFAC-PapersOnLine* (Vol. 53, Issue 5, pp. 203–206). https://doi.org/10.1016/j.ifacol.2021.04.099

Bai, X., & Feng, J. (2023). Unlocking safer driving: How answering questions help takeovers in partially automated driving. In *Proceedings of the Human Factors and Ergonomics Society* (Vol. 67, Issue 1, pp. 1221–1227). https://doi.org/10.1177/21695067231192202

Boelhouwer, A., van den Beukel, A. P., van der Voort, M. C., & Martens, M. H. (2019). Should I take over? Does system knowledge help drivers in making take-over decisions while driving a partially automated car? In *Transportation Research Part F: Traffic Psychology and Behaviour* (Vol. 60, pp. 669–684). https://doi.org/10.1016/j.trf.2018.11.016

Chai, C., Weng, S., Feng, R., Wang, J., Wong, Y. D., & Wang, Y. (2025). A behavioral inoculation method to improve critical takeover performance of novice drivers in conditionally automated driving. In *Traffic Injury Prevention*. https://doi.org/10.1080/15389588.2025.2451699

Chen, K.-T., Chen, H.-Y. W., Bisantz, A., Shen, S., & Sahin, E. (2023). Where Failures May Occur in Automated Driving: A Fault Tree Analysis Approach. *Journal of Cognitive Engineering and Decision Making*, *17*(2), 147–165. https://doi.org/10.1177/15553434221116254

Chen, Q., Li, J., Miyoshi, J. K., & Tei, K. (2023). Designing visual-auditory attention-guiding takeover request for semi-autonomous driving. *2023 IEEE 13th International Conference on Consumer Electronics - Berlin (Icce-Berlin)*, 1–6. https://doi.org/10.1109/ICCE-Berlin58801.2023.10375658

Chen, S.-H., Wang, J.-F., Wei, Y., Shang, J., & Kao, S.-Y. (2011). The implementation of real-time on-line vehicle diagnostics and early fault estimation system. *2011 Fifth International Conference on Genetic and Evolutionary Computing*, 13–16.

Chen, W., Sawaragi, T., & Hiraoka, T. (2023). Comparing driver reaction and mental workload of visual and auditory take-over request from perspective of driver characteristics and eye-tracking metrics. In *Transportation Research Part F: Traffic Psychology and Behaviour* (Vol. 97, pp. 396–

410). https://doi.org/10.1016/j.trf.2023.07.012
Chia, W. M. D., Keoh, S. L., Goh, C., & Johnson, C. (2022). Risk Assessment Methodologies for Autonomous Driving: A Survey. *IEEE Transactions on Intelligent Transportation Systems*, *23*(10), 16923–16939. IEEE Transactions on Intelligent Transportation Systems. https://doi.org/10.1109/TITS.2022.3163747
Cohen-Lazry, G., Borowsky, A., & Oron-Gilad, T. (2020). The impact of auditory continual feedback on take-overs in Level 3 automated vehicles. In *Transportation Research Part F: Traffic Psychology and Behaviour* (Vol. 75, pp. 145–159). https://doi.org/10.1016/j.trf.2020.10.003
DeGuzman, C. A., & Donmez, B. (2024). Training benefits driver behaviour while using automation with an attention monitoring system. In *Transportation Research Part C: Emerging Technologies* (Vol. 165). https://doi.org/10.1016/j.trc.2024.104752
DeGuzman, C. A., Hopkins, S. A., & Donmez, B. (2020). Driver Takeover Performance and Monitoring Behavior with Driving Automation at System-Limit versus System-Malfunction Failures. *Transportation Research Record: Journal of the Transportation Research Board*, *2674*(4), 140–151. https://doi.org/10.1177/0361198120912228
Ding, W., Xu, C., Arief, M., Lin, H., Li, B., & Zhao, D. (2023). A Survey on Safety-Critical Driving Scenario Generation—A Methodological Perspective. *IEEE Transactions on Intelligent Transportation Systems*, *24*(7), 6971–6988. IEEE Transactions on Intelligent Transportation Systems. https://doi.org/10.1109/TITS.2023.3259322
Ebnali, M., Hulme, K., Ebnali-Heidari, A., & Mazloumi, A. (2019). How does training effect users' attitudes and skills needed for highly automated driving? In *Transportation Research Part F: Traffic Psychology and Behaviour* (Vol. 66, pp. 184–195). https://doi.org/10.1016/j.trf.2019.09.001
Forster, Y., Naujoks, F., Neukum, A., & Huestegge, L. (2017). Driver compliance to take-over requests with different auditory outputs in conditional automation. In *Accident Analysis and Prevention* (Vol. 109, pp. 18–28). https://doi.org/10.1016/j.aap.2017.09.019
He, D. (2020). *Understanding and Supporting Anticipatory Driving in Automated Vehicles* [Ph.D. Dissertation]. University of Toronto.
Hergeth, S., Lorenz, L., & Krems, J. F. (2017). Prior Familiarization with Takeover Requests Affects Drivers' Takeover Performance and Automation Trust. In *Human Factors* (Vol. 59, Issue 3, pp. 457–470). https://doi.org/10.1177/0018720816678714
Highway Loss Data Institute. (2022). Predicted availability of safety features on registered vehicles—A 2022 update. *Highway Loss Data Institute Bulletin*, *2*(39), 1–16.
Hong, S., Maeng, J., Kim, H. J., & Yang, J. H. (2022). Development of Warning Methods for Planned and Unplanned Takeover Requests in a Simulated Automated Driving Vehicle. *Proceedings of the 14th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, AutomotiveUI '22*, 65–74. https://doi.org/10.1145/3543174.3545999
Huang, C., Wang, Z., & He, D. (2024). The effect of dual training on the hazard response and attention allocation of novice drivers when driving with advanced driver assistance system. In *Accident Analysis and Prevention* (Vol. 208). https://doi.org/10.1016/j.aap.2024.107802
Huang, W.-C., Fan, L.-H., Han, Z.-J., & Niu, Y.-F. (2024). Enhancing safety in conditionally automated driving: Can more takeover request visual information make a difference in hazard scenarios with varied hazard visibility? In *Accident Analysis and Prevention* (Vol. 205). https://doi.org/10.1016/j.aap.2024.107687
ISO. (2018). *Road vehicles—Functional safety—Part 1: Vocabulary* (ISO 26262-1:2018).

ISO. (2022a). *Road vehicles—Safety of the intended functionality* (ISO 21448:2022).

ISO. (2022b). *Road vehicles—Test scenarios for automated driving systems—Scenario based safety evaluation framework* (ISO 34502:2022).

Ito, M. (2021). ODD description methods for automated driving vehicle and verifiability for safety. *JUCS - Journal of Universal Computer Science*, *27*, 796–810. https://doi.org/10.3897/jucs.72333

Jansen, R. J., Tinga, A. M., de Zwart, R., & van der Kint, S. T. (2022). Devil in the details: Systematic review of TOR signals in automated driving with a generic classification framework. In *Transportation Research Part F: Traffic Psychology and Behaviour* (Vol. 91, pp. 274–328). https://doi.org/10.1016/j.trf.2022.10.009

Jung, K. H., Labriola, J. T., & Baek, H. (2023a). Projecting the planned trajectory of a Level–2 automated vehicle in the windshield: Effects on human drivers' take–over response to silent failures. In *Applied Ergonomics* (Vol. 111). https://doi.org/10.1016/j.apergo.2023.104047

Jung, K. H., Labriola, J. T., & Baek, H. (2023b). Projecting the planned trajectory of a Level–2 automated vehicle in the windshield: Effects on human drivers' take–over response to silent failures. *Applied Ergonomics*, *111*. https://doi.org/10.1016/j.apergo.2023.104047

Kalb, L., Streit, L., & Bengler, K. (2018). What Drivers Make of Directional Maneuver Information in a Take-Over Scenario. In *Proceedings—2018 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2018* (pp. 3859–3864). https://doi.org/10.1109/SMC.2018.00654

Kanaan, D., & Donmez, B. (2024). How Are Automation Failures Characterized in the Driving Domain? Insights From a Scoping Review. *Journal of Cognitive Engineering and Decision Making*, 15553434241230604. https://doi.org/10.1177/15553434241230604

Kim, J., Kim, W., Kim, H.-S., Lee, S.-J., Kwon, O.-C., & Yoon, D. (2022). A novel study on subjective driver readiness in terms of non-driving related tasks and take-over performance. *ICT Express*, *8*(1), 91–96. https://doi.org/10.1016/j.icte.2021.04.008

Ko, S., Kutchek, K., Zhang, Y., & Jeon, M. (2022). Effects of Non-Speech Auditory Cues on Control Transition Behaviors in Semi-Automated Vehicles: Empirical Study, Modeling, and Validation. In *International Journal of Human-Computer Interaction* (Vol. 38, Issue 2, pp. 185–200). https://doi.org/10.1080/10447318.2021.1937876

Körber, M., Prasch, L., & Bengler, K. (2018). Why Do I Have to Drive Now? Post Hoc Explanations of Takeover Requests. In *Human Factors* (Vol. 60, Issue 3, pp. 305–323). https://doi.org/10.1177/0018720817747730

Kraus, J., Scholz, D., Stiegemeier, D., & Baumann, M. (2020). The More You Know: Trust Dynamics and Calibration in Highly Automated Driving and the Effects of Take-Overs, System Malfunction, and System Transparency. In *Human Factors* (Vol. 62, Issue 5, pp. 718–736). https://doi.org/10.1177/0018720819853686

Lai, H.-Y., Chou, C.-H., Wang, P.-K., Kuo, T.-Y., & Chen, Y.-J. (2026). Effects of readiness deprivation on takeover with varying time budget in conditional automated driving scenarios. *IEEE Transactions on Human-Machine Systems*, *56*(1), 171–181. https://doi.org/10.1109/THMS.2025.3595269

Lai, H.-Y., Kuo, T.-Y., Chou, J.-H., Wang, P.-K., & Chen, Y.-J. (2025). Predicting takeover performance and identifying behavioral patterns in autonomous vehicles based on readiness state and scenario complexity. *IEEE Transactions on Intelligent Transportation Systems*, *26*(11), 21108–21122. https://doi.org/10.1109/TITS.2025.3589326

Lai, H.-Y., Tsai, C.-C., & Chen, Y.-J. (2025). Incorporating situational information with varying

context accessibility for designing advanced takeover requests. In *International Conference on Human-Computer Interaction*. International Conference on Human-Computer Interaction. https://doi.org/10.1007/978-3-031-94159-7_39

Lee, S. C., Yoon, S. H., & Ji, Y. G. (2021). Effects of non-driving-related task attributes on takeover quality in automated vehicles. *International Journal of Human–Computer Interaction*, *37*(3), 211–219. https://doi.org/10.1080/10447318.2020.1815361

Lee, S., Hong, J., Jeon, G., Jo, J., Boo, S., Kim, H., Jung, S., Park, J., Choi, I., & Kim, S. (2023). Investigating effects of multimodal explanations using multiple In-vehicle displays for takeover request in conditionally automated driving. In *Transportation Research Part F: Traffic Psychology and Behaviour* (Vol. 96, pp. 1–22). https://doi.org/10.1016/j.trf.2023.05.014

Li, X., Schroeter, R., Rakotonirainy, A., Kuo, J., & Lenné, M. G. (2020). Effects of different non-driving-related-task display modes on drivers' eye-movement patterns during take-over in an automated vehicle. In *Transportation Research Part F: Traffic Psychology and Behaviour* (Vol. 70, pp. 135–148). https://doi.org/10.1016/j.trf.2020.03.001

Li, Y., Li, K., Zheng, Y., Morys, B., Pan, S., & Wang, J. (2021). Threat Assessment Techniques in Intelligent Vehicles: A Comparative Survey. *IEEE Intelligent Transportation Systems Magazine*, *13*(4), 71–91. IEEE Intelligent Transportation Systems Magazine. https://doi.org/10.1109/MITS.2019.2907633

Litman, T. (2023). *Autonomous vehicle implementation predictions: Implications for transport planning*. Victoria Transport Policy Institute Victoria, Canada.

Liu, T., Zhou, H., Itoh, M., & Kitazaki, S. (2018). The Impact of Explanation on Possibility of Hazard Detection Failure on Driver Intervention under Partial Driving Automation. In *IEEE Intelligent Vehicles Symposium, Proceedings* (Vols. 2018-June, pp. 150–155). https://doi.org/10.1109/IVS.2018.8500521

Liu, W., Li, Q., Wang, Z., Wang, W., Zeng, C., & Cheng, B. (2022). Takeover Directly or Gradually? Comparison of Single Stage and Dual Stage Human-Machine Interface on Drivers' Visual Behaviors and Subjective Ratings over Cognitive Demand, Motoric Demand, and Time Demand. *Proceedings of the 4th International Conference on Big Data Engineering, BDE '22*, 60–70. https://doi.org/10.1145/3538950.3538959

Llorca, D. F. (2021). *From driving automation systems to autonomous vehicles: Clarifying the terminology* (arXiv:2103.10844). arXiv. https://doi.org/10.48550/arXiv.2103.10844

Matsuo, R., Liu, H., Hiraoka, T., & Wada, T. (2024). Enhancing the driver's comprehension of ADS's system limitations: An HMI providing request-to-intervene trigger and reason explanation. In *2024 IEEE 4th International Conference on Human-machine Systems (ICHMS)* (pp. 1–7). https://doi.org/10.1109/ICHMS59971.2024.10555611

McCall, R., McGee, F., Meschtscherjakov, A., Louveton, N., & Engel, T. (2016). Towards A Taxonomy of Autonomous Vehicle Handover Situations. *Proceedings of the 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 193–200. https://doi.org/10.1145/3003715.3005456

Merlhiot, G., & Yousfi, E. (2024). Augmented reality HMI for distracted drivers in a level 3 automation: Effects on takeover performance and safety. In *Transportation Research Part F: Traffic Psychology and Behaviour* (Vol. 107, pp. 820–833). https://doi.org/10.1016/j.trf.2024.10.002

Meteier, Q., Capallera, M., de Salis, E., Sonderegger, A., Angelini, L., Carrino, S., Abou Khaled, O., & Mugellini, E. (2020). The Effect of Instructions and Context-Related Information about

Limitations of Conditionally Automated Vehicles on Situation Awareness. *12th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, AutomotiveUI '20*, 241–251. https://doi.org/10.1145/3409120.3410649

Michon, J. A. (1985). A Critical View of Driver Behavior Models: What Do We Know, What Should We Do? In L. Evans & R. C. Schwing (Eds.), *Human Behavior and Traffic Safety* (pp. 485–524). Springer US. https://doi.org/10.1007/978-1-4613-2173-6_19

Minhas, S., Hernandez-Sabate, A., Ehsan, S., & McDonald-Maier, K. D. (2022). Effects of Non-Driving Related Tasks during Self-Driving Mode. In *IEEE Transactions on Intelligent Transportation Systems* (Vol. 23, Issue 2, pp. 1391–1399). https://doi.org/10.1109/TITS.2020.3025542

Mishler, S., & Chen, J. (2023). Effect of automation failure type on trust development in driving automation systems. In *Applied Ergonomics* (Vol. 106). https://doi.org/10.1016/j.apergo.2022.103913

Mobileye. (2020, July 23). *Understanding L2+ in five questions*. Mobileye. https://www.mobileye.com/blog/understanding-l2-in-five-questions/

Morando, A., Victor, T., Bengler, K., & Dozza, M. (2021). Users' response to critical situations in automated driving: Rear-ends, sideswipes, and false warnings. In *IEEE Transactions on Intelligent Transportation Systems* (Vol. 22, Issue 5, pp. 2809–2822). https://doi.org/10.1109/TITS.2020.2975429

Najm, W. G., Smith, J. D., & Yanagisawa, M. (2007). *Pre-Crash Scenario Typology for Crash Avoidance Research* (DOT HS 810 767; p. 767). National Highway Traffic Safety Administration (NHTSA).

Neelofar, & Aleti, A. (2022). *Identifying and Explaining Safety-critical Scenarios for Autonomous Vehicles via Key Features* (arXiv:2212.07566; Version 1). arXiv. http://arxiv.org/abs/2212.07566

NHTSA. (2022). *Standing General Order on Crash Reporting*. National Highway Traffic Safety Administration (NHTSA). https://www.nhtsa.gov/laws-regulations/standing-general-order-crash-reporting

NTSB. (2017). *Collision Between a Car Operating With Automated Vehicle Control Systems and a Tractor-Semitrailer Truck Near Williston, Florida May 7, 2016* (Highway Accident Report NTSB/HAR-17/02). National Transportation Safety Board. https://www.ntsb.gov/investigations/AccidentReports/Reports/HAR1702.pdf

NTSB. (2019). *Collision Between Vehicle Controlled by Developmental Automated Driving System and Pedestrian, Tempe, Arizona, March 18, 2018* (Highway Accident Report NTSB/HAR-19/03). National Transportation Safety Board. https://www.ntsb.gov/investigations/accidentreports/reports/har1903.pdf

Ono, S., Sasaki, H., Kumon, H., Fuwamoto, Y., Kondo, S., Narumi, T., Tanikawa, T., & Hirose, M. (2019). Improvement of driver active interventions during automated driving by displaying trajectory pointers—A driving simulator study. In *Traffic Injury Prevention* (Vol. 20, Issue sup1, pp. S152–S156). https://doi.org/10.1080/15389588.2019.1610170

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *The BMJ*, *372*, n71. https://doi.org/10.1136/bmj.n71

Pan, H., Payre, W., Wang, Y., & Gao, Z. (2025). How do visual and cognitive non-driving related tasks affect drivers' visual attention and takeover performance in conditionally automated driving? In *Journal of Transportation Safety & Security* (Vol. 17, Issue 1, pp. 97–123). https://doi.org/10.1080/19439962.2024.2368118

Payre, W., Perelló-March, J., & Birrell, S. (2023). Under pressure: Effect of a ransomware and a screen failure on trust and driving performance in an automated car simulation. In *Frontiers in Psychology* (Vol. 14). https://doi.org/10.3389/fpsyg.2023.1078723

Pendleton, S. D., Andersen, H., Du, X., Shen, X., Meghjani, M., Eng, Y. H., Rus, D., & Ang, M. H. (2017). Perception, planning, control, and coordination for autonomous vehicles. *Machines*, *5*(1), 6. https://doi.org/10.3390/machines5010006

Petersen, L., Robert, L., Yang, X. J., & Tilbury, D. (2019). *Situational Awareness, Driver's Trust in Automated Driving Systems and Secondary Task Performance* (SSRN Scholarly Paper No. 3345543). https://doi.org/10.2139/ssrn.3345543

Pratticò, F. G., Valente, L., & Lamberti, F. (2025). Crying jaywalker! Notifying take-over-requests and critical events in operational driving domain of autonomous vehicles via multimodal interfaces. In *International Conference on Intelligent User Interfaces, Proceedings IUI* (pp. 463–476). https://doi.org/10.1145/3708359.3712126

Qiu, Z., Lai, H., Wang, M., Wu, H., Hu, X., Liu, H., & Hu, Z. (2025). Takeover requests signaled by arrows in an automated driving system: The influence of information direction and lead time on performance. In *Transportation Research Record*. https://doi.org/10.1177/03611981251327204

Roberts, S. C. (2024). Failures in Driving Automation Systems: Definitions, Taxonomy, and Prevention Mechanisms. *Journal of Cognitive Engineering and Decision Making*, 15553434241227534. https://doi.org/10.1177/15553434241227534

Roberts, S. C., Hanson, W., Ebadi, Y., Talreja, N., Knodler, M. A., & Fisher, D. L. (2024). Evaluation of a 3M (mistakes, mentoring, and mastery) training program for transfer of control situations in a level 2 automated driving system. In *Applied Ergonomics* (Vol. 116). https://doi.org/10.1016/j.apergo.2023.104215

SAE International. (2021). *Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles* (SAE J3016).

Saito, Y., Watahiki, Y., Leung, C., Zhou, H., & Itoh, M. (2022). Effect of verbal messages with reminders to communicate driving situations to alter driver behavior in conditional driving automation. In *Transportation Research Part F: Traffic Psychology and Behaviour* (Vol. 85, pp. 69–82). https://doi.org/10.1016/j.trf.2022.01.003

Samuel, S., Borowsky, A., Zilberstein, S., & Fisher, D. L. (2016). Minimum time to situation awareness in scenarios involving transfer of control from an automated driving suite. *Transportation Research Record: Journal of the Transportation Research Board*, *2602*(1), 115–120. https://doi.org/10.3141/2602-14

Seppelt, B. D., & Lee, J. D. (2007). Making adaptive cruise control (ACC) limits visible. *International Journal of Human-Computer Studies*, *65*(3), 192–205. https://doi.org/10.1016/j.ijhcs.2006.10.001

Shahini, F., Park, J., Welch, K., & Zahabi, M. (2023). Effects of unreliable automation, non-driving related task, and takeover time budget on drivers' takeover performance and workload. In *Ergonomics* (Vol. 66, Issue 2, pp. 182–197). https://doi.org/10.1080/00140139.2022.2069868

Staplin, L., Mastromatto, T., Lococo, K. H., Kenneth, W., Gish, K. W., & Brooks, J. O. (2018). *A*

framework for automated driving system testable cases and scenarios (DOT HS 812 623). National Highway Traffic Safety Administration (NHTSA).

Sun, M., & He, D. (2025). The influence of cognitive distractions and driving experience on hazard perception performance during partially automated driving. *Accident Analysis & Prevention*, *221*, 108202. https://doi.org/10.1016/j.aap.2025.108202

Tan, X., & Zhang, Y. (2023). Analyzing driver strategy for scheduled takeovers under the effect of multi-stage takeover request design. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *67*(1), 1197–1203. https://doi.org/10.1177/21695067231192422

Tesla. (2024). *Autopilot and full self-driving capability*. Tesla. https://www.tesla.com/support/autopilot

Tesla. (2025). *Model 3 owner's manual* [Concept]. Tesla. https://www.tesla.com/ownersmanual/model3/en_us/GUID-20F2262F-CDF6-408E-A752-2AD9B0CC2FD6.html

UNECE. (2021). *UN regulation no. 157—Automated lane keeping systems (ALKS)* (E/ECE/TRANS/505/Rev.3/Add.156). https://unece.org/transport/documents/2021/03/standards/un-regulation-no-157-automated-lane-keeping-systems-alks

Wandtner, B., Schömig, N., & Schmidt, G. (2018). Effects of Non-Driving Related Task Modalities on Takeover Performance in Highly Automated Driving. In *Human Factors* (Vol. 60, Issue 6, pp. 870–881). https://doi.org/10.1177/0018720818768199

Wang, L., Yu, B., Zhang, H., & Hu, H. (2022). Effects of visual planning support on take-over performance in conditional automated driving. In *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC* (Vols. 2022-October, pp. 3219–3224). https://doi.org/10.1109/ITSC55140.2022.9922165

Wright, T. J., Agrawal, R., Samuel, S., Wang, Y., Zilberstein, S., & Fisher, D. L. (2017). Effects of alert cue specificity on situation awareness in transfer of control in level 3 automation. In *Transportation Research Record* (Vol. 2663, pp. 27–33). https://doi.org/10.3141/2663-04

Wright, T. J., Agrawal, R., Samuel, S., Wang, Y., Zilberstein, S., & Fisher, D. L. (2018). Effective cues for accelerating young drivers' time to transfer control following a period of conditional automation. In *Accident Analysis and Prevention* (Vol. 116, pp. 14–20). https://doi.org/10.1016/j.aap.2017.10.005

Wu, Z., Zhao, L., Liu, G., Chai, J., Huang, J., & Ai, X. (2023). The Effect of AR-HUD Takeover Assistance Types on Driver Situation Awareness in Highly Automated Driving: A 360-Degree Panorama Experiment. In *International Journal of Human-Computer Interaction*. https://doi.org/10.1080/10447318.2023.2254645

Yamani, Y., Glassman, J., Alruwaili, A., Yahoodik, S. E., Davis, E., Lugo, S., Xie, K., & Ishak, S. (2023). Post take-over performance varies in drivers of automated and connected vehicle technology in near-miss scenarios. *Human Factors*, 187208231219184. https://doi.org/10.1177/00187208231219184

Yan, S., Huang, C., & He, D. (2024). *CH-LSTTM: a taxonomy of traffic hazards*. 2024 IEEE 4th International Conference on Human-Machine Systems (ICHMS).

Yang, B., Saito, T., Wang, Z., Kitazaki, S., & Nakano, K. (2022). Influences of Different Traffic Information on Driver Behaviors While Interacting with Oncoming Traffic in Level 2 Automated Driving. In *International Journal of Human-Computer Interaction*.

https://doi.org/10.1080/10447318.2022.2121202
Yang, Y., Karakaya, B., Dominioni, G. C., Kawabe, K., & Bengler, K. (2018). An HMI Concept to Improve Driver's Visual Behavior and Situation Awareness in Automated Vehicle. In *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC* (Vols. 2018-November, pp. 650–655). https://doi.org/10.1109/ITSC.2018.8569986
Yao, H., An, S., Zhou, H., & Itoh, M. (2020). How does driver takeover worsen in a sudden system failure of conditionally automated driving? In *2020 59th Annual Conference of the Society of Instrument and Control Engineers of Japan, SICE 2020* (pp. 1469–1474). https://doi.org/10.23919/SICE48898.2020.9240345
Yao, H., An, S., Zhou, H., & Itoh, M. (2021). Driver takeover performance in conditionally automated driving: Sudden system failure situation versus ODD exit situation. In *SICE Journal of Control, Measurement, and System Integration* (Vol. 14, Issue 1, pp. 89–96). https://doi.org/10.1080/18824889.2021.1913861
Yu, Z., Zhai, L., Jiang, K., Yu, S., Zhang, B., Deng, Q., & Huang, Z. (2025). Impact of information-assisted modalities and levels on driver takeover performance in conditional automated driving. In *Accident Analysis and Prevention* (Vol. 220). https://doi.org/10.1016/j.aap.2025.108158
Zang, J., & Jeon, M. (2025). When more is less: Finding the optimal balance of intelligent agents' transparency in level 3 automated vehicles. In *International Journal of Human-Computer Studies* (Vol. 193). https://doi.org/10.1016/j.ijhcs.2024.103384
Zhang, J., Zhang, Z., Zhang, T., Zhang, Y., & Chen, S. (2025). Effects of time interval and request modality on driver takeover responses: Identifying the optimal time interval for two-stage warning system. In *Accident Analysis and Prevention* (Vol. 215). https://doi.org/10.1016/j.aap.2025.108008
Zhang, W., Ma, S., Yang, Z., Wu, C., Li, H., & Shi, J. (2023). How to Determine the Time-Intervals of Two-Stage Warning Systems in Different Traffic Densities? An Investigation on the Takeover Process in Automated Driving. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): 14018 LNAI* (pp. 406–422). https://doi.org/10.1007/978-3-031-35389-5_28
Zhang, X., Tao, J., Tan, K., Torngren, M., Sanchez, J. M. G., Ramli, M. R., Tao, X., Gyllenhammar, M., Wotawa, F., & Mohan, N. (2022). Finding Critical Scenarios for Automated Driving Systems: A Systematic Mapping Study. *IEEE Transactions on Software Engineering*.
Zhang, Y., Lintern, G., Gao, L., & Zhang, Z. (2021). *A Study on Functional Safety, SOTIF and RSS from the Perspective of Human-Automation Interaction* (SAE Technical Paper Nos. 2021-01–0858). SAE International. https://doi.org/10.4271/2021-01-0858
Zhang, Y., Zhou, X., Wang, W., Hu, Y., & Sun, X. (2023). Keeping in the lane! Investigating drivers' performance handling silent vs. Alerted lateral control failures in monotonous partially automated driving. In *International Journal of Industrial Ergonomics* (Vol. 95). https://doi.org/10.1016/j.ergon.2023.103429
Zhou, H., Itoh, M., & Kitazaki, S. (2019). Long-term effect of experiencing system malfunction on driver take-over control in conditional driving automation. In *Conference Proceedings—IEEE International Conference on Systems, Man and Cybernetics* (Vols. 2019-October, pp. 1950–1955). https://doi.org/10.1109/SMC.2019.8913968
Zhou, H., Itoh, M., & Kitazaki, S. (2020). Effect of instructing system limitations on the intervening behavior of drivers in partial driving automation. In *Cognition, Technology and Work* (Vol. 22, Issue 2, pp. 321–334). https://doi.org/10.1007/s10111-019-00568-1

Zhou, H., Itoh, M., & Kitazaki, S. (2021a). How does explanation-based knowledge influence driver take-over in conditional driving automation? In *IEEE Transactions on Human-Machine Systems* (Vol. 51, Issue 3, pp. 188–197). https://doi.org/10.1109/THMS.2021.3051342

Zhou, H., Itoh, M., & Kitazaki, S. (2021b). How does instructed knowledge influence drivers' decision-making in conditional driving automation? In *Lecture Notes in Networks and Systems: 221 LNNS* (pp. 845–852). https://doi.org/10.1007/978-3-030-74608-7_104

Zhou, H., Itoh, M., & Kitazaki, S. (2021c). Influence of Prior General Knowledge on Older Adults' Takeover Performance and Attitude Toward Using Conditionally Automated Driving Systems. In *Proceedings of the Human Factors and Ergonomics Society* (Vol. 65, Issue 1, pp. 1327–1331). https://doi.org/10.1177/1071181321651111

Zhou, H., Kamijo, K., Itoh, M., & Kitazaki, S. (2021). Effects of explanation-based knowledge regarding system functions and driver's roles on driver takeover during conditionally automated driving: A test track study. In *Transportation Research Part F: Traffic Psychology and Behaviour* (Vol. 77, pp. 1–9). https://doi.org/10.1016/j.trf.2020.11.015

Autor Biography

Song Yan received his PhD degree from The Hong Kong University of Science and Technology, a Master's degree from The University of Tokyo, and a Bachelor's degree from Zhejiang University. His research focuses on human factors in automated driving and human-automation interaction.

Ange Wang received his Ph.D from the Hong Kong University of Science and Technology. His research interests lie in human factors in automated driving, cognitive load assessment, and human-centered hardware user experience.

Jiyao Wang received an M.Sc. degree from the Hong Kong University of Science and Technology (HKUST) in 2022, and a Ph.D. degree from HKUST, Guangzhou campus in 2025. Currently, he is a postdoctoral researcher at McGill University, Canada. His research interests include physiological signal measurement and human-aware intelligent systems.

Chunxi Huang is currently an Assistant Professor at the School of Design, Hunan University. He received his PhD degree from the Hong Kong University of Science and Technology. His research mainly focuses on human factors in transportation and human-centered design.

Dengbo He received an M.S. degree from Shanghai Jiao Tong University in 2016 and a PhD degree from the University of Toronto in 2020. He is currently an Assistant Professor at the Thrust of Intelligent Transportation, the Hong Kong University of Science and Technology (Guangzhou).